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Inan et al.

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(54) **WEARABLE TECHNOLOGIES FOR JOINT HEALTH ASSESSMENT**

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A61B 5/0295 (2006.01)

A61B 5/0537 (2021.01)

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(52) **U.S. Cl.**

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(2013.01); *A61B 5/0295* (2013.01); *A61B*
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A61B 5/4585 (2013.01); *A61B 7/006*
(2013.01); *A61B 5/1116* (2013.01); *A61B*
5/1123 (2013.01); *A61B 5/4878* (2013.01);
A61B 5/6828 (2013.01); *A61B 5/7207*
(2013.01)

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(58) **Field of Classification Search**

None

See application file for complete search history.

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(56) **References Cited**

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607/48

(*) Notice: Subject to any disclaimer, the term of this
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U.S.C. 154(b) by 220 days.

* cited by examiner

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(74) *Attorney, Agent, or Firm* — Troutman Pepper

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(65) **Prior Publication Data**

US 2018/0289313 A1 Oct. 11, 2018

(57) **ABSTRACT**

Multi-modal sensing relating to joint acoustic emission and joint bioimpedance. Custom-design analog electronics and electrodes provide high resolution sensing of bioimpedance, microphones and their front-end electronics for capturing sound signals from the joints, rate sensors for identifying joint motions (linear and rotational), and a processor unit for interpretation of the signals. These components are packed into a wearable form factor, which also encapsulates the hardware required to minimize the negative effects of motion artifacts on the signals.

Related U.S. Application Data

(63) Continuation-in-part of application No. 15/577,253,
filed as application No. PCT/US2016/034874 on May
27, 2016.

(Continued)

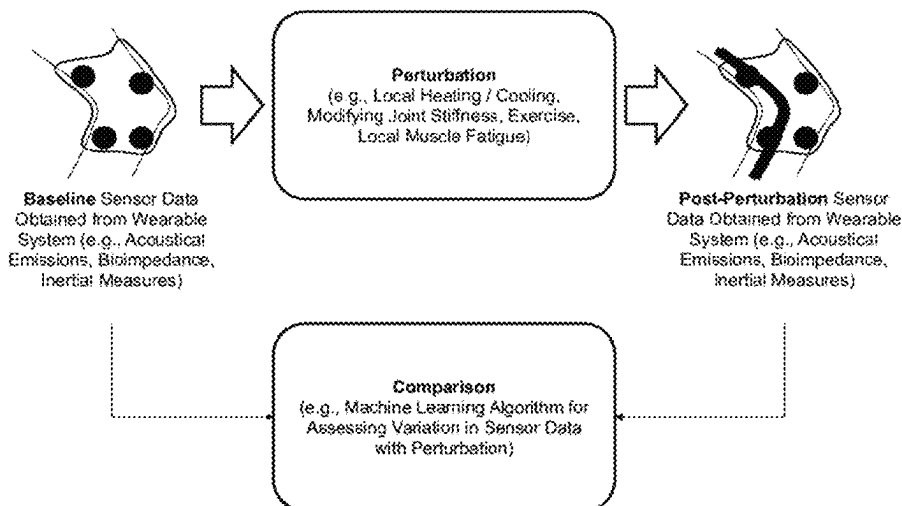
(51) **Int. Cl.**

A61B 5/053 (2021.01)

A61B 5/00 (2006.01)

A61B 5/026 (2006.01)

16 Claims, 32 Drawing Sheets



Related U.S. Application Data

- (60) Provisional application No. 62/505,578, filed on May 12, 2017, provisional application No. 62/166,889, filed on May 27, 2015.

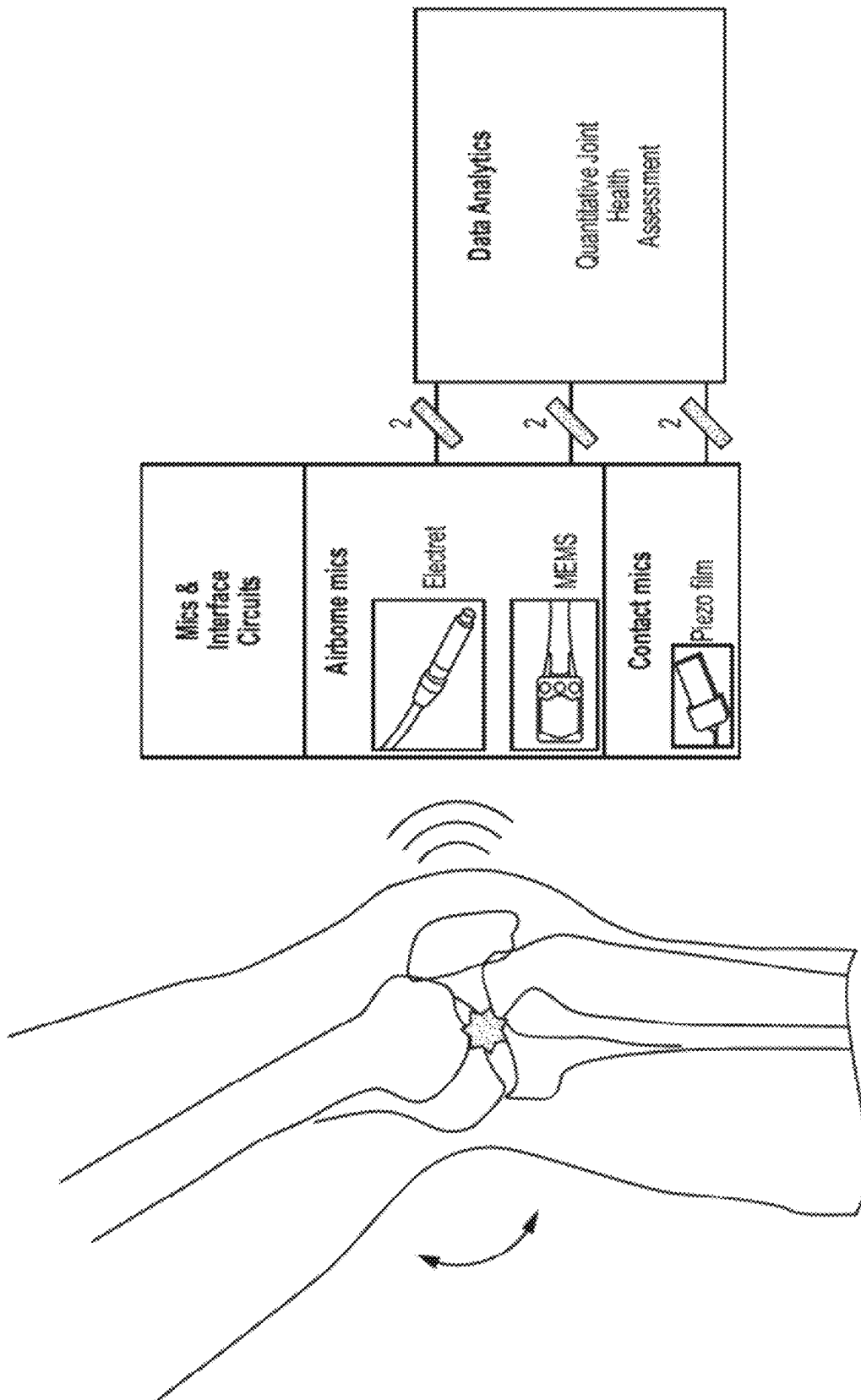


FIG. 1

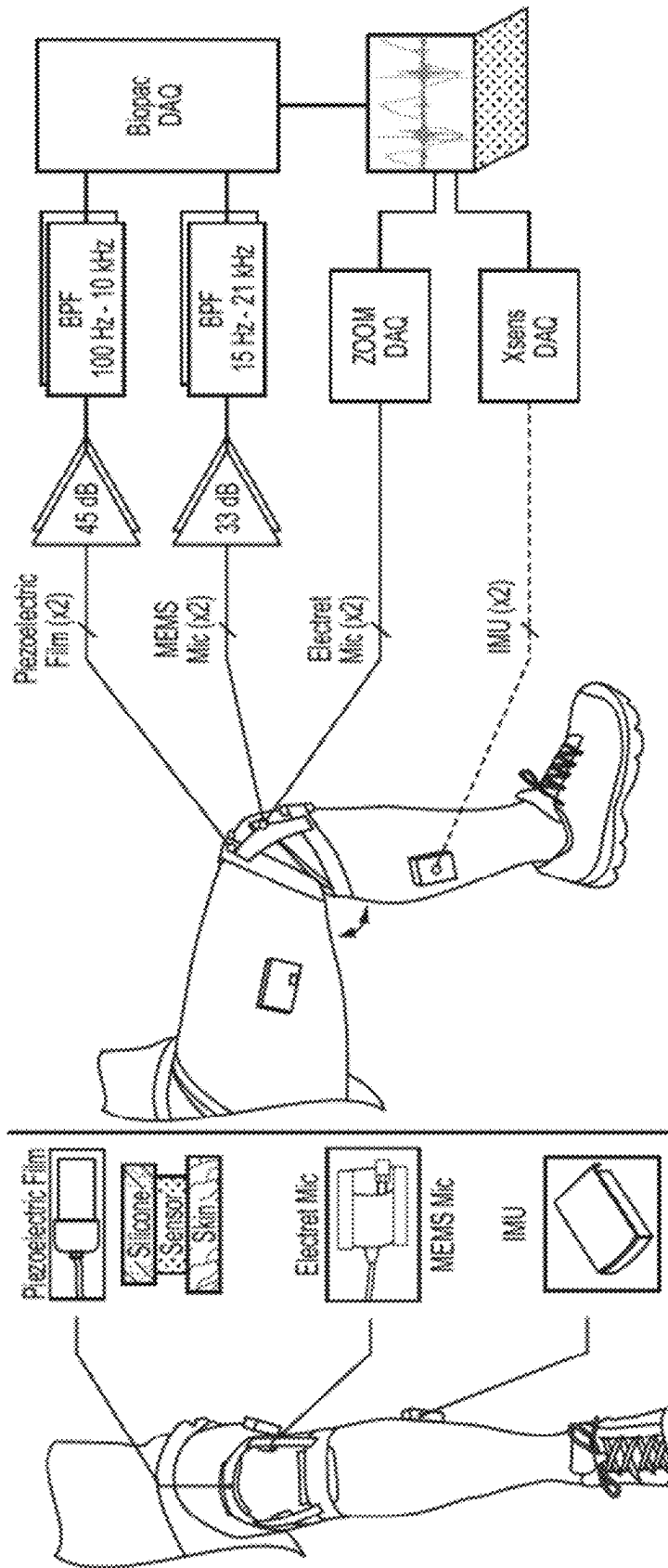


FIG. 2B

FIG. 2A

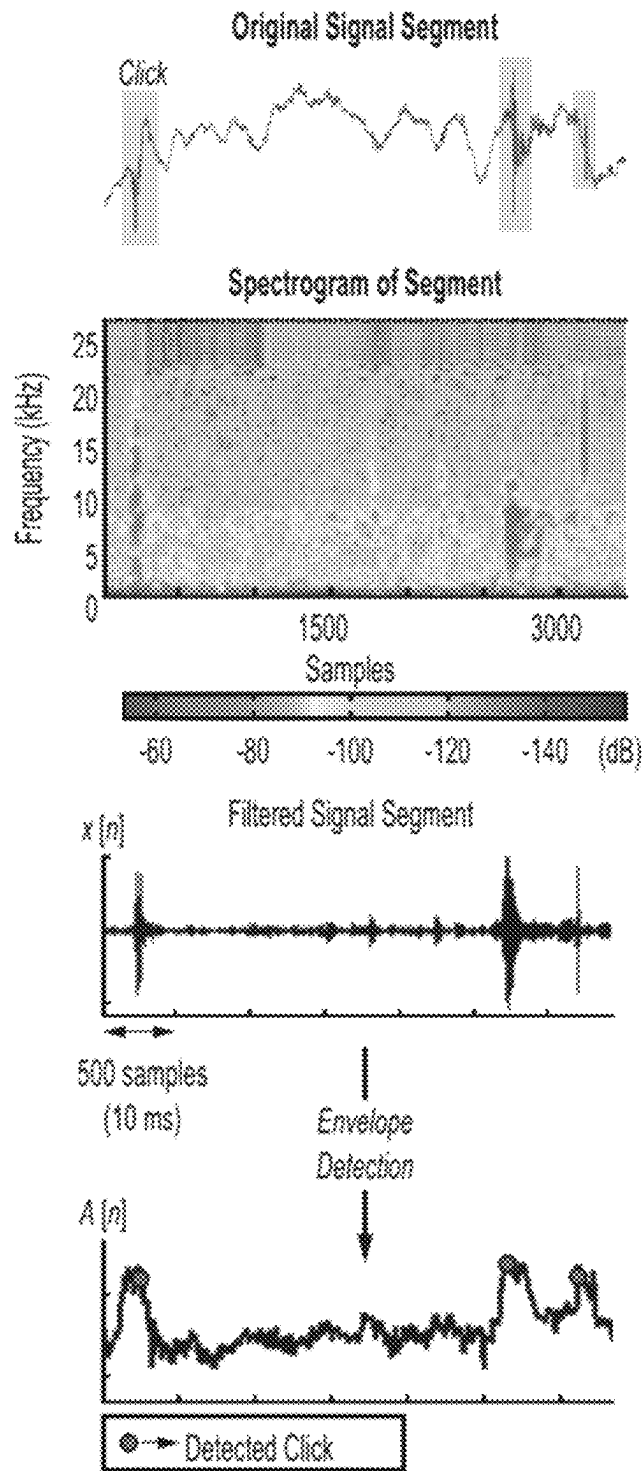


FIG. 3A

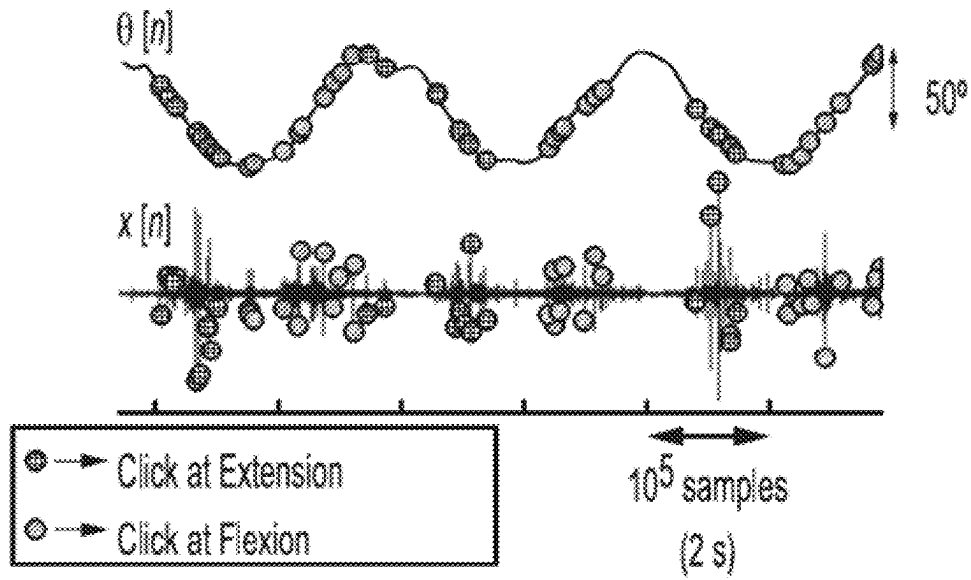


FIG. 3B

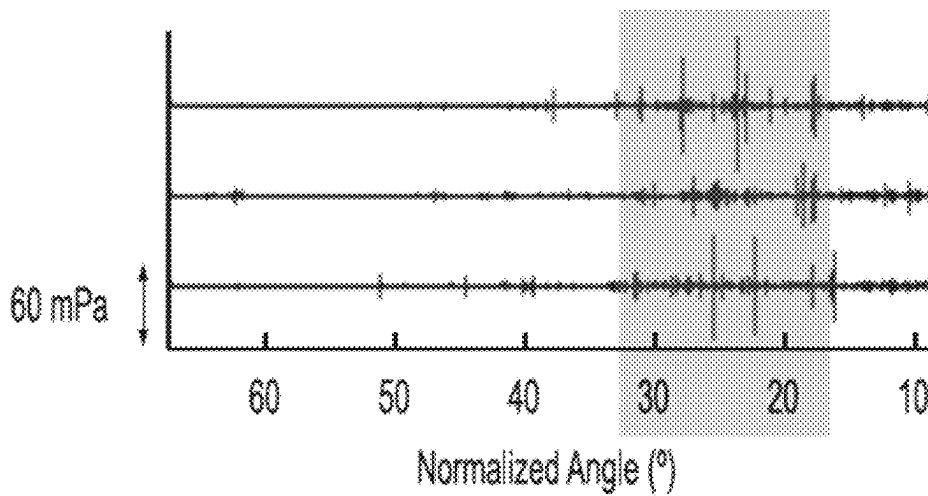


FIG. 3C

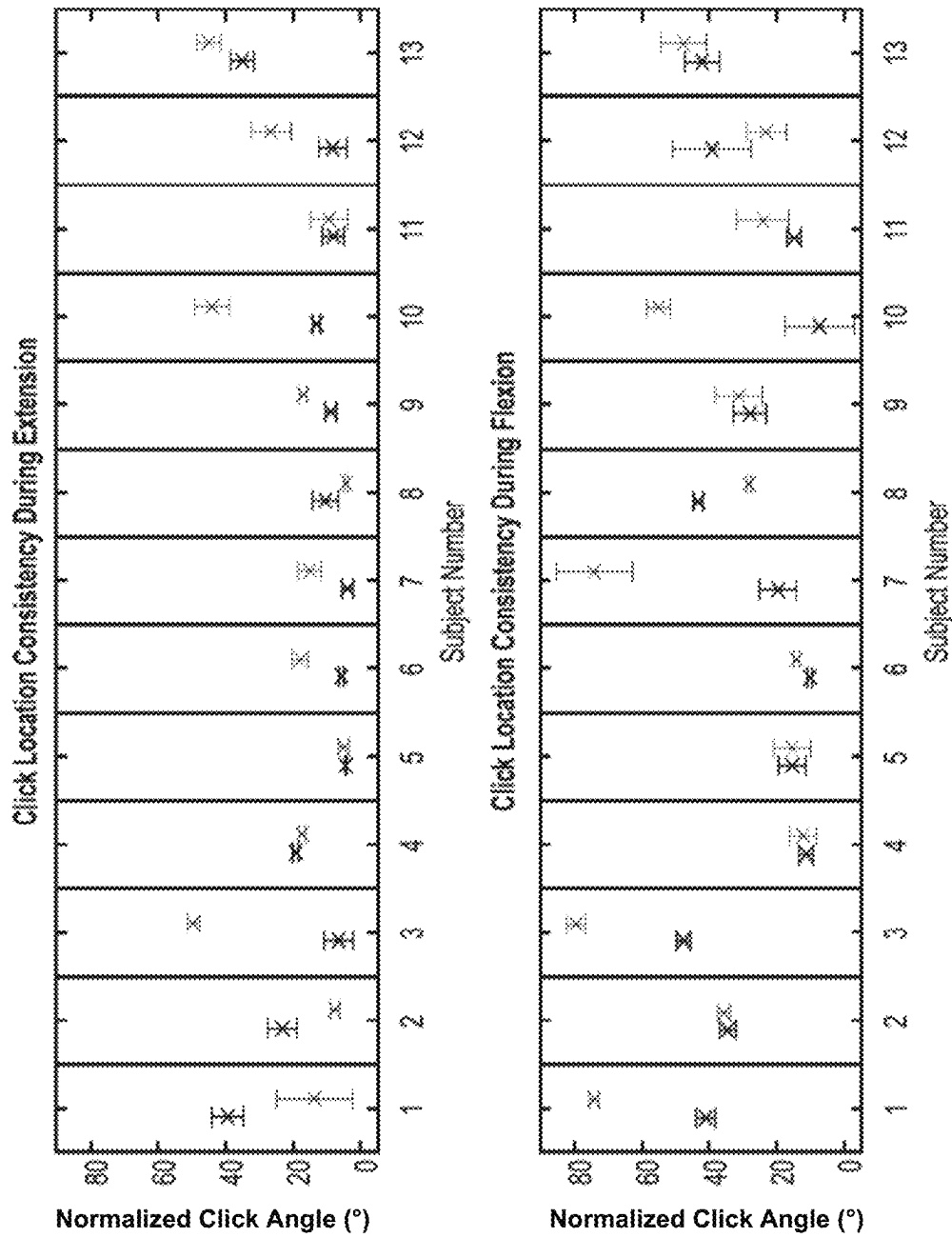


FIG. 3D

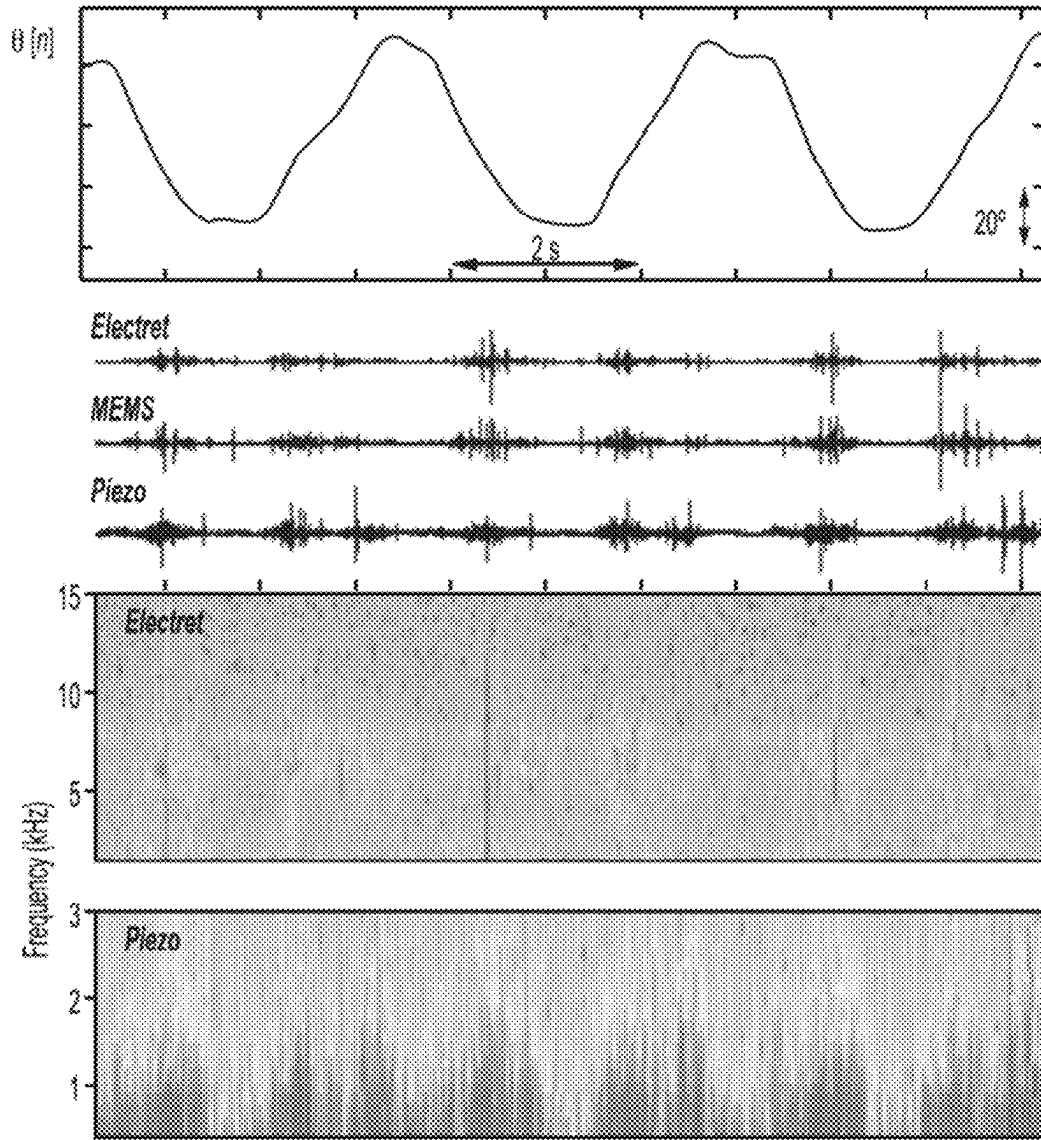


FIG. 4A

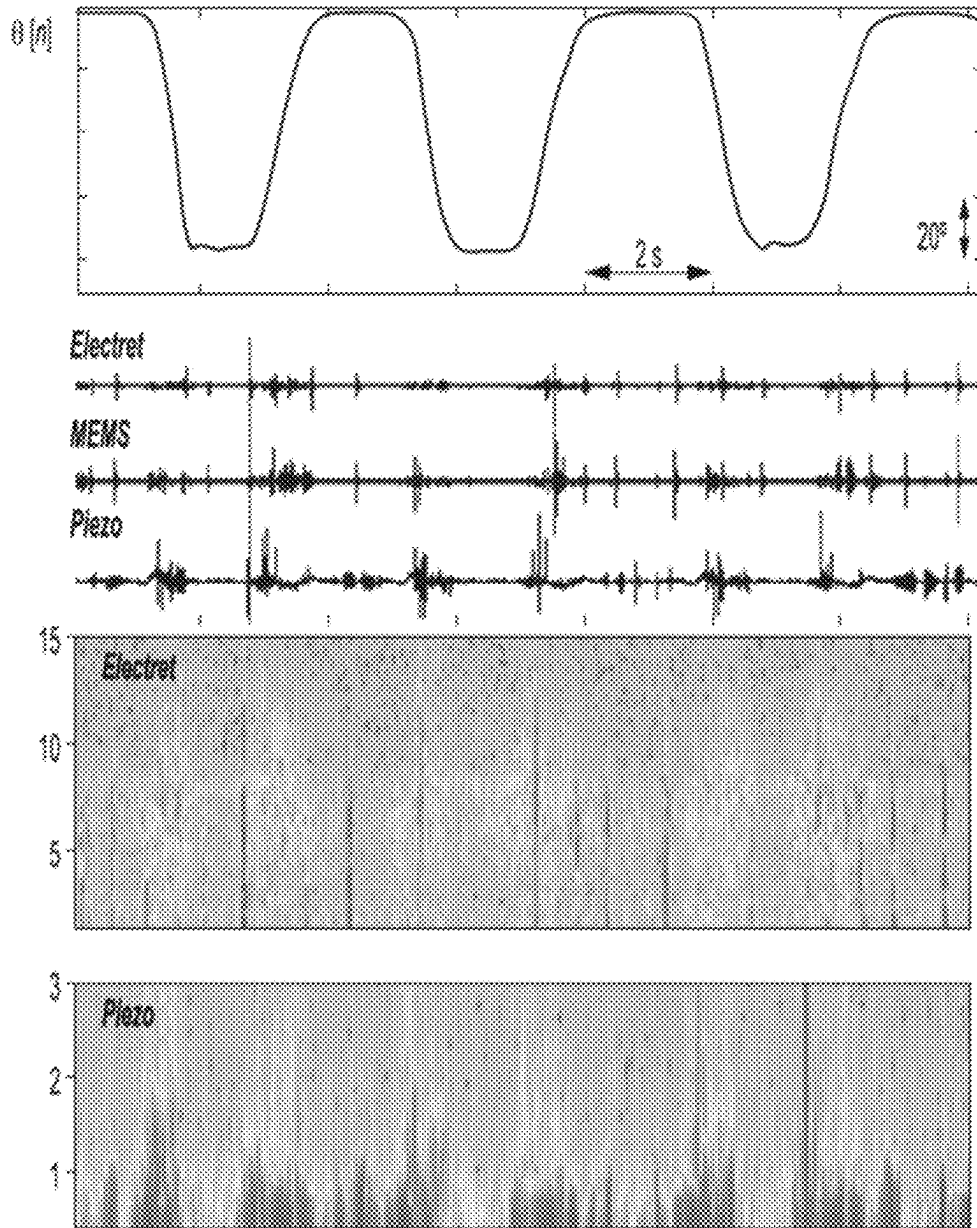


FIG. 4B

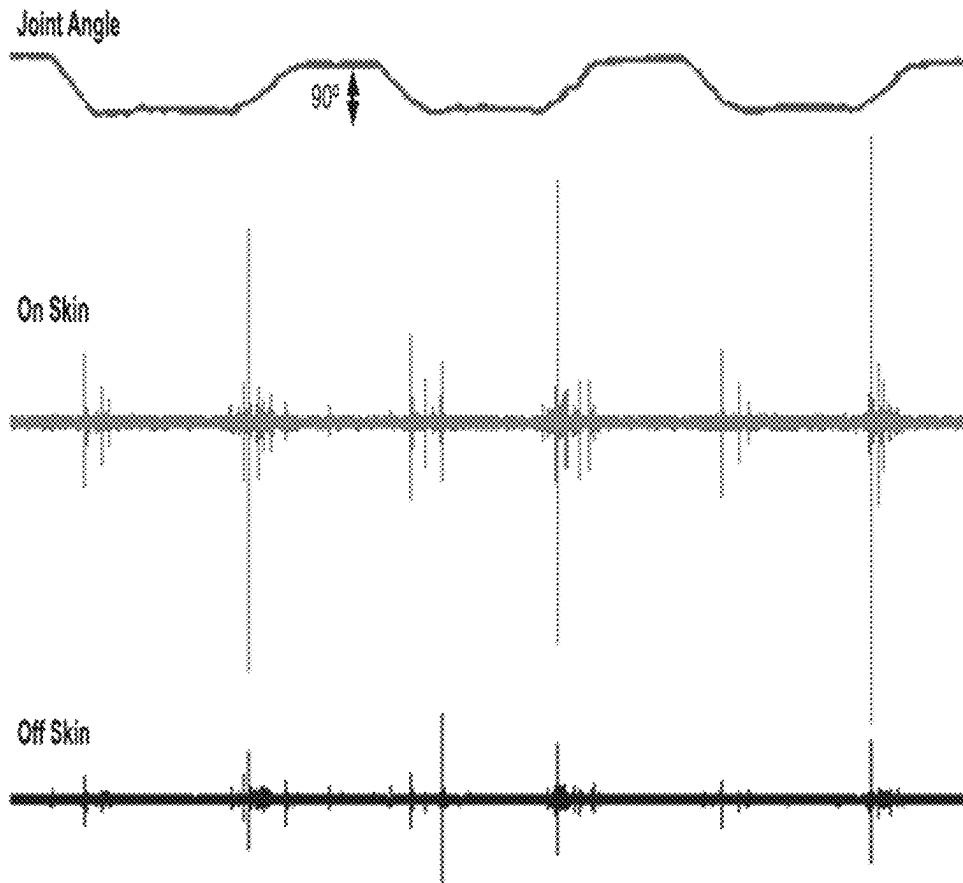


FIG. 5

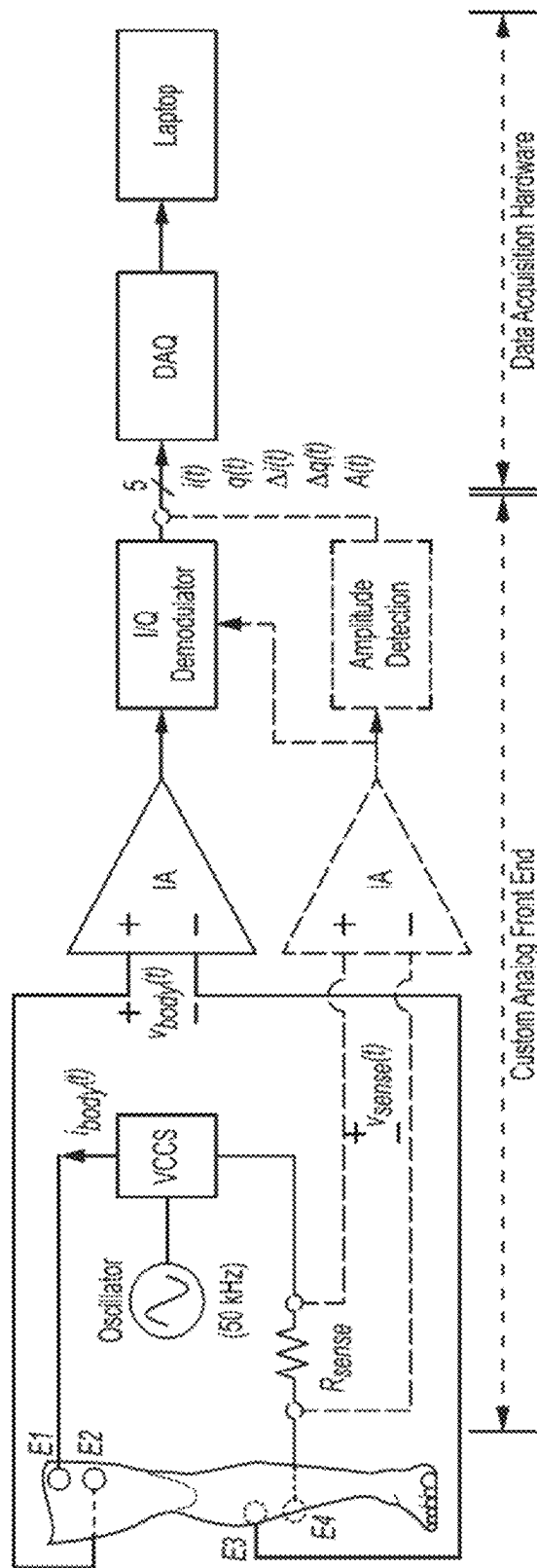


FIG. 6A

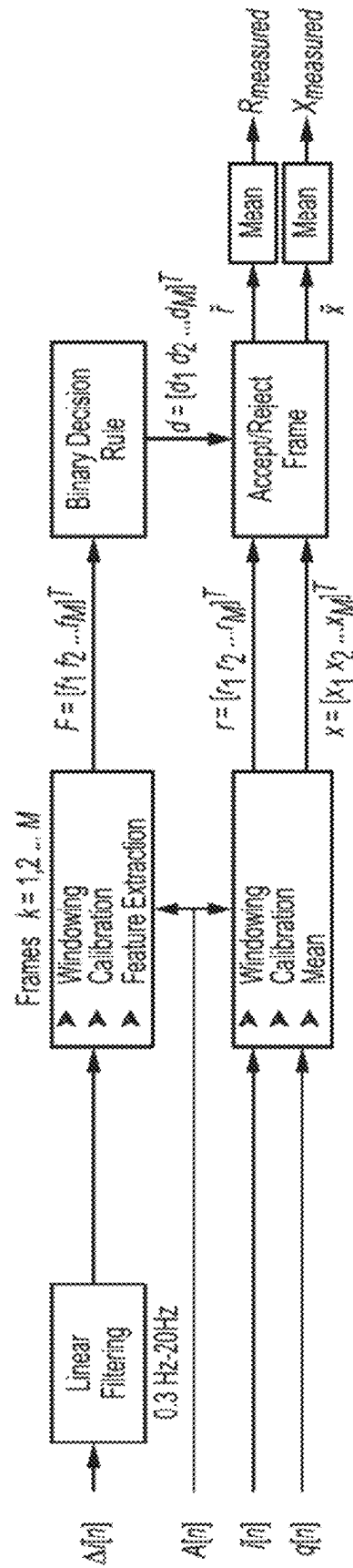


FIG. 6B

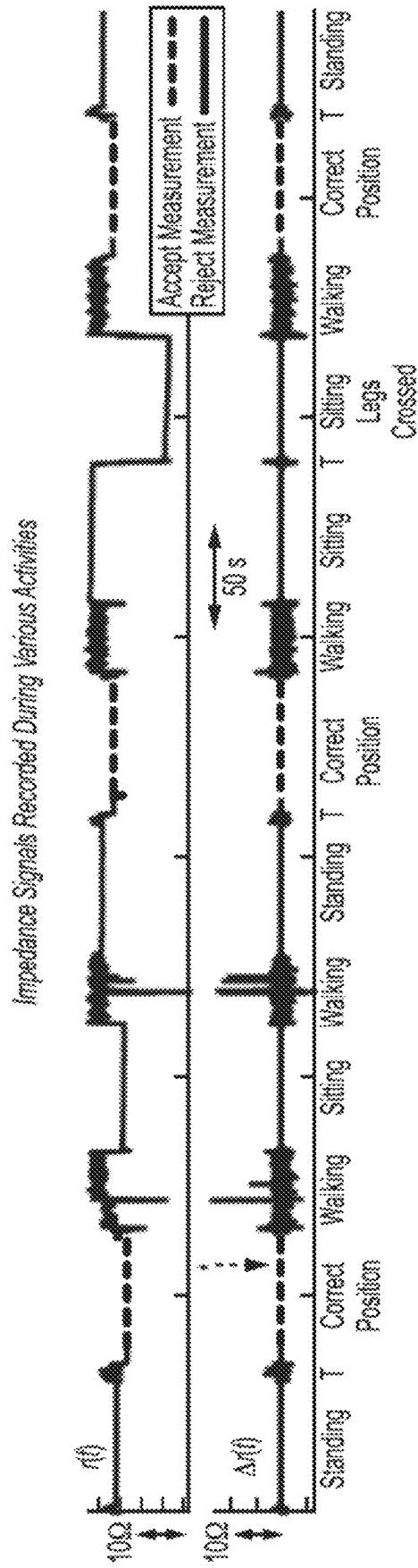


FIG. 7A

Dynamic Resistance ($\Delta r(f)$) Signal at *

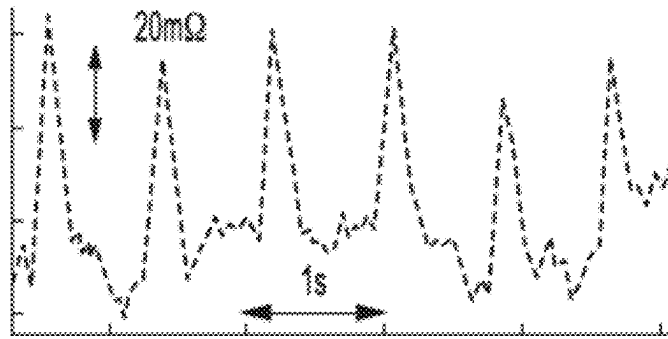


FIG. 7B

Ensemble Averaged $\Delta r(f)$

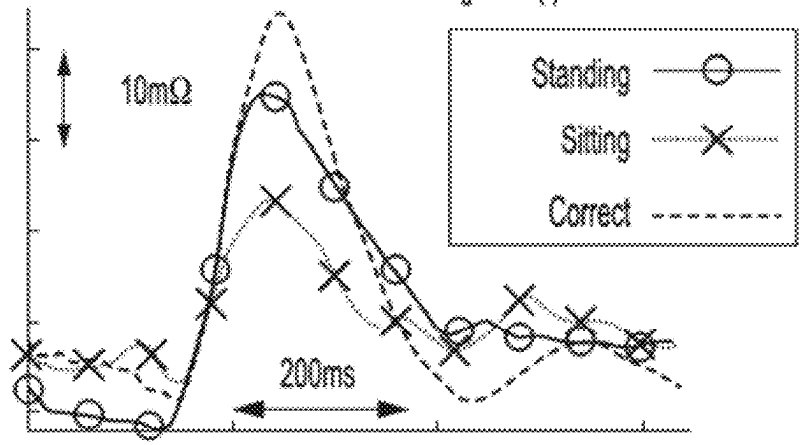


FIG. 7C

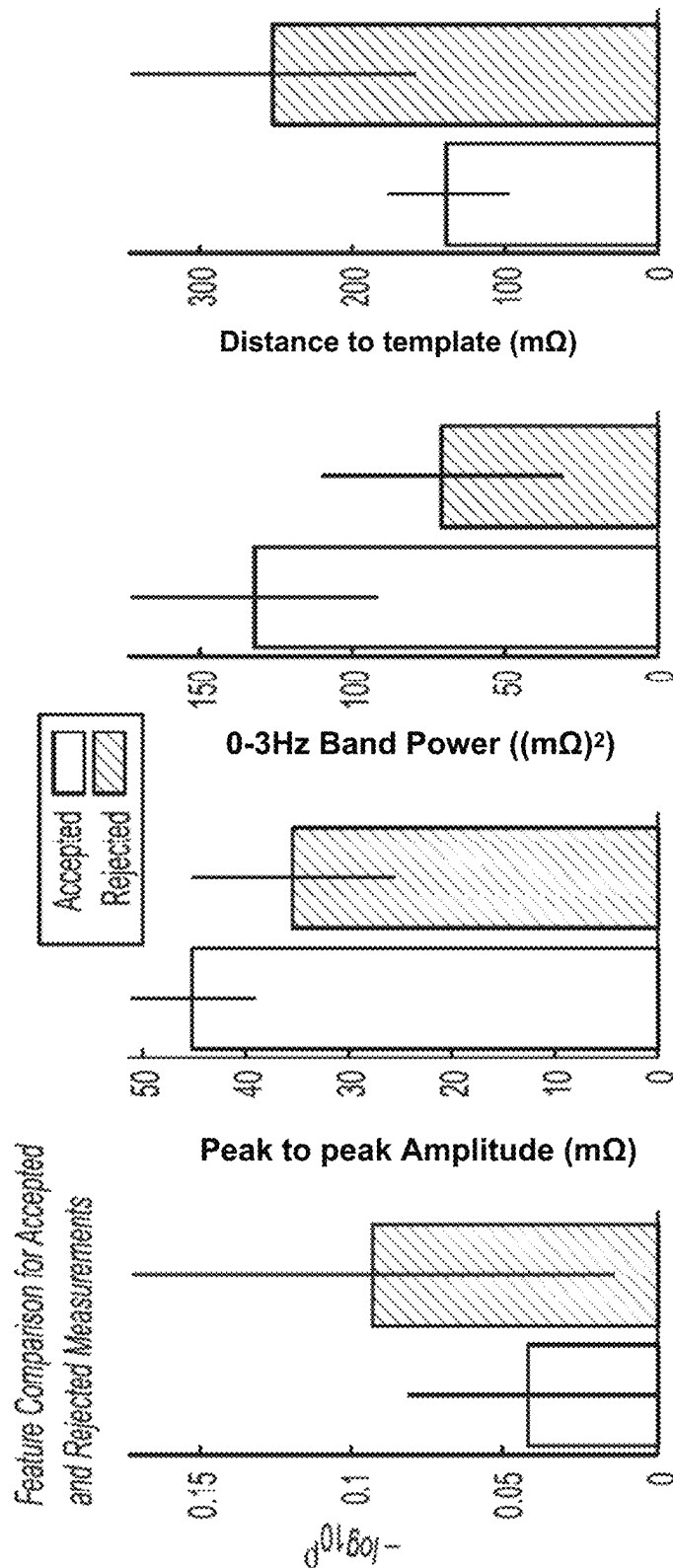


FIG. 7D

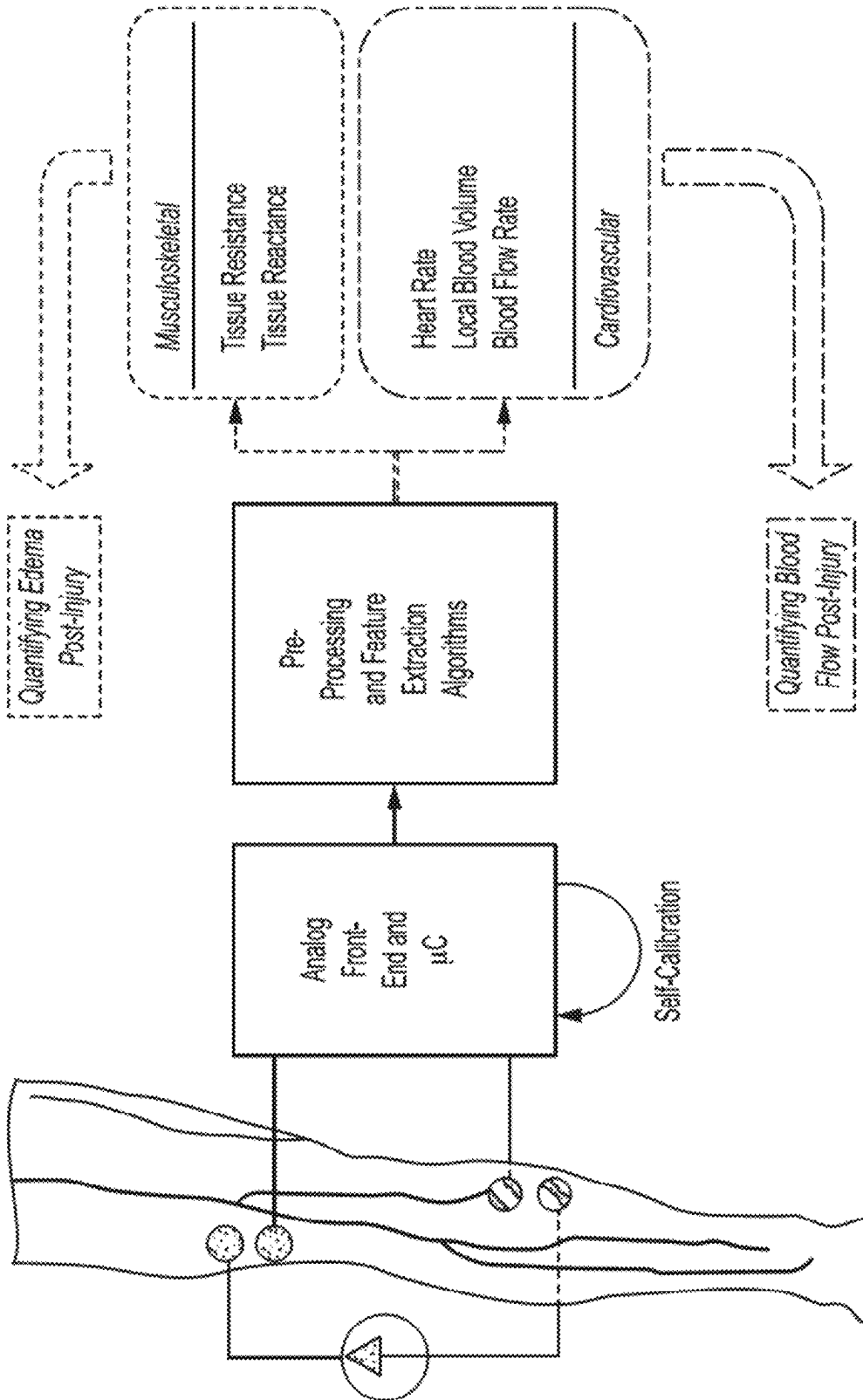


FIG. 8

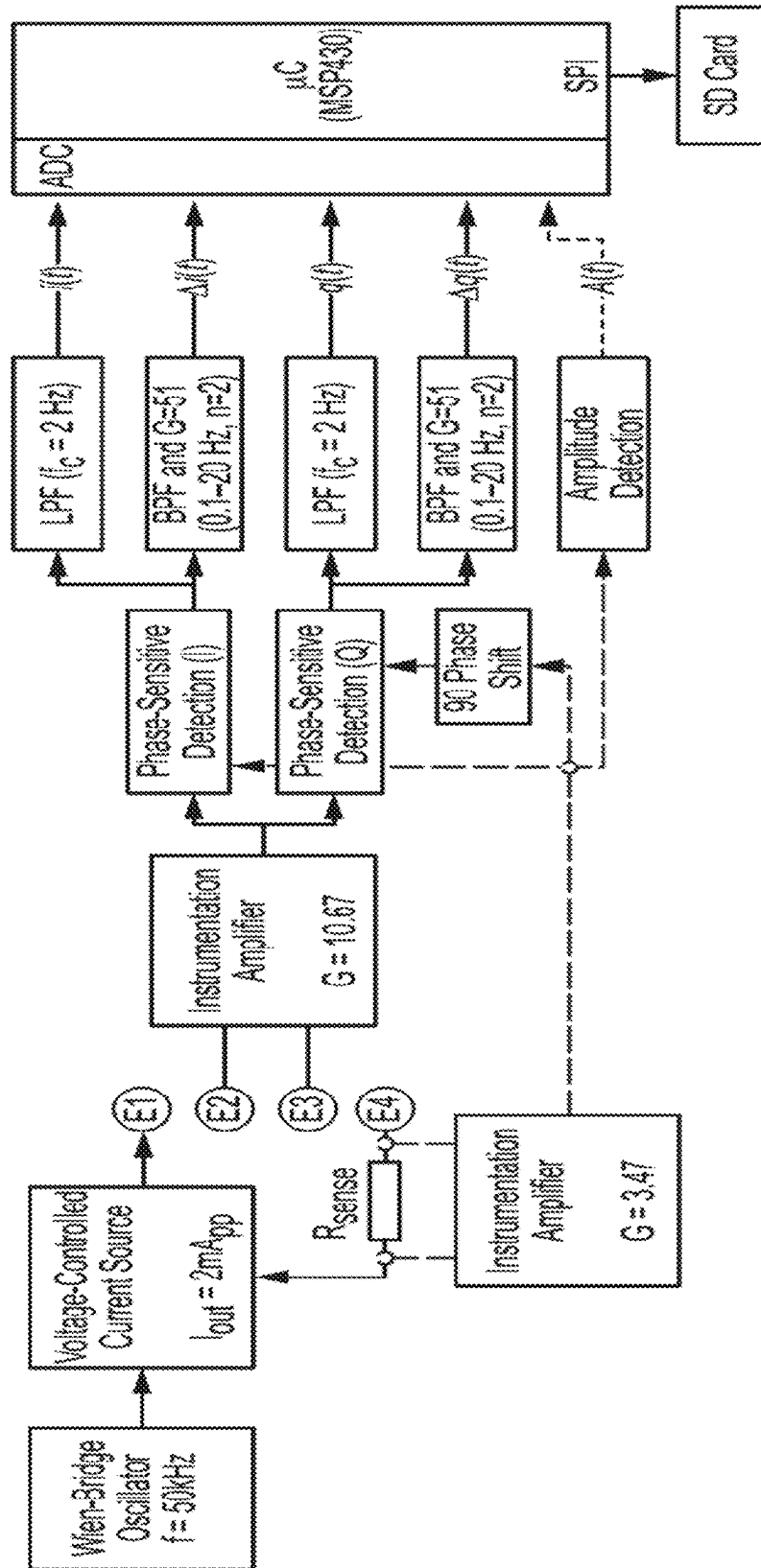


FIG. 9

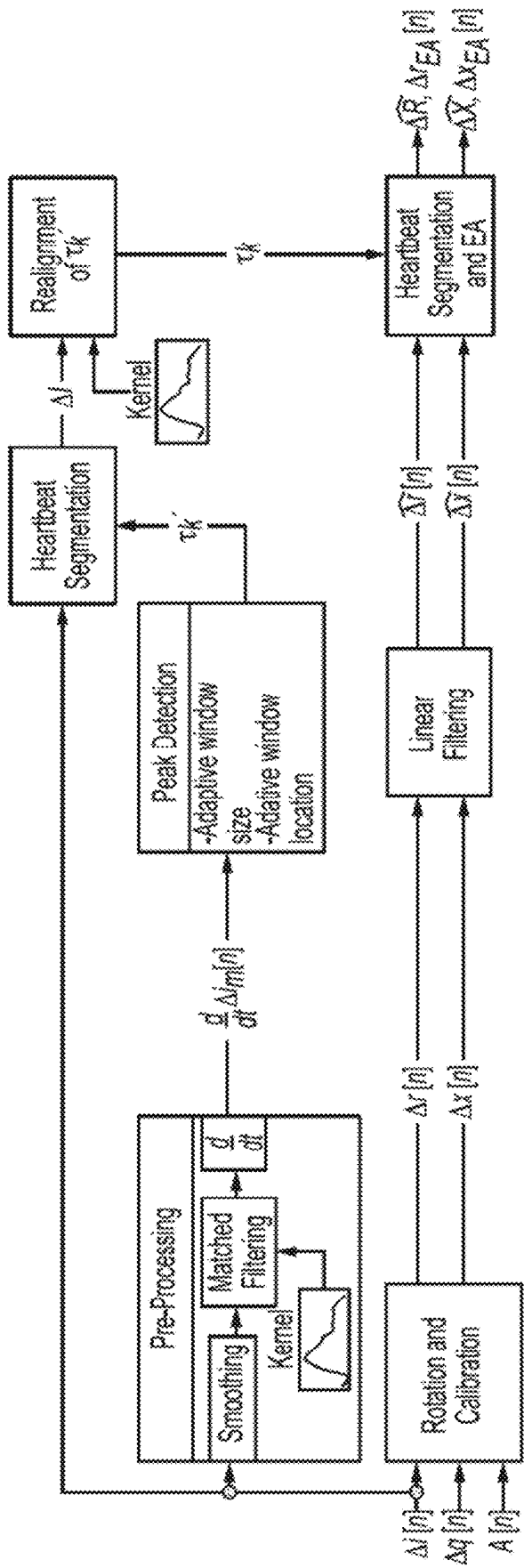


FIG. 10

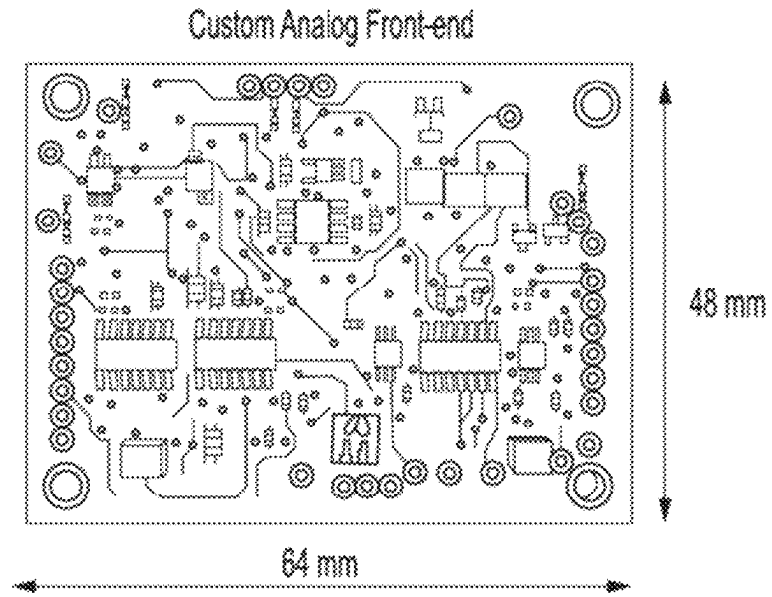


FIG. 11A

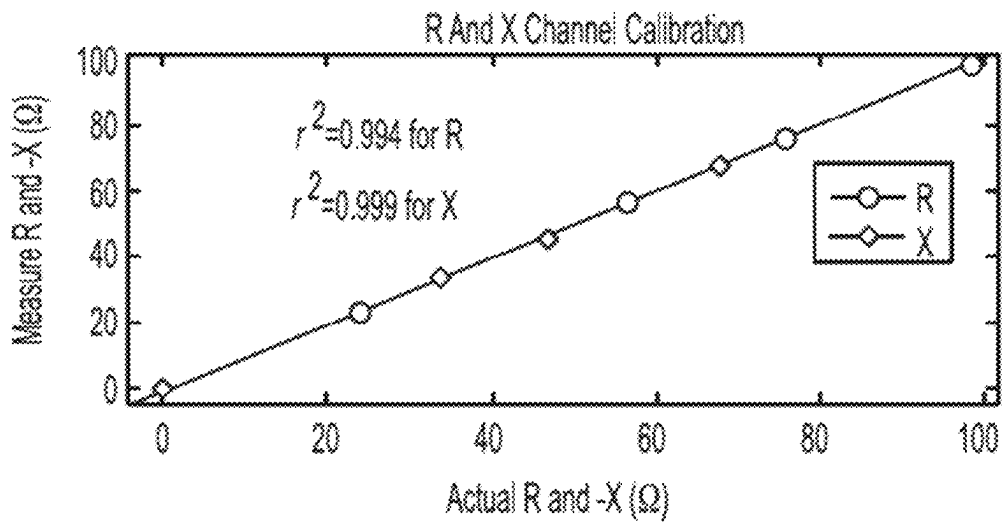


FIG. 11B

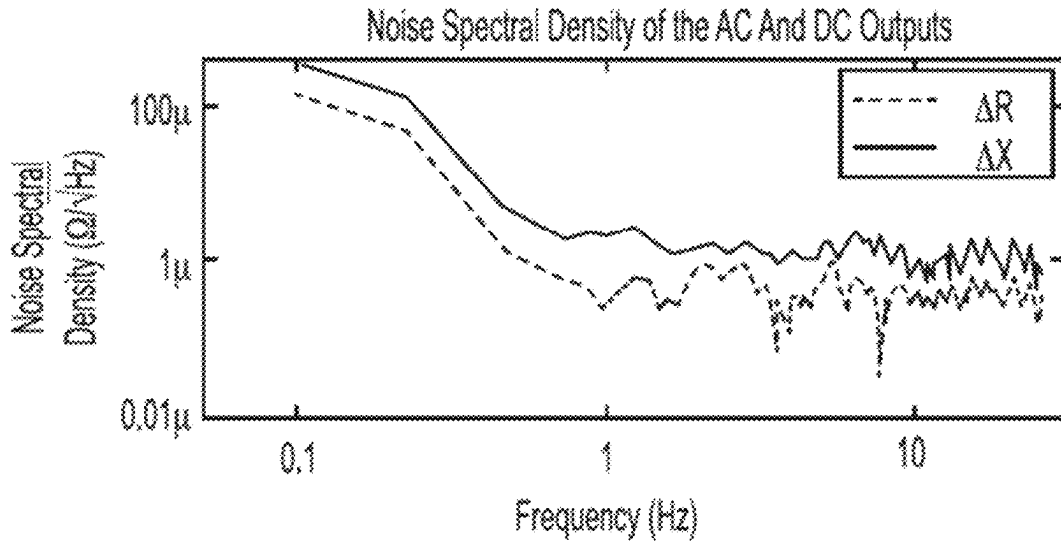


FIG. 11C

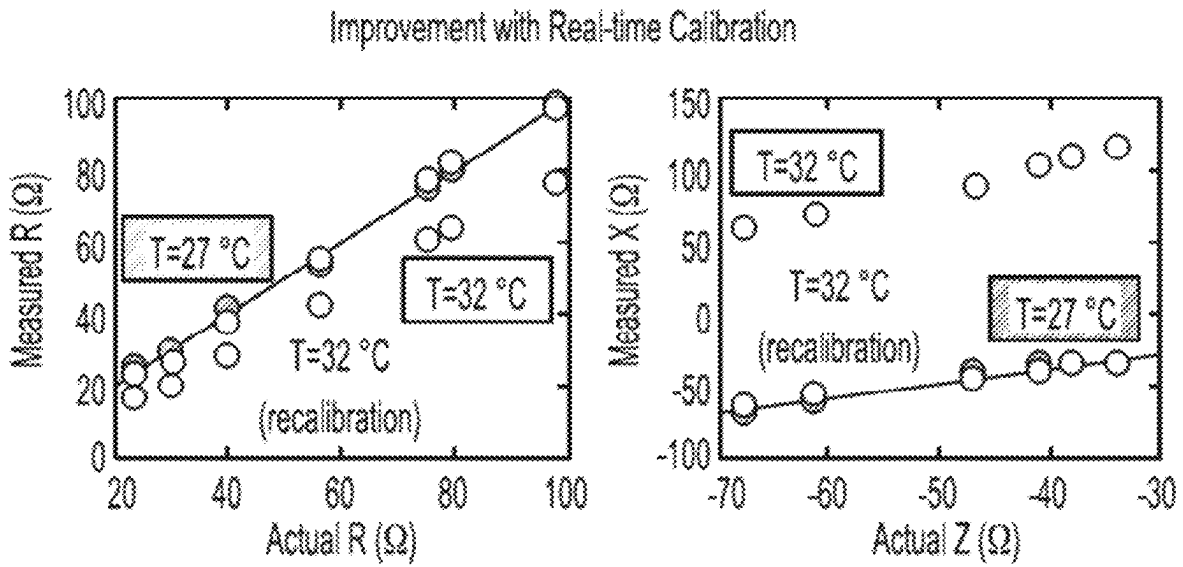


FIG. 11D

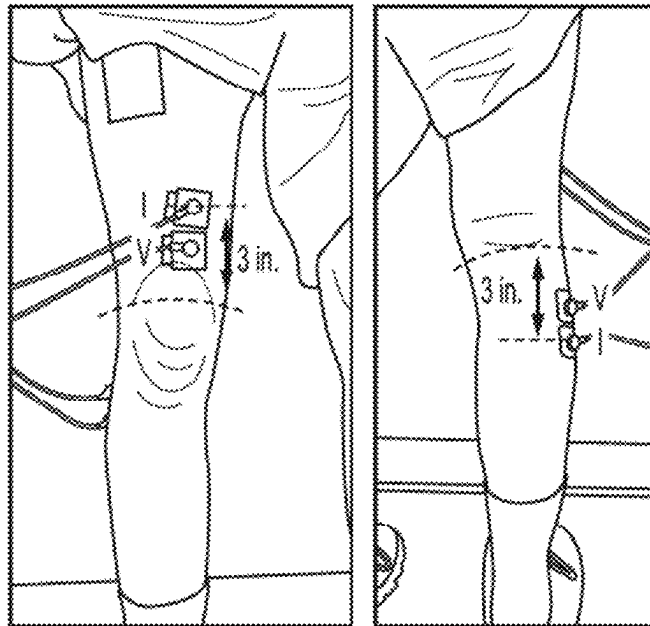


FIG. 12A

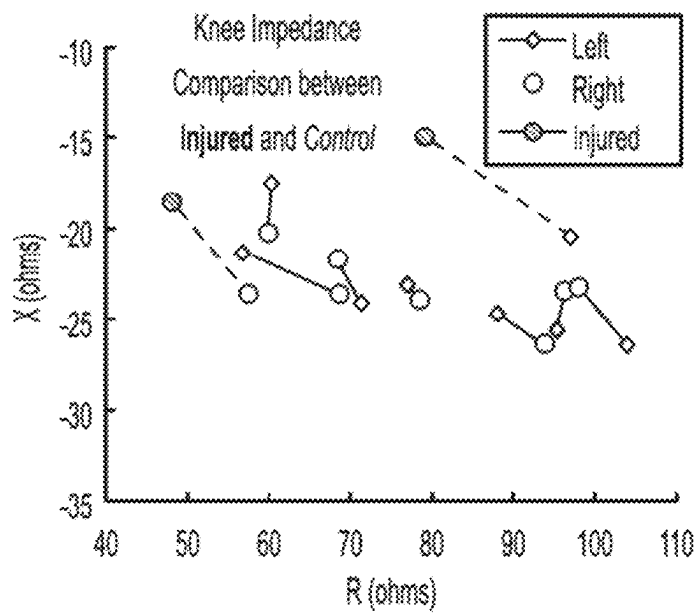


FIG. 12B

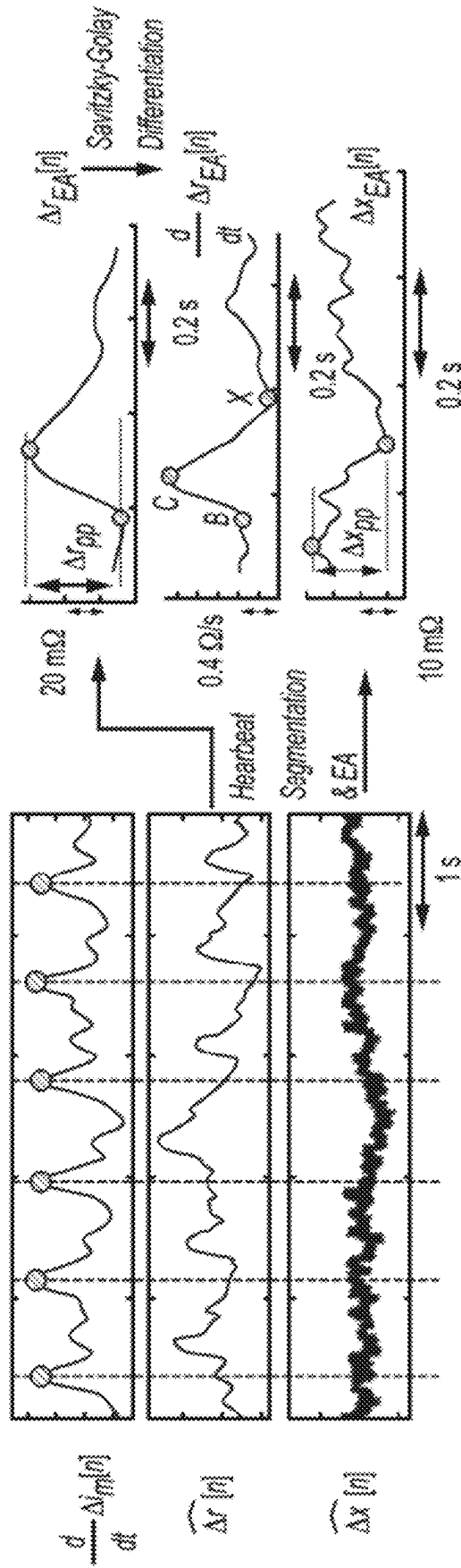


FIG. 12C

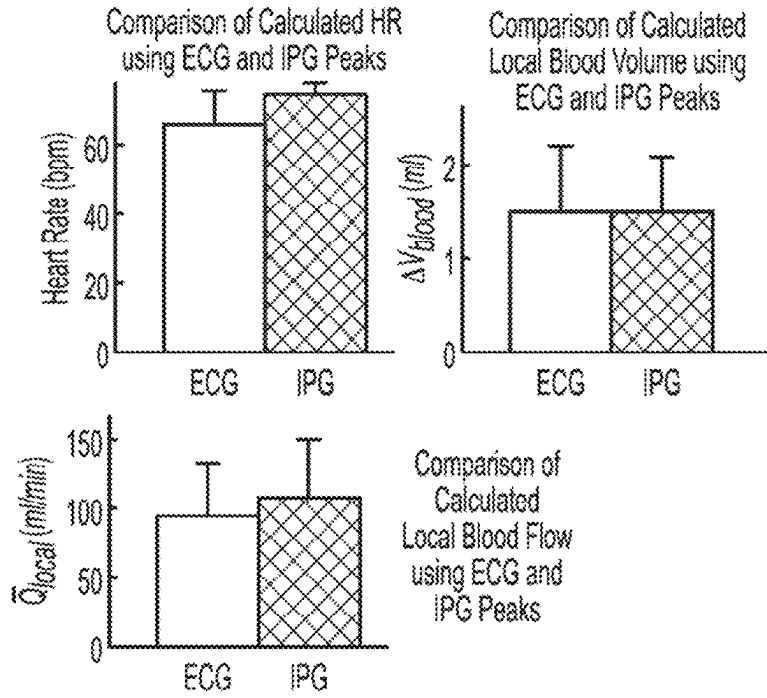


FIG. 12D

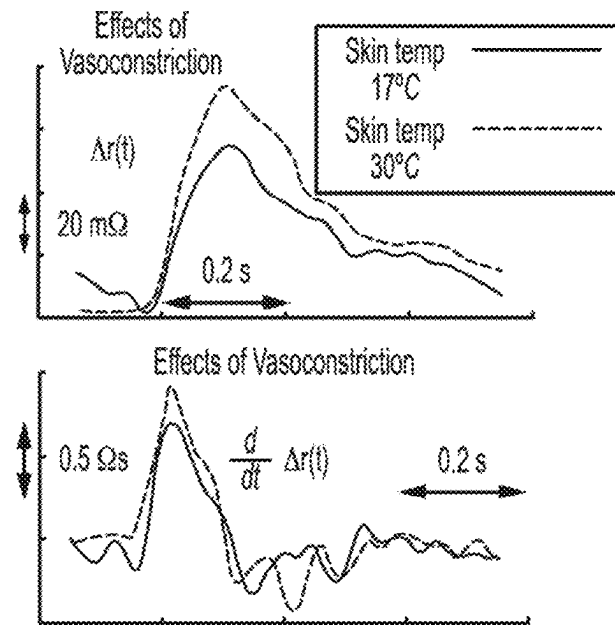


FIG. 12E

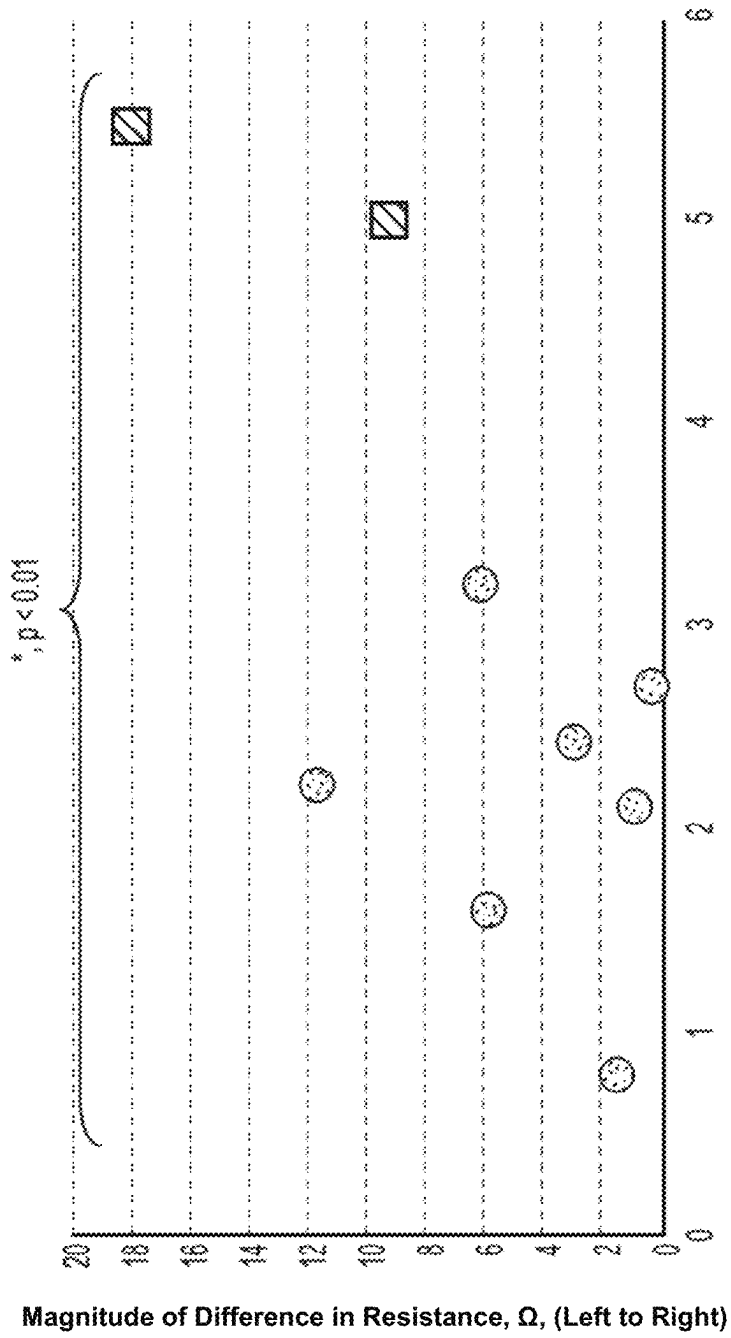


FIG. 13

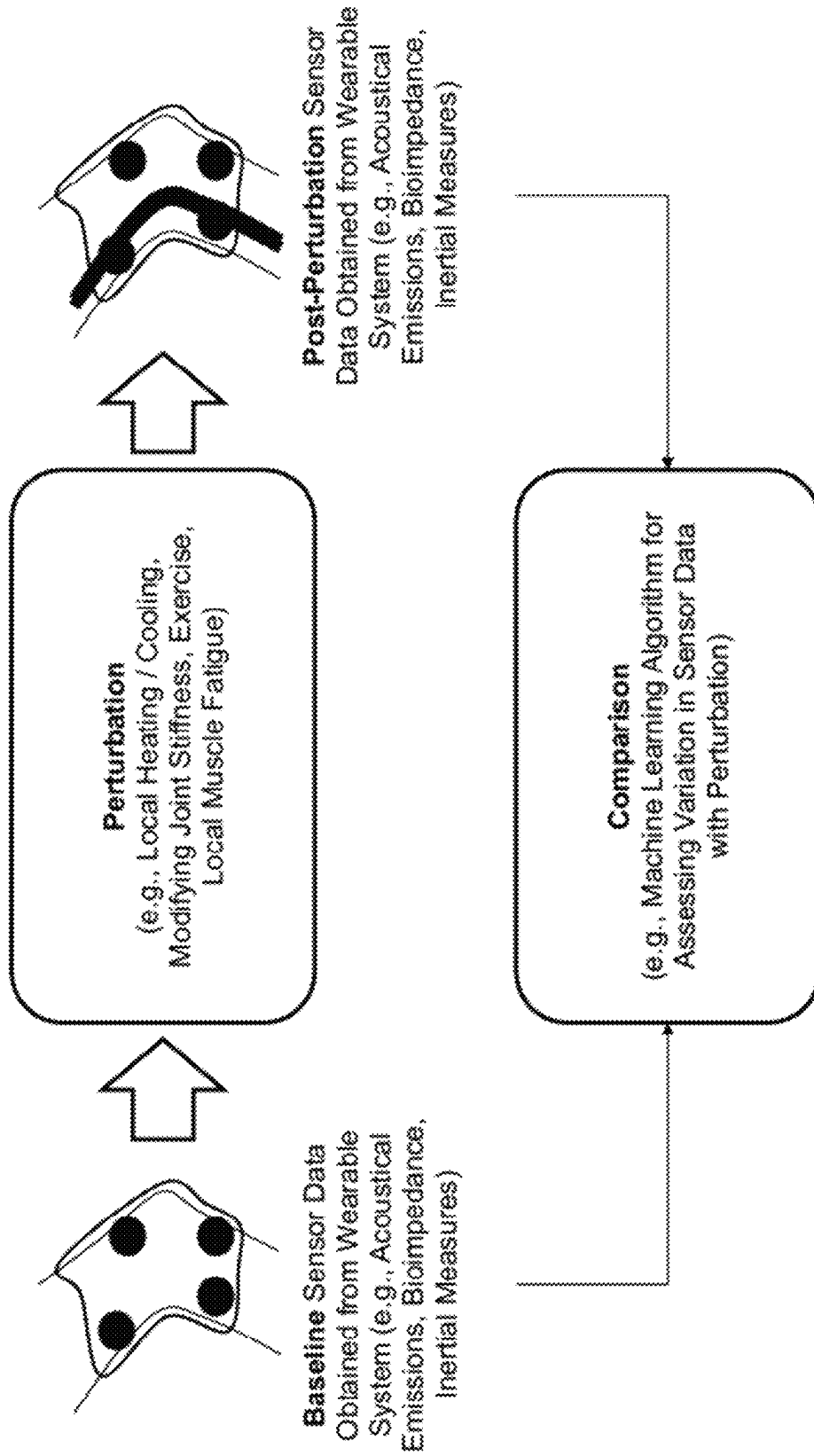


FIG. 14

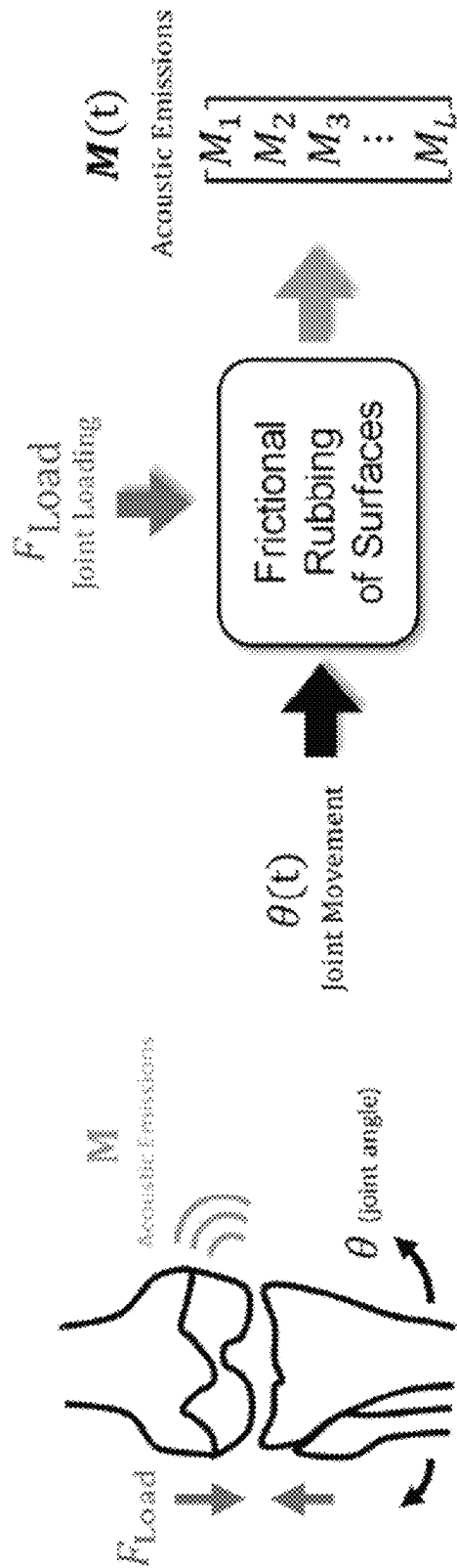


FIG. 15

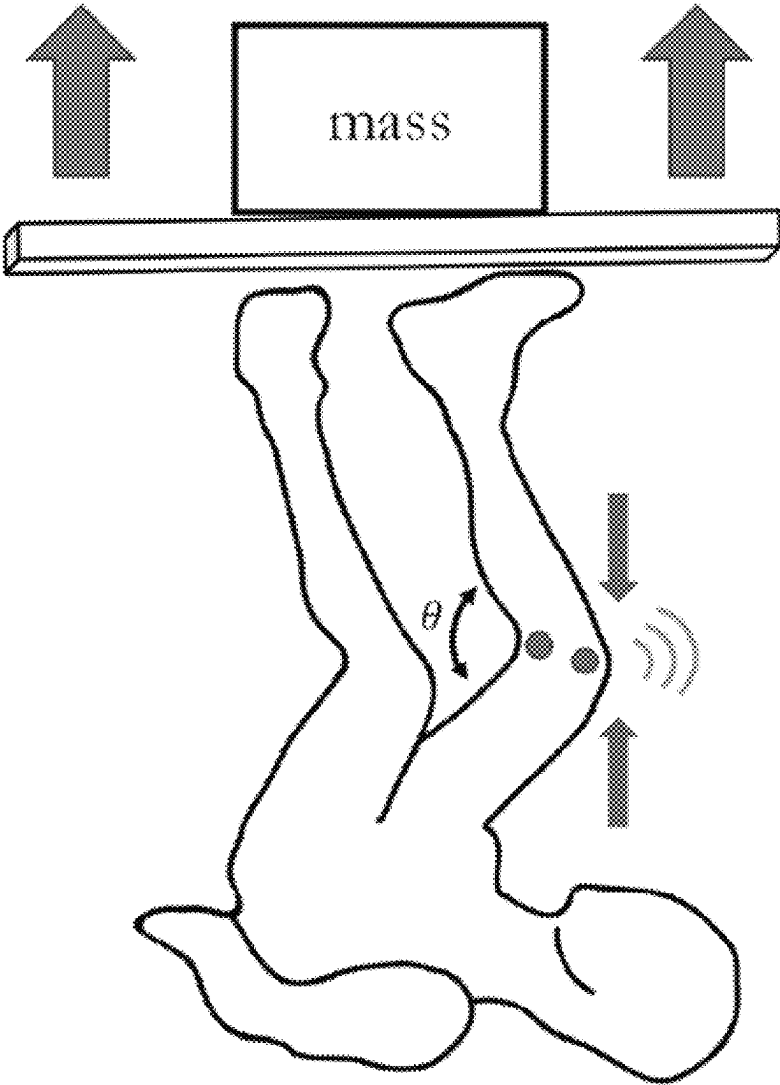


FIG. 16

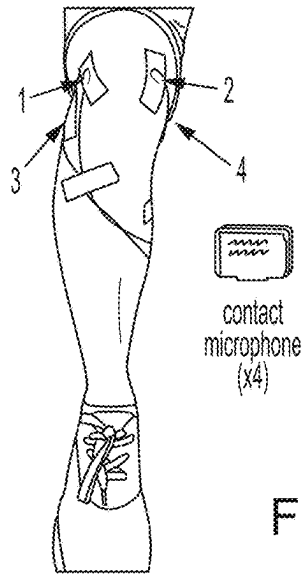


FIG. 17

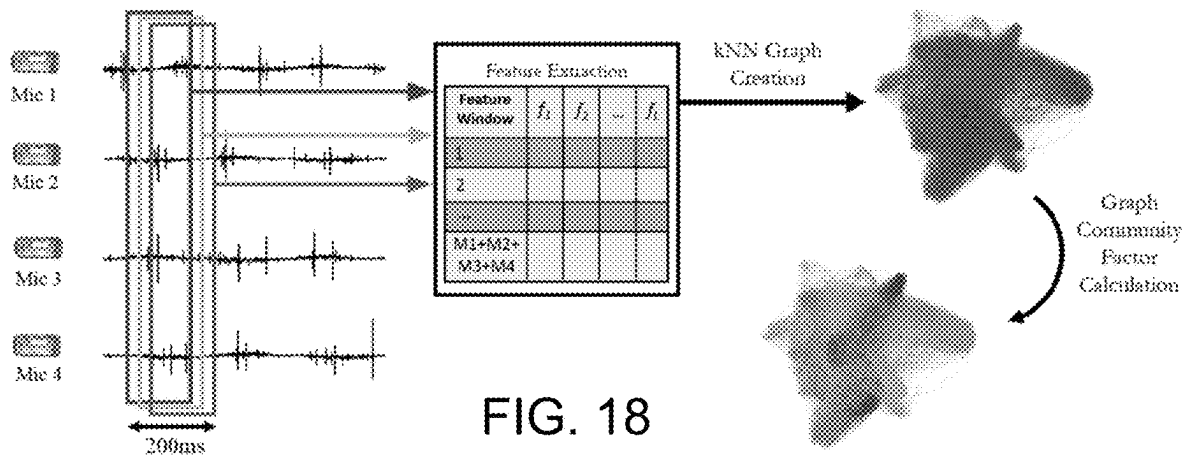


FIG. 18

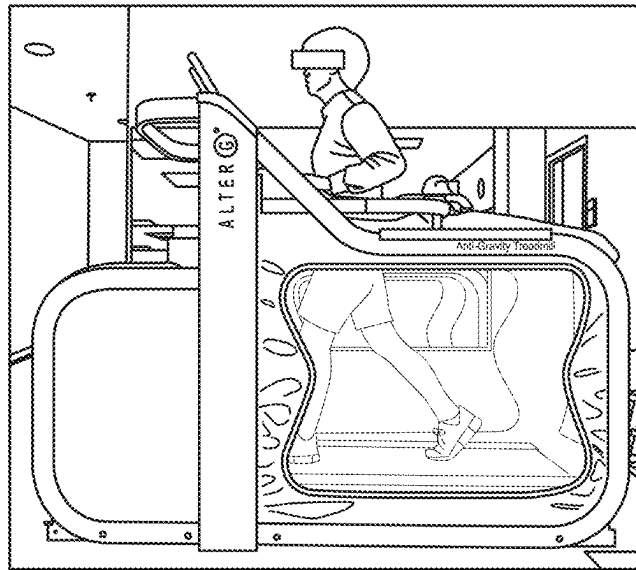


FIG. 19

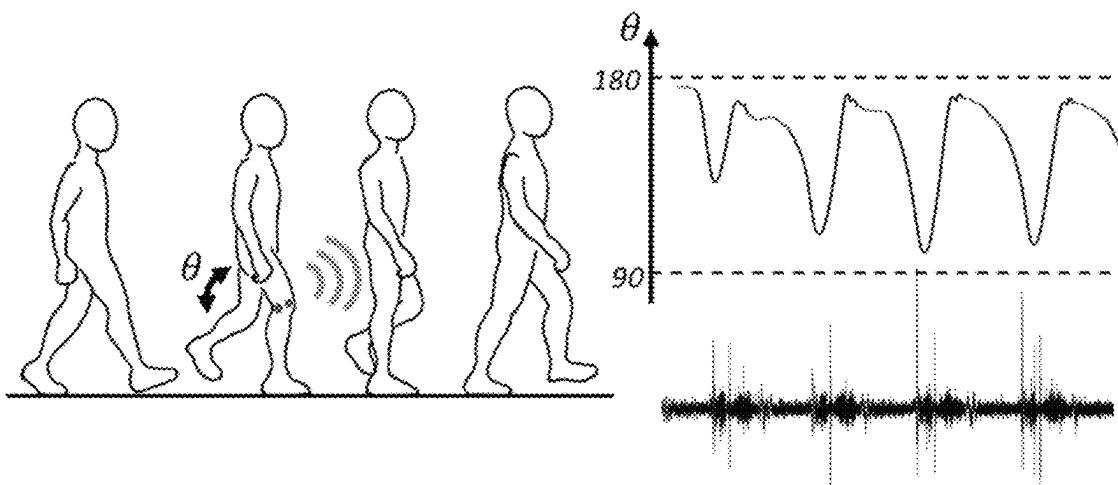


FIG. 20

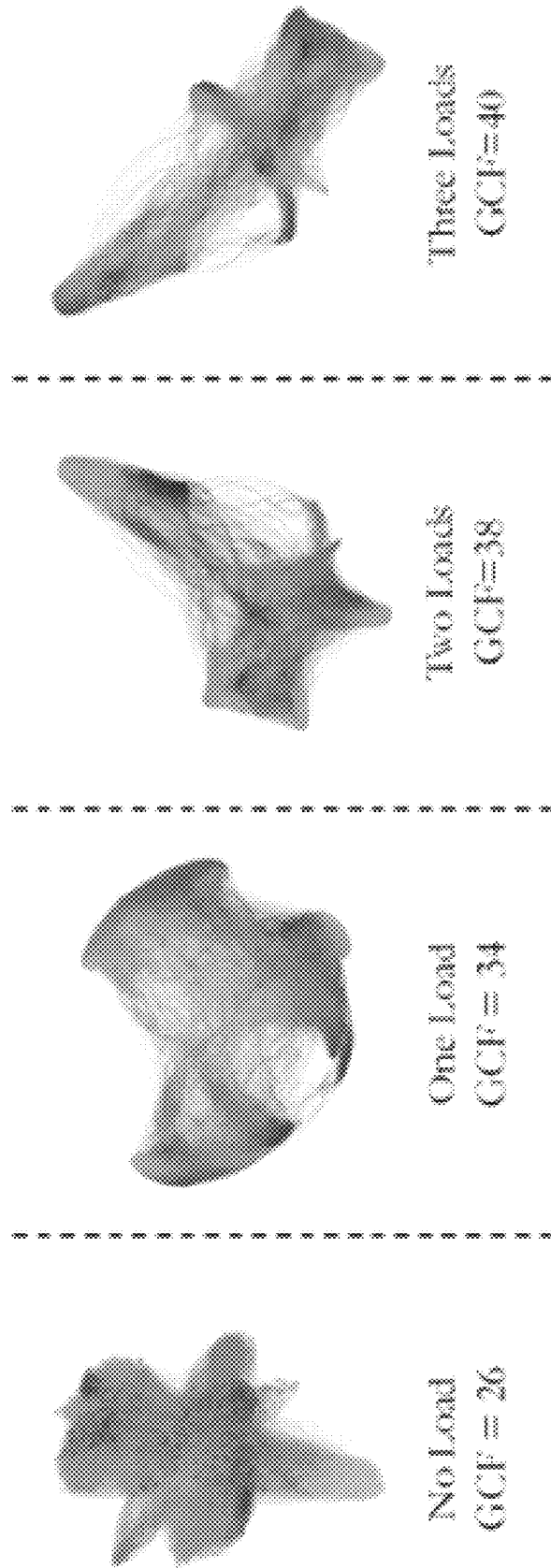


FIG. 21

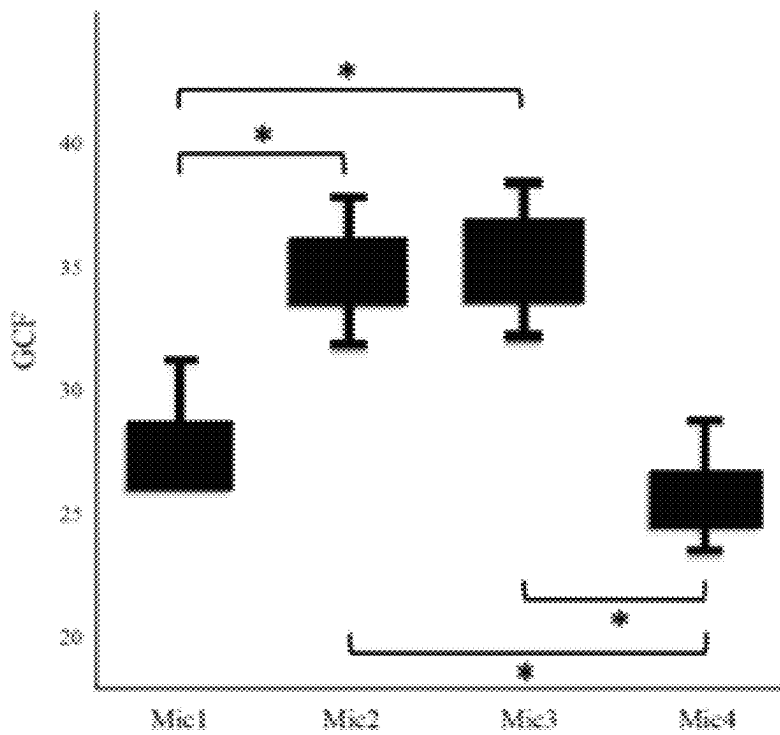
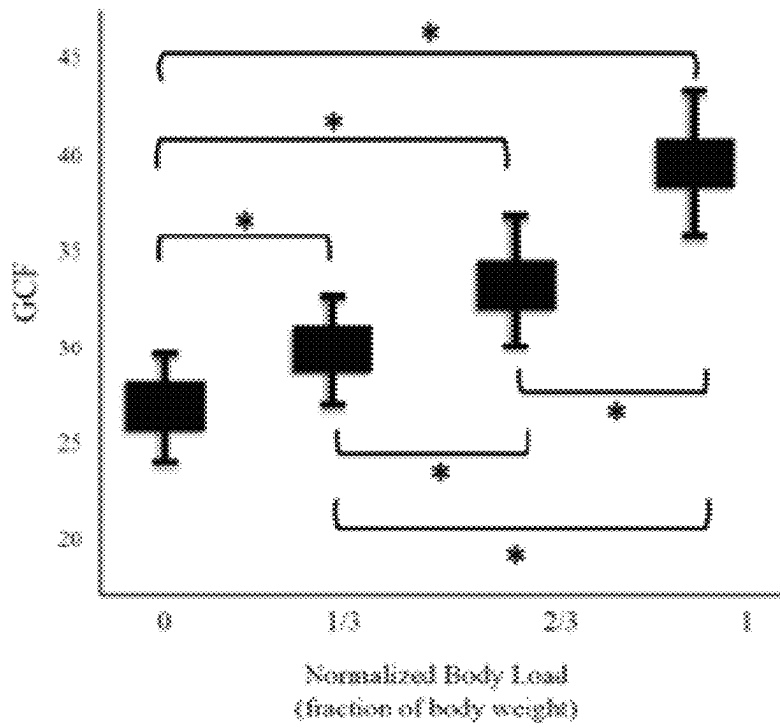




FIG. 24

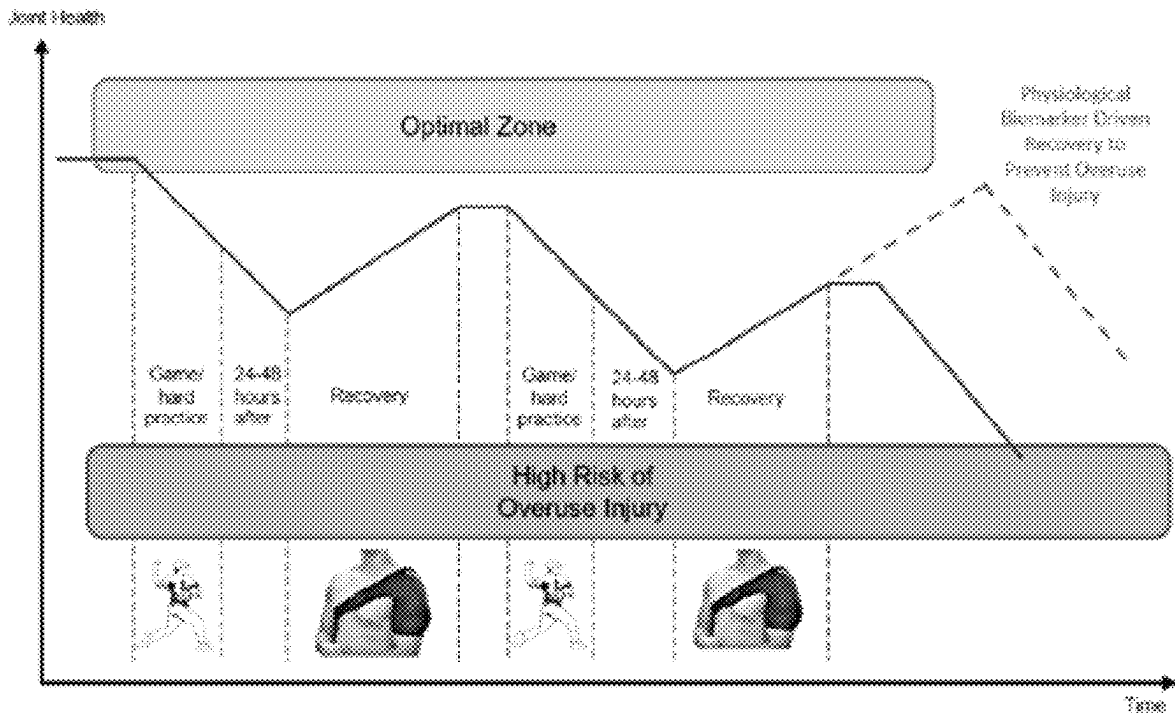


FIG. 25

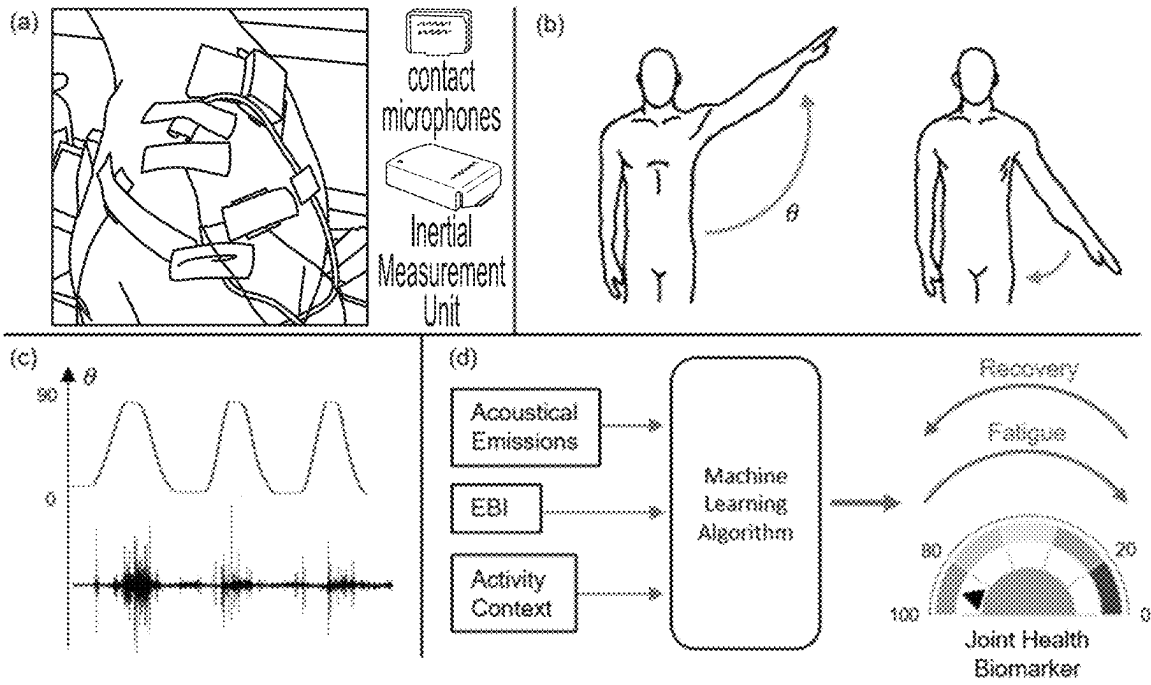


FIG. 26

WEARABLE TECHNOLOGIES FOR JOINT HEALTH ASSESSMENT

CROSS-REFERENCE TO RELATED APPLICATIONS

This application is a continuation-in-part of U.S. patent application Ser. No. 15/577,253, filed 27 Nov. 2017, which is a US National Stage of International Application No. PCT/US16/34874, filed 27 May 2016, which claims the benefit of U.S. Provisional Patent Application No. 62/166,889, filed 27 May 2015. This application also claims the benefit of U.S. Provisional Patent Application No. 62/505,578, filed 12 May 2017. Each application is hereby incorporated herein by reference in its entirety.

STATEMENT REGARDING FEDERALLY SPONSORED RESEARCH

This invention was made with government support under grant numbers R01 EB023808 awarded by the National Institutes of Health and W911NF-14-C-0058 awarded by the United States Army Research Laboratory. The government has certain rights in the invention.

BACKGROUND OF THE INVENTION

1. Field of the Invention

The present invention relates generally to a wearable system and method that assesses the health status of a user's joint and informs the user and/or caregiver of the results, and more particularly to the fusion of health parameters derived from multiple modalities of wearable sensors quantifying joint physiology and structure for predicting overuse injury risk and thus serving as a decision aid for a user (and/or coach, parent, trainer) to, for example, make informed decisions regarding training or competition.

2. Description of Related Art

The knee is subject to major stresses during normal daily life as well as athletic activities with multidirectional forces exerted on the joint during movement. As a result, the knee represents not only one of the most frequently injured body parts but also accounts for many severe injuries in terms of time of restricted and/or total loss of participation among athletes, military personnel, and other populations engaged in high performance activities.

Knee injuries are not exclusive to active populations; sedentary populations may be at higher risk for such injuries due to poor cardiovascular health, atrophied surrounding muscles which fail to properly stabilize the joint, and lack of training and warm-up.

This frequency across populations combined with the extensive treatment requirements—often entailing surgery and/or substantial rehabilitation—result in approximately 10.4 million patient visits annually in the United States. To this extent, these injuries are considerable in their effect on not only the health care system but also on patients' daily lives given the knee's significance in performing ambulatory motions and other everyday activities.

Joint disorders are highly prevalent and limit physical activity, which may cause reduced quality of life. Symptoms that are common to many joint disorders are swelling, increased blood flow, and reduced movement capability. In clinical conditions, the joint health is assessed based on

qualitative observations of the clinician; standard examinations do not yield any quantitative feedback to the physician or patient regarding, for example, the swelling, range of motion, or structural integrity of the joint. Examination methods based on diagnostic imaging do provide quantitative metrics of joint health, but are less commonly used because they are expensive and time consuming.

Beyond the clinic, such as in the home or with wearable technologies, there are no viable solutions available for providing in-depth, quantitative joint health assessment. Wearable assistive technologies for monitoring joint health can help rehabilitating injured patients perform physical therapy and assess their progress in the comfort of their home, or collect objective clinical data during unsupervised rehabilitation programs in athletes and soldiers, provided that the devices are unobtrusive and accurate.

Thus, to alleviate such strains on the health care system and facilitate monitoring of patients during daily activities, researchers have explored the use of wearable devices to unobtrusively acquire health information. Regarding musculoskeletal and biomechanical-related disorders and injuries, these systems provide new ways to collect objective and quantitative data.

Acoustics can provide an unobtrusive method—and thus a possible wearable platform—for capturing information regarding underlying physical structures and alignments, articulating surfaces, and soft tissue characteristics. Friction between the structures and articulating components of the knee joint gives rise to various kinds of vibrations. These vibrations (i.e., acoustical energy) travel to the skin surface where they encounter a large impedance mismatch between the fluid-filled tissue and air. Because of this, most of the acoustical energy manifests itself as vibrations signals on the skin with the majority of the energy reflected back into the tissue.

However, there is a small amount of energy that propagates to the air, resulting in audible joint sounds. While some early work in this area studied airborne signals using “air” microphones, the majority of research has largely utilized vibration sensors as “contact” microphones (e.g., accelerometers, piezoelectric devices, stethoscopes) to measure joint sound vibrations.

Researchers have concentrated on the efficacy of joint acoustic emissions, or vibroarthrographic signals (VAG), as clinically-relevant biomarkers for joint health, and notably, the majority of the research has worked towards developing diagnostic techniques to differentiate “healthy” vs. “unhealthy” knee joints, primarily as it concerns cartilage-based conditions such as osteoarthritis and chondromalacia.

Research has included measuring acoustic emissions from the knee using a condenser microphone and captured low frequency signals (<100 Hz) and using wide-band piezoelectric sensors to record emissions in the ultrasonic band (>20 kHz). This research observed differences between healthy knees and those afflicted with osteoarthritis and found that osteoarthritic knees produce more frequent, higher peak, and longer duration acoustic emissions compared to healthy knees. Osteoarthritic subjects were also evaluated using an accelerometer and led to the classification of three different conditions of the patellofemoral joint. To achieve such outcomes, significant work has been devoted to developing various signal processing techniques for conditioning and classifying VAG signals. Algorithms have leveraged linear prediction and autoregressive modeling, statistical parameter investigation, Fourier and time-

frequency analysis, wavelet decomposition, and neural networks and other classifier methods such as dynamic weighted classifier fusion.

Another recent technology that has been investigated for local joint health assessment is electrical bioimpedance (EBI). EBI has been demonstrated as a possible means of evaluating knee osteoarthritis, edema (swelling) related to lower limb muscle injuries, and edema for total knee arthroplasty surgery and rehabilitation.

For EBI measurements, a small electrical current is injected into a volume of tissue—such as the volume of tissue encapsulating a knee joint—and the resultant voltage drop across the tissue is measured. The ratio of this voltage to the injected current yields the electrical impedance of this tissue and can change based on the structural composition of the medium (e.g. increased edema decreases the tissue impedance since fluid is less resistive than muscle, fat, or bone).

EBI has also been used in cardiovascular physiology research as a means of quantifying blood flow and volume, such as for estimating cardiac output or the local blood flow rate to (or blood volume pulse at) a limb. While EBI measurements for structural assessment typically examine the static (varying over the course of hours to days) component of tissue impedance, measurements for cardiovascular assessment examine the dynamic (varying over the course of milliseconds) components.

Additionally, while static EBI measurements involve magnitudes of changes on the order of 1 s to 10 s of Ohms, dynamic cardiovascular measures from limbs can be as small as 10 s of milli-Ohms. Accordingly, the performance of the analog front-end circuitry for EBI measurements becomes significantly more challenging when targeting both static and dynamic measurements.

Nevertheless, advances over the past several years have been made in EBI circuit and system design, including improving the current source for high frequency implementation, increasing the output impedance and accuracy of complementary metal-oxide semiconductor (CMOS) current drivers for EBI, developing error correction algorithms, and investigating solutions for textile electrode interfaces. In the literature, such dynamic measurements of limb impedance are referred to as impedance plethysmography (IPG).

In addition to quantifying edema with static EBI, quantifying the local blood flow patterns following a joint injury with IPG could provide significant insight into joint rehabilitation progress. An increase in local blood flow may follow an injury to the joint, associated with inflammation and scar tissue formation, while decrease in local blood flow may be indicative of improving status. Such changes in blood flow patterns are believed to precede changes in structure (edema) or range of motion and can potentially provide early biomarkers for changing joint health status.

Beyond local blood flow, IPG measurements can also provide a window to evaluating the overall cardiovascular physiology and autonomic nervous system (ANS) balance through heart rate variability (HRV), thus providing an index of a person's sympathetic arousal which has been shown to increase in response to pain.

However, no existing bioimpedance technologies are capable of providing both the required resolution to capture edema measures and blood flow and operate on sufficiently low power consumption such that several hours of use on a small battery is feasible.

In a specific example of the use of multi-modal joint acoustics and bioimpedance sensing to allow for joint health status monitoring, the use of such multi-modal sensing technologies can be applied in a preventative/proactive

manner with an aim of reducing acute overuse injuries that may result for over-training or sub-optimal training regimens.

Overuse injuries result from repeated exposure of a joint to micro-traumas with a cumulative effect that leads to gradual increases in observed symptoms such as pain, swelling, and reduced performance. Such injuries represent approximately one quarter of all sports-related injuries, with a recent epidemiologic study of collegiate athletes showing a rate of 18.5 overuse injuries per 10,000 athletic exposures. For the lower limbs, some commonly encountered overuse injuries are tendinopathies, stress fractures, and shin splints.

In some sports, overuse injuries are becoming more common as children are starting to train more intensely, and year-round, starting from a young age. An archetypal example is baseball pitching: overuse, high-velocity throwing is believed to increase the risk of ulnar collateral ligament (UCL) injuries requiring surgical reconstruction (i.e., “Tommy John” procedure).

For an athlete attempting to attain peak performance, heavy training regimens are typically required: during such training, differentiating between normal muscle soreness and pain or swelling associated with overuse that can potentially increase the risk of injury is nearly impossible. Moreover, pain is subjective from person to person, and is not a reliable marker of when the person should reduce the intensity of training or rest rather than continuing.

An additional complication is the phenomenon called “Delayed Onset Muscle Soreness” (DOMS): tenderness and debilitating pain in a muscle from 24-48 hours following training. This long delay between when the training or athletic performance is conducted and when the body senses pain/tenderness feedback renders such sensory feedback useless in optimizing the intensity or type of activity that is appropriate.

Thus, researchers have investigated multiple approaches to providing markers of overuse that can be used to proactively adjust training regimens or competition to theoretically maximize performance while minimizing the risk of acute overuse injury.

Serum biomarkers—in particular inflammatory markers—have been measured and correlated against severity of upper body overuse with promising preliminary results in small cohorts. Wearable arrays of inertial measurement units (IMUs) have been used to quantify movement of the arm and torso for baseball players during pitching to estimate speed of movement and other parameters that may potentially relate to overuse. The most common approach in conventional practice to determine the intensity and type of activity that is appropriate for training, however, is one based on anecdotal evidence and subjective evaluations from athletic trainers, coaches, athletes themselves, and parents (for children participating in athletics).

It would be beneficial to find solutions to the above deficiencies in conventional monitoring and assessment technologies, providing systems and methods that can provide around-the-clock monitoring of joint acoustics and bioimpedance during normal activities of daily living, and prescribed rehabilitation activities that elicit specific signatures indicative of improving or worsening joint health.

It would also be beneficial to fuse health parameters derived from multiple modalities of wearable sensors quantifying joint physiology and a structure for predicting overuse injury risk, serving as a decision aid for a user (and/or coach, parent, trainer) to, for example, make informed decisions regarding training or competition.

It is to the provision of such systems and methods using miniature sensors that can be readily integrated into a wearable device enabling, for the first time, wearable joint acoustics and bioimpedance sensing that are primary objects of the present invention.

BRIEF SUMMARY OF THE INVENTION

In an exemplary embodiment of the present invention, the present invention quantifies the degree of injury at a joint through observation of joint disorder symptoms by accurately monitoring two sensing modalities and interpreting them in the context of joint motion. For example, the multi-modal sensing can include at-home monitoring sensing regimes for one type of joint characteristic, like joint acoustic emission, wherein the multi-modal sensing incorporates contact-based and non-contact based (airborne) measurement of joint acoustic emission system. Other types of joint characteristics include joint edema and blood flow assessments. These joint characteristics can be investigated via vector bioimpedance measurements.

In another exemplary embodiment, the present invention quantifies the degree of wear-and-tear or usage of a joint through observation of joint physiological or structural changes associated with repetitive motions and interprets them in the context of motion or position. The present invention relates to the fusion of health parameters derived from multiple modalities of wearable sensors quantifying joint physiology and structure for predicting overuse injury risk and thus serving as a decision aid for a user (and/or coach, parent, trainer) to, for example, make informed decisions regarding training or competition. For example, the multi-modal sensing can include sensing regimes for one type of joint characteristic, like joint acoustic emission, wherein the multi-modal sensing incorporates contact-based and non-contact based (airborne) measurement of joint acoustic emissions. Other types of joint characteristics include joint edema and skin temperature assessments. These joint characteristics can be investigated via vector bioimpedance and temperature measurements.

In an exemplary embodiment, the present invention can combine at least two of the following sensing modalities: joint acoustical emissions, electrical bioimpedance, and inertial measures. At least two of these modalities can be fused together in a wearable system that the user wears for some period of time, during which the present invention learns the characteristics of the measured signals for that particular user using, for example, machine learning algorithms. When the characteristics of the signals digress from the normal levels by a threshold—that can be determined either using a calibration period for that particular user or from population-based data—the user can be alerted. Alternatively, the present invention can output a numerical indication or score to the user representative of the “usage” of the joint, such that the user can decide for himself how to interpret and use the data for guiding his training/competition.

The present invention can also inform the coach, physical therapist, or parent of an athlete regarding the degree to which the joint has been used and/or overused for a given sport. For example, information regarding wear-and-tear and repetitive joint usage effects on internal structures and/or physiology can be extracted from the wearable sensor data and outputted as a joint health score to the athlete, coach, parent, or team physician, or any other individual involved in the planning of training and competition schedules and regimens.

In another example, the multi-modal sensing can include at-home monitoring sensing regimes for more than one type of joint characteristic, for instance both joint acoustic emission and joint bioimpedance measurements.

In an exemplary embodiment of the present invention, wherein the multi-modal sensing relates to one type of joint characteristic, like joint acoustic emission, the invention can comprise systems and methods of wearable joint rehabilitation assessment following musculoskeletal injury using three types of sensors to obtain joint sounds in healthy collegiate athletes during unloaded flexion/extension. The sensors can comprise microphones and include more than one type of microphone. In exemplary embodiments, one or more microphone types are selected from the group consisting of electret, MicroElectrical-Mechanical System (MEMS), and piezoelectric film microphones.

Joint sounds in healthy collegiate athletes during unloaded flexion/extension were investigated, and the robustness of each microphone’s measurements evaluated via: (i) signal quality and (ii) within-day consistency. It was found that air microphones acquired higher quality signals than contact microphones (signal-to-noise-and-interference ratio of 11.7 dB and 12.4 dB for electret and MEMS, respectively, vs. 8.4 dB for piezoelectric). Furthermore, air microphones measured similar acoustic signatures on the skin and 5 cm off the skin (~4.5× smaller amplitude). It was also found that the main acoustic event during repetitive motions occurred at consistent joint angles (the intraclass correlation coefficient (ICC) (1, 1)=0.94 and ICC(1, k)=0.99). Additionally, it was found that this angular location was similar between right and left legs, with asymmetry observed in only a few individuals.

In one embodiment, air microphones are used for wearable joint sound sensing, where for practical implementation of contact microphones in a wearable device, interface noise must be reduced. Airborne signals can be measured consistently, and healthy left and right knees often produce a similar pattern in acoustic emissions.

In an exemplary embodiment of the present invention, wherein bioimpedance measurements are examined, a robust vector bioimpedance measurement system leveraging embedded systems concepts for longitudinal knee joint health assessment are used. The systems and methods can comprise a custom analog front-end based on discrete components to achieve high resolution static (slowly varying over the course of hours to days) and dynamic (rapidly varying on the order of milli-seconds) bioresistance and bioactance measurements within a footprint and power consumption feasible for a wearable, on-body implementation.

In one embodiment, occupying an area of 64×48 mm² and consuming 0.66 W when supplied with ±5 V, the front-end achieves a dynamic range of 345Ω and noise floor of 0.018 mΩ_{rms} (resistive) and 0.055 mΩ_{rms} (reactive) within a bandwidth of 0.1-20 Hz. A microcontroller allows real-time calibration to minimize errors in measurements due to environmental variability (e.g. temperature) that can be experienced outside of clinical or lab environments and enables data storage on a micro secure digital (SD) card. The acquired signals are then processed using customized physiology-driven algorithms to extract musculoskeletal (edema) and cardiovascular (local blood volume pulse) features from the knee joint.

Statistically significant differences (p<0.01) were found between the injured and contralateral static knee impedance measures for two subjects with recent unilateral knee injury compared to seven controls. Specifically, the impedance was

lower for the injured knees, supporting the physiological expectations for increased edema and damaged cell membranes. Further, the sensitivity of the dynamic impedance measures with a cold pressor test were demonstrated, with a 20 mΩ decrease in the pulsatile resistance and 0.2Ω/s decrease for the time derivative of resistance associated with increased downstream peripheral vascular resistance.

In another exemplary embodiment of the present invention, the multi-modal sensing relates to more than one type of joint characteristic, for example both joint acoustic emission and joint bioimpedance, the more than one sensing modalities are interpreted in the context of joint motion. The present invention can comprise custom-design analog electronics and electrodes for high resolution sensing of bioimpedance, microphones and their front-end electronics for capturing sound signals from the joints, rate sensors for identifying joint motions (linear and rotational), and a processor unit for interpretation of the signals. These components are packed into a wearable form factor, which also encapsulates the hardware required to minimize the negative effects of motion artifacts on the signals.

The present invention makes use of bioimpedance measurements to monitor the amount of swelling and the blood flow rate at the joint. To measure changes in slow-varying fluid volume and fast-varying blood flow rate, the bioimpedance hardware outputs both static and dynamic components of the joint bioimpedance, which has a resistive and reactive component. To detect even small changes in blood flow rate, the bioimpedance hardware is a custom-designed analog front-end with improved noise performance.

The bioimpedance measurements are done by delivering current to the joint site through the electrodes, which are in quadripolar configuration to reduce the effect of electrode-skin interface impedance and measuring the potential difference across the joint through amplification and phase-sensitive detection stages. The static and dynamic components are later separated by a filter stage at the output. The injected current magnitude is below a safety threshold that does not create damage at the measurement site, and its frequency is such that it can propagate through both intra and extra-cellular fluids.

Under motion, joints emit acoustical waves propagating through the tissue. Depending on the fluid content of the joint, various parameters (e.g., rms power, frequency content) of the waveforms change. The present invention incorporates measurements to record the acoustical emissions and extract joint-health-related features from the changes in sound waveform parameters. Contact microphones are used to capture the sound waves originated by the mechanical vibrations. To improve the noise performance and therefore accuracy of the system, airborne microphones that are more immune to noise originated from the skin-microphone interface, are used in a complementary manner. In general, the microphones are placed around the joint, but the exact number and positions vary with the joint of interest. Custom-designed analog front-end circuitry is used to amplify and filter the sound signals to further improve the noise performance.

Joints are dynamic structures by their nature, and therefore the system performs activity-contextualized joint health assessment. To autonomously classify the joint motion with its parameters (i.e., range-of-motion, frequency), the present invention makes use of rate sensors that are placed on the moving parts of the joint of interest. The activity classification is also used to improve the energy-efficiency of the system while operating with minimum user intervention—

the system wakes up from a sleep-mode only when the user performs certain activities to be pre-defined by the clinician.

Designed to be worn on the body and used under unsupervised conditions, the system hosts smart packaging elements (e.g., thin contact pressure sensors at the skin-sensor interfaces) that minimize the effects of motion artifacts on the measured signals.

A central processor unit processes all sensory data to extract joint-health-related features. The processing is done in digital, analog, or mixed-signal domains using multipurpose devices (e.g., microprocessor, field-programmable analog array) or custom-designs (e.g., application-specific integrated circuit, discrete circuit). The present invention informs the user and/or caregiver of the status of the joint health that the processor outputs.

In another exemplary embodiment, the present invention comprises systems and methods to decide if a user of an exemplary wearable system of the present invention is in an acceptable position for bioimpedance measurements to be taken or not. Since bioimpedance measurements are greatly impacted by motion artifacts, subject position, electromagnetic interference and voltage fluctuations of the skin electrode interference, an innovative solution is needed to provide consistency that measurements should be taken when subject is still in a given position and in the absence of electromagnetic interference and skin electrode interface related fluctuations (such as an electrode losing contact with the skin). The present invention can provide a solution by presenting inertial measurement units along with the dynamic resistance (impedance plethysmography) signals that are used together to decide if the user is in an acceptable position for bioimpedance measurements to be taken or not.

In another exemplary embodiment, the present invention is a system for assessing joint health comprising a first sensing assembly for sensing characteristics related to joint physiology, a second sensing assembly for sensing characteristics related to joint structure, and a health assessor that provides an assessment of joint health through interpretation of characteristics from the first and the second sensing assemblies.

The system can further comprise an output assembly capable of providing an indication of joint health to a user of the system.

The first sensing assembly can comprise wearable acoustic sensors to measure acoustic emissions from the joint during movement. The first sensing assembly comprises wearable sensors to measure at least one non-acoustic characteristic of joint movement. A non-acoustic characteristic of joint movement can be selected from the group consisting of linear acceleration and angular velocity.

The first sensing assembly can comprise wearable sensors to measure linear acceleration and angular velocity of joint movement.

The second sensing assembly can comprise wearable sensors to measure bioimpedance of the joint. The wearable sensors to measure bioimpedance of the joint can comprise at least four surface electrodes configured to measure proximal EBI of tissue and blood in proximity of the joint.

In another exemplary embodiment, the present invention is a system for assessing joint health comprising a first sensing assembly for sensing characteristics related to joint physiology, the first sensing assembly comprising acoustic sensors to measure acoustic emissions from the joint during movement, and sensors to measure at least one non-acoustic characteristic of joint movement selected from the group consisting of linear acceleration and angular velocity, a second sensing assembly for sensing characteristics related

to joint structure comprising sensors to measure bioimpedance of the joint, a health assessor that provides an assessment of joint health through interpretation of characteristics from the first and the second sensing assemblies, and an output assembly capable of providing an indication of joint health to a user of the system.

At least a portion of the acoustic sensors can comprise wearable acoustic sensors for placement proximate the joint. At least a portion of the acoustic sensors can comprise sensors for placement distal the joint.

The sensors to measure at least one non-acoustic characteristic of joint movement and the sensors to measure bioimpedance of the joint can comprise wearable sensors for placement proximate the joint.

The wearable sensors to measure bioimpedance of the joint can comprise at least four surface electrodes configured to measure EBI of tissue and blood proximate the joint.

The wearable acoustic sensors can comprise piezoelectric film and are capable of measuring surface vibrations of the skin associated with acoustic emissions from the joint.

The acoustic sensors distal the joint can comprise microphones capable of measuring airborne acoustic emissions from the joint.

At least a portion of the acoustic sensors can comprise wearable acoustic sensors for placement proximate the joint capable of measuring surface vibrations of the skin associated with acoustic emissions from the joint, wherein the sensors to measure at least one non-acoustic characteristic of joint movement and the sensors to measure bioimpedance of the joint can comprise wearable sensors for placement proximate the joint, and wherein at least a portion of the acoustic sensors can comprise microphones distal the joint and capable of measuring airborne acoustic emissions from the joint.

At least a portion of the wearable sensors can comprise surface silver/silver-chloride (Ag/AgCl) gel electrodes.

At least a portion of the wearable sensors can comprise capacitive dry electrodes.

At least a portion of the wearable sensors can comprise textile electrodes.

In another exemplary embodiment, the present invention is a system for assessing joint health comprising a first sensing assembly for sensing characteristics related to joint physiology, the first sensing assembly comprising acoustic sensors capable of sending at least one signal representative of acoustic emissions from the joint during movement, and sensors capable of sending at least one signal representative of at least one non-acoustic characteristic of joint movement selected from the group consisting of linear acceleration and angular velocity, a second sensing assembly for sensing characteristics related to joint structure comprising sensors capable of sending at least one signal representative of bioimpedance of the joint, a health assessor comprising at least one processor that provides an assessment of joint health through processing the signals from the first and the second sensing assemblies, and an output assembly capable of providing an indication of the joint health from the health assessor to a user of the system.

The second sensing assembly can further comprise an electronic interface to the sensors capable of sending at least one signal representative of bioimpedance of the joint.

At least one of the health assessor processors can automatically and periodically calibrates the bioimpedance measurements using electronic loads and an algorithm.

At least one of the health assessor processors can process at least one signal representative of acoustic emissions from the joint in the context of joint angle.

At least one of the health assessor processors can process acoustic emissions from the joint using filter banks to separate signals based on frequency content.

At least one of the health assessor processors can detect a type of activity occurring in proximity to the joint, and processes acoustic emissions from the joint during the activity based on the type of activity. A type of activity can be selected from the group consisting of unloaded knee flexion/extension exercise, sit-to-stand exercise, walking, and stair-climbing.

At least one of the health assessor processors can process at least one signal representative of bioimpedance of the joint, which processing provides an indication of joint swelling.

At least one of the health assessor processors can process at least one signal representative of bioimpedance of the joint, which processing provides an indication of blood flow proximate the joint.

At least one of the health assessor processors can process at least one signal representative of bioimpedance of the joint, which processing provides an indication of blood volume proximate the joint.

In another exemplary embodiment, the present invention is a wearable system for assessing joint health of a user comprising a first sensing modality assembly for sensing characteristics related to joint physiology, a second sensing modality assembly for sensing characteristics related to joint structure, and a health assessor that quantifies a degree of injury at the joint through interpretation of characteristics from the first and the second sensing modality assemblies.

The system can further comprise an output assembly capable of providing an indication of joint health to the user of the system. The system can further comprise an output assembly capable of providing an indication of joint health to a care giver of the user of the system.

The first sensing modality assembly can comprise an acoustical assembly.

The second sensing modality assembly can comprise a bioimpedance assembly.

The acoustical assembly and health assessor can be capable of determining acoustical emissions proximate the joint and distal the joint.

The bioimpedance assembly and health assessor can be capable of determining joint swelling.

The bioimpedance assembly and health assessor can be capable of determining blood flow proximate the joint.

The bioimpedance assembly and health assessor can be capable of determining blood volume proximate the joint.

In another exemplary embodiment, the present invention is a system for assessing joint health of a user comprising a first sensing modality assembly for sensing characteristics related to joint physiology, the first sensing modality assembly comprising an acoustical assembly including wearable proximate joint acoustic sensors capable of sending at least one signal representative of acoustic emissions from the joint during movement, distal joint acoustic sensors capable of sending at least one signal representative of airborne acoustic emissions from the joint during movement, and wearable proximate joint sensors capable of sending at least one signal representative of at least one non-acoustic characteristic of joint movement selected from the group consisting of linear acceleration and angular velocity, a second sensing modality assembly for sensing characteristics related to joint structure, the second sensing modality assembly comprises a bioimpedance assembly, and a health

assessor that provides an assessment of joint health through processing of characteristics from the first and the second sensing assemblies.

The bioimpedance assembly and health assessor can be capable of determining characteristics related to joint structure selected from the group consisting of joint swelling, blood flow, and blood volume.

The bioimpedance assembly can comprise a source of current and a receiver, and a processor capable of measuring the potential difference across the joint through amplification and phase-sensitive detection stages.

The source of current comprises electrodes.

The source of current can be capable of delivering current to the joint through the electrodes.

The source of current can deliver current below a safety threshold that does not create damage at the joint.

The source of current can deliver current at a frequency such that it can propagate through both intra and extracellular fluids.

The electrodes can comprise a quadripolar configuration to reduce the effect of electrode-skin interface impedance.

The blood flow characteristic can comprise a static component and a dynamic component.

The static component of the blood flow characteristic can relate to relatively slow-varying fluid volume.

The dynamic component of the blood flow characteristic can relate to relatively fast-varying blood flow rate.

The wearable proximate joint acoustic sensors can comprise contact microphones that capture sound waves originated by mechanical vibrations in proximity of the joint.

In another exemplary embodiment, first a baseline recording can be obtained with the multiple modalities of sensors, then the joint and/or muscles around the joint, can be perturbed, then a second recording can be obtained by the same set of sensors. The differences between the joint characteristics before and after the perturbation can be quantified and used to augment the joint health score calculation.

As used herein, perturbation means a deviation of the joint or location of interest, from its regular or normal state of path, caused by an outside influence. The joint or location of interest can have a first state (pre-perturbed) and a second stage (post-perturbed). Thus, perturbation can include many outside influences including activity, temperature change, sound, and other electromagnetic fields that might, for example, perturb the joint from a first state to a second state.

The perturbation can involve, for example, local heating or cooling of the skin at the joint to modify internal fluid levels by changing pre and post capillary pressures.

The perturbation can comprise exercise performed by the user, such as running or jumping.

The perturbation can comprise local muscle fatigue for the muscles surrounding the joint, such as the quadriceps for a knee joint health sensing system. Such fatigue can be induced, for example, using eccentric contraction protocols such as downhill running.

The perturbation can comprise changing the local stiffness conditions at the joint, such as by applying external forces to resist the motion of the joint.

These and other objects, features and advantages of the present invention will become more apparent upon reading the following specification in conjunction with the accompanying drawing figures.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. 1 is a block diagram of knee joint acoustic emissions sensing and interpretation for quantifying joint health during rehabilitation according to an exemplary embodiment of the present invention.

FIGS. 2(a)-(b) illustrate sensor placement and measurement block diagrams according to an exemplary embodiment of the present invention.

FIGS. 3(a)-(d) illustrate joint sound processing of recordings taken with an electret microphone positioned at the lateral side of the patella (a-c) and results (d) according to an exemplary embodiment of the present invention.

FIGS. 4(a)-(b) illustrate joint sounds simultaneously sensed by electret, MEMS, and piezoelectric film microphones during three repetitions of (a) flexion/extension and (b) sit-to-stand exercises according to an exemplary embodiment of the present invention.

FIG. 5 illustrates joint sounds measured on the skin and 5 cm off the skin during flexion/extension exercises according to an exemplary embodiment of the present invention.

FIG. 6(a) is a block diagram of a bioimpedance measurement system according to an exemplary embodiment of the present invention. FIG. 6(b) is an algorithm for identifying the time intervals when the user is in the correct position to acquire measurements (sitting, legs extended and supported) according to an exemplary embodiment of the present invention.

FIG. 7(a) show static and dynamic resistance signals ($r(t)$ and $\Delta r(t)$) measured from a subject during various activities according to an exemplary embodiment of the present invention. FIG. 7(b) is a segment of the dynamic resistance signal, zoomed in at * (see FIG. 7(a)). FIG. 7(c) is an ensemble averaged dynamic resistance signals while the subject assumes different positions. FIG. 7(d) illustrates the means and the standard deviations of four features extracted from $\Delta r(t)$ shown in bar graphs for the accepted and rejected measurement time intervals.

FIG. 8 is a block diagram of the bioimpedance measurement system for local joint health assessment according to an exemplary embodiment of the present invention.

FIG. 9 is another block diagram of the bioimpedance measurement system for local joint health assessment according to an exemplary embodiment of the present invention.

FIG. 10 is a physiology-driven algorithm design for extracting cardiovascular parameters automatically from the dynamic component (i.e. IPG) of the bioimpedance signals according to an exemplary embodiment of the present invention.

FIGS. 11(a)-(d) illustrate circuit verification. (a) Photo of the printed circuit board (PCB) fabricated for the analog front-end. (b) Calibration of the resistance and reactance measurements demonstrated high linearity and consistency (points are shown for multiple measurements taken on different days). (c) Noise spectral density plots for dynamic impedance measurements (i.e. IPG). The total noise integrated from 0.8-20 Hz was found to be $18 \mu\Omega_{rms}$ for the resistive and $55 \mu\Omega_{rms}$ for the reactive dynamic components, lower than any other previously reported design in the existing literature. (d) Demonstration of improvement of calibration using the innovative microcontroller-enabled automatic calibration methods according to an exemplary embodiment of the present invention.

FIGS. 12(a)-(e) illustrate human subject measurements according to an exemplary embodiment of the present invention. (a) Electrode placement for knee IPG acquisition. (b) Static impedance measurements. (c) Example waveforms from the intermediate stages of the preprocessing and the feature extraction. (d) Comparison of extracted features using ECG-based vs. IPG-based ensemble averages. (e) Evaluation of the system in response to changes in physiology (vasoconstriction after 2 minutes cold pressor test).

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FIG. 13 is a graph of the magnitude of difference in resistance versus reactance between the left and right leg for control subjects (circle markers) versus following acute knee injury (square markers) according to an exemplary embodiment of the present invention. This small feasibility study already demonstrated a statistically significant difference between the populations, as evident by the clear separation between the groups, and in accordance with prior studies in the existing literature with bench-top bioimpedance measurement circuits.

FIG. 14 illustrates the concept of acquiring two sets of recordings with the system, the first taken as a baseline recording, and the second taken following a perturbation.

FIG. 15 is an illustration of the effects of vertical loading forces on the acoustic emissions resulting from frictional rubbing of internal surfaces in the knee.

FIG. 16 is an illustration of the measurement setup, with the subject performing vertical leg press at varying weights up to the body weight, and the measurements of acoustical emission.

FIGS. 17-18 illustrate sensor placement and overview of the method of how the signals acquired are analyzed. In FIG. 17, four contact microphones are placed on the medial and lateral sides of the patella and superficially to the medial and lateral meniscus. In FIG. 18, the signal analysis workflow for knee joint sounds. The signals from the dominant knee of the subjects are filtered and standardized (to zero mean and unity variance) and windowed (frame length of 200 ms with 90% overlap). The features are extracted for all four mics and vertically concatenated where columns represent the features and rows represent all the windowed segments. A k-Nearest Neighbor graph (kNN graph) is constructed from the matrix formed using data from the dominant knee and calculates the graph community factor (GCF) using the graph community detection algorithm.

FIGS. 19-20 show an alternative exercise that can measure joint sounds with different loads. FIG. 19—Alter G device allows the user to reduce their body weight by a designated percentage down to 20 percent. FIG. 20 is an illustration of the activity and measurements of acoustical emissions from the joint with contact microphones with respect to the angle of the dominant knee.

FIG. 21 are graphs created based on the sound features for all windows of the recording and calculating the GCF score. Example graph from one subject are shown with the associated loading condition and GCF.

FIG. 22 is a box plot showing GCF increases with loading for subject (n=11), indicating more heterogeneity for all acoustical signatures. The asterisk (*) represents the p-value less than 0.01 which is calculated using a non-parametric paired Kolmogorov-Smirnov test.

FIG. 23 is a box plot showing GCF for different microphones (locations on the knee). The data matrix consists of all loading conditions per microphone for each subject. The asterisk (*) indicates the p-value less than 0.01 which is calculated using a non-parametric paired Kolmogorov-Smirnov test.

FIG. 24 are graphs related to the set-up of FIGS. 19-20, being graphs created based on the sound features for all windows of the recording and calculating the GCF score. Example graph from one subject is shown with different percentage of the body weight.

FIG. 25 is an illustration of concept for how physiological biomarker driven recovery can ensure that a player remains in the optimal zone (or at least outside the zone where there is a high risk of overuse injury) by quantifying when the elbow and shoulder joint health is sufficiently recovered.

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FIGS. 26(a)-(d) illustrate (a) an overview of sensing technologies and hardware, (b) example movements used to generate acoustical emissions from the joints, (c) joint angle (top) and acoustical emission (bottom) signals measured in preliminary work, and (d) machine learning based approach to quantifying recovery/fatigue of a joint.

DETAIL DESCRIPTION OF THE INVENTION

To facilitate an understanding of the principles and features of the various embodiments of the invention, various illustrative embodiments are explained below. Although exemplary embodiments of the invention are explained in detail, it is to be understood that other embodiments are contemplated. Accordingly, it is not intended that the invention is limited in its scope to the details of construction and arrangement of components set forth in the following description or illustrated in the drawings. The invention is capable of other embodiments and of being practiced or carried out in various ways. Also, in describing the exemplary embodiments, specific terminology will be resorted to for the sake of clarity.

It must also be noted that, as used in the specification and the appended claims, the singular forms “a,” “an” and “the” include plural references unless the context clearly dictates otherwise. For example, reference to a component is intended also to include composition of a plurality of components. References to a composition containing “a” constituent is intended to include other constituents in addition to the one named.

Also, in describing the exemplary embodiments, terminology will be resorted to for the sake of clarity. It is intended that each term contemplates its broadest meaning as understood by those skilled in the art and includes all technical equivalents which operate in a similar manner to accomplish a similar purpose.

Ranges may be expressed herein as from “about” or “approximately” or “substantially” one particular value and/or to “about” or “approximately” or “substantially” another particular value. When such a range is expressed, other exemplary embodiments include from the one particular value and/or to the other particular value.

Similarly, as used herein, “substantially free” of something, or “substantially pure”, and like characterizations, can include both being “at least substantially free” of something, or “at least substantially pure”, and being “completely free” of something, or “completely pure”.

By “comprising” or “containing” or “including” is meant that at least the named compound, element, particle, or method step is present in the composition or article or method, but does not exclude the presence of other compounds, materials, particles, method steps, even if the other such compounds, material, particles, method steps have the same function as what is named.

It is also to be understood that the mention of one or more method steps does not preclude the presence of additional method steps or intervening method steps between those steps expressly identified. Similarly, it is also to be understood that the mention of one or more components in a composition does not preclude the presence of additional components than those expressly identified.

The materials described as making up the various elements of the invention are intended to be illustrative and not restrictive. Many suitable materials that would perform the same or a similar function as the materials described herein are intended to be embraced within the scope of the invention. Such other materials not described herein can include,

but are not limited to, for example, materials that are developed after the time of the development of the invention.

Methods for Sensing Acoustical Emissions from the Knee for Wearable Joint Health Assessment

In an exemplary embodiment of the present invention, wherein the multi-modal sensing relates to one type of joint characteristic, like joint acoustic emission, the invention can comprise systems and methods of wearable joint rehabilitation assessment following musculoskeletal injury using miniature sensors readily integrated into a wearable device enabling, for the first time, wearable joint acoustics sensing (FIG. 1).

Microphone Selection

When investigating types of sensors to use in the present invention, the following were considered: (i) their ability to sense acoustic emissions, and (ii) their practicality for integration within a wearable system. Analysis of how joint sounds propagate through the tissue and transmit to the air suggest contact microphones are the most appropriate sensor for acquiring joint sounds, and a review of conventional systems illustrated that most research employed contact microphones successfully in clinical/lab applications. A contact microphone should theoretically acquire the highest quality acoustic signal since it senses the original, non-attenuated signal and is not sensitive to background noise.

However, during motion and unsupervised at-home activity, loss of the sensor-to-skin interface is likely and of significant concern, for any compromise to the interface will be detrimental to the signal. In the extreme case that the sensor loses contact with the skin, the system will be unable to record joint sounds completely.

To improve robustness, air microphones provide complementary sensing capabilities. The signal obtained by air microphones is inherently different from contact microphones. Air microphones will only detect the airborne sounds: attenuated, higher frequency signals. Additionally, while not limited by the sensor-to-skin interface like contact microphones, air microphones are much more susceptible to background noise. For these reasons, the present invention employed both sensing modalities—contact and air microphones—to more robustly capture the acoustic emissions from the joint in a wearable device.

For the contact microphone, a piezoelectric film (SDT, Measurement Specialties, Hampton, Va., US) was selected because its form factor seemingly lends itself to a wrap and other devices conventionally worn on the knee. Furthermore, piezoelectric films have wider bandwidths compared to miniature, low cost accelerometers, allowing for sensing of high frequency audio signals.

Two types of air microphones were selected to supplement the piezoelectric film in acquiring acoustic emissions from the knee joint. The first was a commercially-available electret microphone (Sanken Microphone Co., Ltd., Japan). The second was a MEMS microphone, specifically the MP33AB01 (STMicroelectronics, Geneva, Switzerland), which was mounted on a custom PCB.

Electret and MEMS microphones sense sounds in a similar manner; however, the commercial electret microphone is much more expensive (~100×) compared to the MEMS microphone. The MEMS's low-cost and sensing capabilities provide a more realistic solution for implementation in a wearable device; however, both the electret and MEMS microphones were used during experiments with the electret microphone acting as the industry standard in terms of the quality of the sound acquired. Recordings from the air

microphones were of primary focus because presently they provide higher quality recordings.

Methods for Microphone Comparison

The similarity of the MEMS and electret microphones in detecting knee joint acoustic emissions was quantified by computing the information radius between the normalized histograms of these signals, which were acquired by both sensors at the same time placed in the same location on the lateral side of the patella. To construct the aforementioned histograms, the signals acquired from the microphones were first normalized such that their amplitudes were limited to the range [0, 1]. The histogram was formed from this normalized signal using 1000 bins.

Next, the quality of each sensor was evaluated by computing the signal-to-noise-and-interference ratio (SNIR). The SNIR for each microphone was calculated by finding the ratio of the peak power of a “click” (i.e., acoustic emission) emitted by the knee joint to the peak power of interface noise in the vicinity of the click. For this calculation, acoustic emissions from the microphones positioned at the medial side of the patella for the air microphones and distal side of the patella for the contact microphone were used.

Lastly, a proof-of-concept experiment was conducted to compare signals measured on and off of the skin. A subject performed three cycles of seated, unloaded knee flexion/extension with two electret microphones positioned at the lateral side of the patella, one on the skin and one located 5 cm off the skin. The resulting signals were then compared.

Interfacing Circuits

The analog front-end for the MEMS microphones comprised a non-inverting amplifier stage with 33 dB gain, which was selected such that the signals do not saturate but are amplified to utilize the full dynamic range of the subsequent analog-to-digital converter, and a high-pass 15 Hz cutoff frequency. This stage was followed by a second-order low-pass filter with a cutoff frequency of 21 kHz. A bandwidth of 15 Hz-21 kHz was chosen, as knee joint sounds can range between these frequencies.

The analog front-end for the piezoelectric film microphones comprised an amplification stage of gain 45 dB and 100 Hz high-pass cut off. This stage was followed by a fourth-order low pass filter with a 10 kHz cut-off frequency. A 100 Hz high-pass cut off was chosen to attenuate the interface and motion artifact noise.

Human Subject Study and Measurement Protocol

Thirteen male subjects without history of knee injuries participated in the study and gave written informed consent approved by the Georgia Institute of Technology Institutional Review Board (IRB) and the Army Human Research Protection Office (AHRPO). The subject population was reasonably homogenous in terms of physical activity level (collegiate athletes) and ranged in age (19-21 years), weight (84.1-135.3 kg), and height (174-195 cm). With this approach, the plan was to assess the variability in the measurements separately from variability due to age or knee joint health.

Following preliminary measures of body composition, height, and weight, an electret and MEMS microphone were both positioned at the lateral and medial sides of the subject's patella targeting the patellofemoral joint while two piezoelectric film sensors were placed on the skin just proximal and distal to the patella. Each sensor was attached using Kinesio Tex tape. In addition to the tape, a thin piece of silicone (5 mm thick) was placed over the piezoelectric film to reduce the interface noise of the tape rubbing against the film. Lastly, two wireless inertial measurement units

(IMUS) (MTW-38 A70G20, Xsens, Enschede, The Netherlands), which contained three-axis accelerometer, gyroscope, and magnetometer as well as built-in sensor fusion outputs, were positioned on the lateral sides of the thigh and shank.

FIG. 2 illustrates sensor placement and measurement block diagram. In FIG. 2(a), eight sensors were used during human subject testing. Two IMUS were placed laterally on the thigh and shank. Piezoelectric film sensors were placed directly proximal and distal of the patella. The air microphones (MEMS and electret) were attached on the lateral and medial sides of the patella. FIG. 2(b) is a block diagram of the data collection hardware used during human subject studies.

While wearing these sensors, each subject completed two exercises: (i) seated, unloaded knee flexion/extension and (ii) sit-to-stand. For each exercise, the subject repeated the motion five times while the microphone and IMU outputs were recorded in a quiet room (FIG. 2(b)). The signals from the piezoelectric and MEMS microphones were passed through custom circuits and then collected at 50 kHz (16 bits/sample) using Biopac data acquisition hardware (Biopac Systems Inc, Goleta, Calif., US) while the signals from the electret microphones were sampled at 44.1 kHz (16 bits/sample) using a Zoom H6 recorder (Zoom Corp., Tokyo, Japan).

The IMU signals were acquired at 50 Hz (16 bits/sample) using their device-specific software suite (MT Manager, Xsens, Enschede, The Netherlands) synched with the Biopac system. Apart from the electret microphone signals, which were stored on an SD card (SanDisk, Milpitas, Calif., US) via the Zoom recorder, all signals were recorded on a laptop. The data were then processed using MATLAB (The Mathworks, Natick, Mass.).

Joint Sound Processing

The signal processing comprises (i) calculation of knee joint angle and contextualization of the joint sounds with joint angle, (ii) identification of significant high frequency acoustic emissions or clicks, and (iii) statistical analysis to quantify the consistency of occurrence of the main clicks with respect to joint angle.

First, the knee joint angle was calculated using the methods that leverage the sensor fusion outputs of 3-axis accelerometer, gyroscope, and magnetometer provided by Xsens, namely the rotation matrix (i.e., Direction Cosine Matrix), and the kinematic constraints of a hinge joint to provide angle data. This method allowed for arbitrary sensor placement and orientation on each segment of the joint (i.e., thigh and shank), eliminating the need for precise calibration techniques and measures. However, this method is potentially susceptible to error, due to deviations from a true hinge joint as a result of skin and motion artifacts. Nevertheless, since the cycles of repetitive motions were analyzed against one another, this error was common to each cycle and thus did not present in the results.

Finally, the signal was normalized between 0° and 90° such that subjects could be compared against one another with respect to location within each subject's range of motion.

FIGS. 3(a)-(d) illustrate joint sound processing of recordings taken with an electret microphone positioned at the lateral side of the patella (a-c) and results (d). FIG. 3(a) is an example 3000 sample (60 ms) joint sound recording window showing three distinct high-amplitude, short-duration, acoustic emissions. The original signal contains ambient noise, which presents as broadband signals up to 7 kHz, and interface noise, which appears as baseline movement.

These components are clearly visualized in the spectrogram of the original signal. To remove the majority of the noise, the signal is bandpass filtered at 7 kHz-16 kHz, resulting in the filtered signal $x[n]$.

The envelope of this signal is found, yielding $A[n]$. Using a thresholding technique based on the moving average, the significant peaks of $A[n]$ are found, roughly corresponding to the clicks of the original signal. These are later refined to match the true locations of the clicks found in the original signal (i.e., such that the locations correspond to where the clicks achieve their maximum amplitudes, positive or negative, in the original signal). FIG. 3(b) illustrates a final result of the click detection algorithm, which displays the identified clicks for three cycles of flexion/extension. FIG. 3(c) illustrates three extension cycles with artificial offsets. These qualitatively show that the main acoustic event of each cycle occurs at similar angular locations. FIG. 3(d) illustrates the final results of click location consistency for five repetitions of flexion/extension for 13 subjects on left and right legs. Across subjects, the standard deviation for click location is small, supporting observations of consistent angular location cycle-to-cycle. Additionally, the mean locations of these clicks are consistent between left and right legs for most of the subjects.

As discussed and in more detail, once knee joint angle was calculated, the phases (flexion or extension) of each cycle were determined (FIG. 3(b)). First, the inflection points of the signal were found. The beginning and ending of each phase were identified by finding pairs of inflection points. These points were then used to segment the microphone signals, contextualizing the data by type of angular motion.

Next, significant acoustic emissions were identified. The most distinct audio signals that were detected by the air microphones were the high amplitude, short duration clicks (FIG. 3(a)). By observing the signal's frequency content (i.e., short-time Fourier transform, STFT), these clicks were broadband with frequencies as high as 20 kHz. This unfiltered signal contained two main sources of noise; ambient noise ranged in frequency up to 7 kHz while interface noise appeared as baseline movement with components up to 1.5 kHz. The first step of this identification stage was to preprocess the signal such that the clicks became more prominent and any interface and/or ambient noise were mostly cancelled. To this extent, the air microphone signals were filtered with a bandpass filter spanning 7 kHz-16 kHz. As seen from FIG. 3(a), the filtered signal ($x[n]$) lacks the original baseline movement, and the clicks are more distinct from other artifacts in the signal.

After this preprocessing step was complete, a modified envelope detection algorithm was implemented. A 1024-bin spectrogram of the signal ($X[n, m]$) was calculated with a window size of 100 samples (i.e., 2 ms) and 90% overlap. The amplitude of the signal was calculated by summing the logarithmic amplitude of the spectrogram across the frequency bins as follows:

$$A[n] = \sum_j 20 \log |X[n, j]| \quad (1)$$

A moving average and standard deviation ($\mu[n]$ and $\sigma[n]$) of $A[n]$ using a window size of 1000 samples were calculated. $A[n]$ was then thresholded such that:

$$T[n] = \begin{cases} A[n], & A[n] > \mu[n] + \alpha \cdot \sigma[n] \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $T[n]$ is the thresholded amplitude signal and α is a constant control coefficient, which was selected as 3.3 by inspection.

Next, the peaks of $T[n]$ were detected by standard peak detection techniques. The peaks that resulted from the same click (i.e., resonances of the initial click, which are specified as peaks within 150 samples of each other) were eliminated, resulting in the raw click locations vector $p_r = [p_{r,1}, p_{r,2}, \dots, p_{r,L}]$. The raw click locations p_r were refined such that each click location corresponded to the point on the original filtered signal where the click achieved its maximum amplitude, positive or negative. The refined click locations matrix $p = [p_1, p_2, \dots, p_L]$ gave the final detected click locations. An example of these detected clicks is shown in FIG. 3(b).

Once the clicks were identified, the consistency of these acoustic emissions was analyzed. FIG. 3(c) provides a visualization of consistent acoustic emission during repetitive motion. For each cycle of a particular exercise (i.e., flexion or extension), the three clicks with the largest amplitudes and their corresponding angular locations were determined. Each combination of the clicks across cycles (i.e., selection of one of the three clicks from each cycle) was found. The combination with the smallest standard deviation for angular location yielded the most consistently occurring major acoustic event. The mean and standard deviation of these locations were calculated.

Given these mean locations, three methods were used to analyze the data. For the first two methods, test-retest reliability was estimated using the ICC. The data was organized into “motions” and “repetitions.” There were 52 “motions,” one for each human subject and exercise combination (e.g., subject 1’s extension data represented one “motion”). The “repetitions” comprises the five click locations (one per cycle) from the selected combination. This dataset will be referred to as the test-retest dataset.

Given this dataset, two ICC values were calculated using one-way random single (i.e., ICC(1, 1)) and average measure (i.e., ICC(1, k)) models to show the reliability of a single cycle’s measure and mean of the five cycles’ measures. Additionally, the 95% confidence intervals (CI) for these two ICC values were determined. The last method for analyzing the data was a paired t-test, which was used to assess whether there were significant differences between the mean click locations for left and right legs.

Results and Discussion

Microphone Comparison

In evaluating microphone selection, many different parameters were considered. First, the similarity of the signals measured by the electret and MEMS microphones were compared. The quality of these microphones was determined by evaluating the quality of their sensing capabilities in terms of SNIR. Moreover, when investigating interface issues for the air microphones, the effect that the sensor-to-knee distance had on the signal acquired was examined. Finally, the quality of the contact microphone was researched.

FIG. 4. illustrates joint sounds simultaneously sensed by electret, MEMS, and piezoelectric film microphones during three repetitions of FIG. 4(a) flexion/extension and FIG. 4(b) sit-to-stand exercises. For both parts FIGS. 4(a)-(b), the

top plot displays the joint angle ($\theta[n]$). The middle and bottom graphs show the time and frequency domain signals from the various microphones. The acoustic signatures of the electret and MEMS microphones exhibit similar characteristics.

As shown in FIGS. 4(a)-(b), the electret and MEMS microphones, measuring frequencies as high as 20 kHz, performed similarly in detecting joint sounds, which were acquired from a subject performing flexion/extension and sit-to-stand exercises respectively. This was confirmed by computing the information radius between the normalized histograms of signals captured by these two microphones, which yielded a value of 0.0025. This value shows a high similarity between these two types of microphones since the information radius ranges from 0 for identical distributions to 2 for maximally different distributions. This shows that the more cost-effective MEMS microphones are a viable substitute for the more expensive electret microphones. This is an important result when designing deployable systems.

As predicted, the signal recorded by the air microphones included noise and interface components in addition to the desired joint sounds; both ambient background interference and interface noise caused by the rubbing of athletic tape, which was used to hold the sensors in place, were sensed by the microphones. The SNIR was 11.7 dB for the electret microphone and 12.4 dB for the MEMS microphone. To minimize issues with noise during initial experiments, measurements were taken in a quiet room. Further investigation can be addressed for implementation of a deployable, wearable system, especially given the fact that many background noises, such as speech and sounds due to ambulatory motion, will reside in-band with the joint sounds.

FIG. 5 illustrates joint sounds measured on the skin and 5 cm off the skin during flexion/extension exercises. Though the off-skin microphone captured a signal with decreased amplitude, the on- and off-skin measurements showed significant similarities in their acoustic signatures. The main acoustic event of each signal occurred at similar locations.

Experiments showed that the air microphones did not need to be directly located at the skin surface to detect airborne joint sounds. As shown in FIG. 5, the sounds obtained from an electret microphone placed on the skin and one located 5 cm off the skin captured similar acoustic signals in both morphology and timing (~4.5× smaller amplitude). This is an important observation because it suggests that the air microphones can record joint sounds in a wearable device where direct contact with the skin may not be constant. However, it will be important to consider this distance when analyzing the captured signals, particularly when the analysis depends on the amplitude of the signal.

In this sense, maintaining a fixed distance between the microphone and skin, especially for use in longitudinal analysis, may be required. Furthermore, placing the microphone off of the skin introduces increased potential for noise; the microphone may have a greater opportunity to strike or rub against the skin. Additionally, changing the distance between the microphone and skin will change the microphone’s sensitivity in sensing these sounds.

The piezoelectric film measured signals up to approximately 3 kHz as seen from the spectrograms of the signals acquired shown in FIG. 4. While the piezoelectric film had the advantage of not detecting background noise, it acquired significantly more interface noise—8.4 dB SNIR—due to the sensor rubbing on the skin and the athletic tape rubbing on both the skin and the sensor. This interface noise had frequency components up to 1.5 kHz and was thus in-band.

During early pilot data collections, the piezoelectric film was attached to the skin using only Kinesio Tex tape. However, this method proved to be very susceptible to interface noise. As the knee extends and flexes, the tape, though stretchable, deformed the film which obscured the low frequency and low amplitude signatures. Furthermore, though acceptable for collecting pilot data, tape proves to be undesirable for long-term monitoring. To mitigate this issue, a piece of silicone was placed above the piezoelectric film. Because silicone has similar compliant mechanical properties to skin and subcutaneous tissue, the joint sounds received did not experience dampening, and the silicone surface provided a suitable surface to stick the tape. Though this method did not completely eliminate interface noise—the sensor still experienced some movement along the skin—it did help to reduce the recorded noise.

Accordingly, while using piezoelectric film or other contact microphones is desired to capture the vibration signal, which represents the majority of the acoustical energy generated, implementation presents practical issues. The piezoelectric film was significantly affected by interface noise. A smaller portion of the signal bandwidth was corrupted by interface noise for the air microphones compared to contact microphones. Furthermore, contact microphones did not pick up higher frequency vibrations as distinctly as air microphones. For these reasons, the use of air microphones for wearable joint sound measurements might be preferable.

Joint Sound Consistency

FIG. 3(d) summarizes the results for mean angular click location for the left and right legs of 13 seated subjects performing five repetitions of knee flexion/extension. Two important findings resulted from this data: (i) significant acoustic events are repeatable during single trial measures, and (ii) left and right legs produce similar sounds.

First, two ICC values were found for the test-retest dataset. An ICC(1,1) value of 0.94 with a 95% CI of 0.92-0.97 and an ICC(1, k) value of 0.99 with a 95% CI of 0.98-0.99 were calculated. Since the ICC values were greater than 0.7, these values showed that the main acoustic emission per cycle of activity were consistent within a single trial of monitoring for both single and average measure reliability. Given that audible joint sounds have not been extensively explored, this was an important finding, demonstrating that airborne signals emit a stable pattern with repeated movement in a healthy hinge joint.

Second, the difference between legs for each exercise suggested that a healthy subject's knees produce similar joint sounds. The difference between left and right legs were not significant at the $p < 0.05$ level. While as a group, there were no significant differences between the left and right legs, some subjects could be grouped as having relatively no difference between right limb and left limb click locations whereas others had notable differences between right and left suggesting the potential for defining clinically relevant "signature traits". Such variations in click location could represent useful knee joint health biomarkers.

Though these results are promising, there are some limitations to the tested system and analysis. First, with regard to the IMUs, sensor positioning, drift, and motion artifacts can all contribute to flexion angle calculations that differ from the true joint angle. Techniques discussed herein, and others will need to be employed to minimize these errors, especially when considering their application in a system which measures longitudinal data. For example, some errors could be minimized by ensuring more rigid sensor position-

ing and leveraging the joint's kinematic constraints directly into the calculation of joint angle to reduce the effect of drift.

Second, the effect of lubrication (e.g., diminished boundary lubrication after an injury) and differing structural components (e.g., damaged ligaments, etc.) on acoustic emissions has not yet been sufficiently studied. These variables may introduce "error" when calculating click location consistency for repeated cycles and measuring differences between legs. In this sense, these isolated, one-time measurements may not prove to be as useful as compared to longitudinal analysis for the same subject over time.

These quantitative findings in terms of measurement consistency form the foundation for understanding the significance of changes in joint sound signatures associated with injury, as well as changes in such signatures during rehabilitation. Moreover, while longitudinal studies will be important towards understanding injury recovery, this work and its focus on robust implementation in a wearable platform also presents opportunities for exploring day-to-day and within-day changes of joint acoustics.

CONCLUSIONS

In an exemplary embodiment of the present invention, wherein the multi-modal sensing relates to knee joint acoustic emission during loaded and unloaded activities, it is demonstrated, quantitatively, that major acoustic events occur at consistent joint angles during repetitive motions for healthy subjects. Furthermore, these locations are similar between left and right legs for most subjects. Whether asymmetry between right and left knee acoustic emissions is related to risk factors for injury or other training-related variables remains to be clarified. Importantly, these findings showed that joint sound measurements from air microphones are repeatable with sensing technology that can be implemented in a relatively inexpensive, wearable form factor. While extensive analysis of the piezoelectric film was not conducted, its use in a wearable device holds promise based on preliminary findings showing that packaging techniques have a large influence on the signal recorded.

The present invention further includes mitigating background and interface noise for both the air and contact microphones. In particular, a focus on the packaging of these sensors into a wearable wrap or sleeve enabling high quality signal measurements during at-home, long-term monitoring is investigated. Additionally, existing algorithms are refined, and new processing techniques developed to detect clinically-relevant acoustic signatures.

Given that therapists and clinicians look at sounds, swelling, structural stability, and range of motion, the present invention investigates methods for quantifying these joint health biomarkers unobtrusively and accurately; namely, it determines which acoustic signatures encapsulate these biomarkers. Furthermore, exploration of these biomarkers as they relate to specific diseases and injuries (e.g., osteoarthritis, anterior cruciate ligament tear, meniscal tear, etc.) are considered. Finally, longitudinal studies on injured subjects allow for the determination and validation of specific acoustic emission features (e.g., consistent angular location) that provide valuable joint health information during rehabilitation following an acute injury.

A Robust System for Longitudinal Knee Joint Edema and Blood Flow Assessment Based on Vector Bioimpedance Measurements

In another exemplary embodiment of the present invention, joint characteristics including edema and blood flow parameters are examined and systems and methods of wear-

able joint rehabilitation assessment following musculoskeletal injury using bioimpedance technologies readily integrated into a wearable device.

In this embodiment of the present invention, systems and methods are disclosed that address technological gap in the area of wearable bioimpedance measurement systems for local joint physiology assessment.

Position Identification Algorithm

Bioimpedance measurements are too greatly impacted by motion artifacts, subject position, electromagnetic interference and voltage fluctuations of the skin electrode interference. Therefore, for consistency, measurements should be taken when subject is still in a given position and in the absence of electromagnetic interference and skin electrode interface related fluctuations (such as an electrode losing contact with the skin). These conditions can be met under user guidance however this kind of guidance is not feasible in a wearable device setting.

As discussed previously, IMUs can be used to decide if the user is still in an acceptable position for measurements to be taken. However, IMUs will not be effective in detecting electromagnetic interference or skin-electrode interface related fluctuations. These kinds of effects can however be detected using the dynamic resistance signal which is greatly influenced by them, as well as the user position and motion artifacts.

IMUs along with the dynamic resistance (impedance plethysmography) signals can be used together to decide if the user is in an acceptable position for bioimpedance measurements to be taken or not. The IMUs would be used to provide information about the subject's limb position (such as knee angle) and the activity that the subject is performing (such as walking, running, sitting still etc.). The dynamic resistance signal can be used to assist in detecting the subject's limb position and the activity being performed. It can also be used to deduce if any of the electrodes were misplaced and if any of the electrodes lost contact with the skin. If any changes on the electrode positioning occur, these can be detected through features extracted from the dynamic resistance signal. The bioimpedance measurements also get affected by muscle contractions. The dynamic resistance signal can also be used to deduce if the limb muscles are relaxed or contracted.

The dynamic resistance signal was used to design an exemplary algorithm that can decide if the user is in an acceptable position for bioimpedance measurements to be taken. IMUs can be used to assist such an algorithm as well. In this exemplary embodiment, only the dynamic resistance signal was used. In this case, the acceptable position was when the subject is motionless, seated with legs fully extended and supported from the bottom. All other positions or activities (sitting legs bent, standing, any kind of motion) were to be marked as rejected measurements. The static impedance measurements were not used in the decision process as these are the measurements to be interpreted and using them in the decision process would create tendency to acquire data within a certain range of values.

FIG. 6(a) is a block diagram of a bioimpedance measurement system according to an exemplary embodiment of the present invention. E1-E4 represent the electrodes that interface to the body. The signals $i(t)$ and $q(t)$ relate to the static (slowly varying on the order of hours to days) component and the signals $\Delta i(t)$ and $\Delta q(t)$ relate to the dynamic component of the knee impedance. $A(t)$ is used to monitor the amplitude of the current ($i_{body}(t)$) passing through the knee joint.

The position identification algorithm is summarized in FIG. 6(b) and used for identifying the time intervals when the user is in the correct position to acquire measurements (sitting, legs extended and supported). The acceptable time intervals are identified by extracting features from the dynamic voltage signal $\Delta i[n]$ and using these features to make a decision. The binary decision rule is trained once before-hand. The accepted time intervals are used to obtain the knee resistance ($R_{measured}$) and reactance ($X_{measured}$) using the static voltage measurements $i[n]$ and $q[n]$. $A[n]$ is used to cancel the effects of any variations in injected current amplitude.

The signal $\Delta i[n]$ is linearly filtered (0.3 Hz-20 Hz) to get rid of respiratory artifacts and high frequency noise. Then, the filtered signal is windowed with a window size of 10 seconds and a step size of 1 second (decided heuristically) creating M frames of the filtered signal. The signal in each frame is amplitude corrected using $A[n]$ and calibrated to give the dynamic resistance signal within the frame.

Features extracted from each frame are placed in a feature matrix $F=[f_1 f_2 \dots f_M]^T$, where each column corresponds to a feature and each row to a frame. These features are then used to decide whether a frame should be accepted (classified with label 1 or rejected classified as 0), producing a vector of binary labels $d=[d_1 d_2 \dots d_M]^T$. Frames with standard deviation of the dynamic resistance signal exceeding 50 mΩ are labeled 0 because it is highly likely they contain motion.

The static voltage measurements $i[n]$ and $q[n]$ are also windowed using the same scheme, amplitude corrected using $A[n]$ and calibrated producing the resistance and reactance signals for each of the M frames. The mean of the resistance and reactance signals for each frame are taken to give the average resistance and average reactance vectors, $\bar{r}=[r_1 r_2 \dots r_M]^T$ and $\bar{x}=[x_1 x_2 \dots x_M]^T$ respectively. These M resistance and reactance measurements are either accepted or rejected according to the labels in vector d. The accepted resistance and reactance measurements are placed into the accepted resistance (\bar{r}) and accepted reactance (\bar{x}) vectors respectively. The mean of \bar{r} and \bar{x} are taken to give the final measured resistance ($R_{measured}$) and reactance ($X_{measured}$).

The binary decision rule mentioned is trained separately before it is applied to new data (a testing set). For this training, $\Delta i[n]$ is recorded while the subject does activities with known labels for a known amount of time: (1) standing (label 0), (2) sitting legs bent (label 0), (3) sitting legs crossed (label 0), (4) sitting legs extended and supported (label 1) and (5) walking (label 0) each for 1 minute.

Feature extraction is performed on $\Delta i[n]$ as shown in FIG. 6(b) to produce a feature vector $F_{training}$ and the corresponding known labels $d_{training}$. Feature subset selection is performed on the features in $F_{training}$ via classifier subset evaluation using a support vector machine (SVM) classifier with a genetic search algorithm. The selected subset of features and $d_{training}$ are used to train an SVM (with a cost parameter of 1.0) resulting in the binary decision rule to be used. Note that $F_{training}$ and $d_{training}$ do not include those frames where the standard deviation of the dynamic resistance signal exceeds 50 mΩ (frames with motion artifacts). The feature subset selection and SVM training were carried out using Weka while all other tasks were done on MATLAB.

The features extracted from each frame are described in three categories. The first category of features is generic features that were derived from audio signal feature extraction techniques. The 10-second frame is further partitioned into sub-frames of size 700 ms with 350 ms step size.

Temporal and FFT related features (30 features) are extracted from each 700 ms sub-frame, these are the short-term features. Statistics also referred to as mid-term statistics, such as mean, median and standard deviation (8 statistics) are computed for each feature across all the 700 ms sub-frames resulting in a total of 240 features per frame.

The second set of features is based on the frequency content of the ensemble average of the dynamic resistance waveform across each frame (4 features). The ensemble average of the waveform across the frame is computed using an algorithm. The last sets of features are temporal features extracted from the ensemble average dynamic resistance signal for each frame (23 features).

FIG. 7(a) show static and dynamic resistance signals ($r(t)$ and $\Delta r(t)$) measured from a subject during various activities. The time intervals marked when the subject is in the correct position for taking measurements (sitting, legs extended and supported). The measurements taken when the subject is in the correct position are to be accepted, all other measurements should be rejected. The position identification algorithm is tested on this data. FIG. 7(b) is a segment of the dynamic resistance signal, zoomed in at * (see FIG. 7(a)). The pulsatile component of the signal due to blood flow is clearly seen. The characteristics of this signal are used for position identification.

FIG. 7(c) is an ensemble averaged dynamic resistance signals while the subject assumes different positions. Each ensemble average was taken over a time interval of 40 seconds. The difference in the ensemble average waveforms as the subject assumes different positions can be seen clearly. FIG. 7(d) illustrates the means and the standard deviations of four features extracted from $\Delta r(t)$ shown in bar graphs for the accepted and rejected measurement time intervals. The first graph shows the bar graph for $(-\log_{10}\rho)$ which is related to the SNR of the signal. The second graph is for the peak to peak amplitude of the ensemble average of the signal. The third graph is the 0-3 Hz band power of the ensemble averaged signal. The final graph is for the Euclidean distance between the ensemble average waveform and a template ensemble average waveform acquired during the one-time training phase while the subject assumes the correct position.

The static and dynamic resistance signals measured, while a subject performs a variety of activities is shown in FIG. 7(a). The time intervals where the subject is in the correct position (seated, legs extended and supported) for the measurement to be acceptable are shown in red, while all others are shown in black: subject standing, seated with legs bent 90°, seated leg crossed, walking). This measurement was made over a course of 12 minutes. It can be seen from this figure that both the dynamic and static resistances are greatly impacted by motion artifacts (transition motion labeled as T, walking), which create variations in the orders of one to tens of Ohms.

A portion of the dynamic resistance waveform while the subject is in the correct position is shown in FIG. 7(b). While the subject is still, this waveform varies periodically over the course of milliseconds, and the variability is in the order of tens of milliohms. The static components of the signal do not have this periodic variability as it has been filtered out.

The ensemble averaged dynamic resistance waveforms for three 80-second time intervals where the subject was in different positions (standing, seated legs bent 90°, correct position) are shown in FIG. 7(c). This figure points out some features that can be effective in classifying the time intervals with the correct position from the others, such as the peak to peak amplitude of the ensemble averaged $\Delta r(t)$ waveform. It

can also be seen that the correct position's waveform looks smoother (and thus less noisy) than both the standing and the sitting position's waveforms. This suggests that features related to the SNR, frequency domain and shape of the ensemble averaged $\Delta r(t)$ waveform are potentially effective features as well.

FIG. 7(d) shows the means and standard deviations of four features extracted from the 10 s time windows where the subject is in the correct position (accepted measurement windows) and incorrect position (rejected measurement windows) for the 12 minute measurement shown in FIG. 7(a). The first feature (shown on the leftmost bar graph) is the minus logarithm of the cross-correlation coefficient between the even and odd sub-averages $(-\log_{10}\rho)$ within the 10 second frame. This feature is inversely related to the SNR of the ensemble average waveform. The second and third features (second and third bar graphs from the left) are the peak to peak amplitude and the 0-8 Hz bandpower of the ensemble averaged $\Delta r(t)$ waveform within each 10 second frame. The final feature shown (the rightmost bar graph) is the Euclidean distance between the ensemble averaged $\Delta r(t)$ waveform, and a template ensemble averaged $\Delta r(t)$ waveform taken during the training phase while the subject was in the current position.

As predicted from FIG. 7(c), these four features show effective class separability. Lilliefors and Kolmogorov-Smirnov tests performed on each class and each of the features showed that the distributions were normal ($p < 0.01$). A two-sample t-test (with unequal and unknown class variances assumed) showed significant class separability in each feature ($p < 0.01$).

The training data was used to train a binary classification rule using the method described above. The confusion matrix for the classifier evaluated on the testing data where frames with motion (standard deviation of $\Delta r(t) > 50$ m Ω) are not included is seen on TABLE I.

TABLE I

| Confusion Matrix for the Position Identification Algorithm Evaluated on the Testing Data | | |
|---|----------------------|----------------------|
| N = 405 | Predicted Reject (0) | Predicted Accept (1) |
| Actual Reject (0) | 261 | 5 |
| Actual Accept (1) | 60 | 79 |

The baseline misclassification rate (when the most probable class is always chosen, reject (0) all the frames in this case) was 34.3%. The misclassification rate of the trained classifier was 16% and the precision was 94%. Therefore, although a significant number of frames that should be accepted are rejected by the algorithm, most frames accepted are actually acceptable, which is what matters the most for measurement consistency. The significant number of false negatives is not important as the system only aims to take 5 to 10 measurements (with a 10 second duration) within a day, which makes missing some measurements non-critical. Infrequent measurements are sufficient to monitor knee joint health as the static knee impedance has physiology related variations in the course of ours to days.

Over the course of 12 minutes of testing when only the actual acceptable frames were used for the binary decision rule, the measured resistance (R_{actual} or mean (\bar{r}) along with $\text{std}(\bar{r})$) was $60.9 \pm 0.6 \Omega$ and the measured reactance was $-13.5 \pm 0.7 \Omega$. The impedance measurements when all frames without motion were accepted were $60.5 \pm 4.8 \Omega$ and

$-13.1 \pm 1.5 \Omega$. The higher standard deviation in the impedance measurements is due to inconsistent measurement positions.

When the binary decision rule trained was used, the impedance measurements were $60.8 \pm 1.5 \Omega$ and $-13.54 \pm 1.0 \Omega$ for resistance and reactance respectively. These values are more consistent (have lower standard deviation) and have lower absolute error compared to accepting every frame without motion, due to more consistent subject positioning.

These results are a demonstration of how an algorithm can be used to automatically decide to take bioimpedance measurements when the subject is in a certain position, eliminating the need for user guidance. An algorithm requiring a one-time training similar to this can be implemented on a smart phone that wirelessly communicates with the bioimpedance hardware, which is a step towards creating a "Smart Brace" monitoring knee impedance.

Bioimpedance Systems and Methods

A system that measures bioimpedance signals and then extracts both musculoskeletal (tissue resistance and reactance), and cardiovascular (heart rate, local blood volume, and flow rate) parameters (FIG. 8) is disclosed.

FIG. 8 is a block diagram of the bioimpedance measurement system for local joint health assessment according to an exemplary embodiment. An innovative combination of both musculoskeletal and cardiovascular parameters will be obtained from the knee joint longitudinally during recovery from acute musculoskeletal injury with a wearable device based on the high-performance circuit and system described here.

These physiological parameters are used to quantify both edema and blood flow during post-injury recovery. The invention advances the state-of-the-art for bioimpedance measurement systems by, among other things, (i) incorporating a custom bioimpedance measurement analog front-end for both tissue impedance (static) and local hemodynamics (dynamic) with the highest resolution given the power consumption and size, compared to similar systems, and/or (ii) employing a self-calibration procedure to minimize drift and inaccuracy due to environmental factors such as temperature, and/or (iii) creating customized physiology-driven algorithms for IPG-based heartbeat detection to alleviate the need for a reference biosignal recording (e.g., an electrocardiogram, ECG) for extracting hemodynamic parameters from the knee.

The aims of quantifying edema and blood-flow in the post-injury period necessitate a small form factor system obtaining accurate bioimpedance measurements from the body in an energy-efficient manner. Towards reaching that goal, a digitally-assisted analog approach was followed: designing a system benefiting from the advantages of both analog (i.e., low power) and digital (i.e., programmability) domains. The present system uses this approach to perform (i) bioimpedance measurements, (ii) calibration, and (iii) preprocessing and feature extraction.

The first function, performing the bioimpedance measurements from the body, is achieved by a custom, analog front-end designed with discrete components. A low-power TI MSP430 series microcontroller (Texas Instruments, Inc., Dallas, Tex., US) is used with a micro secure digital (SD) card as a data logger to enable processing of the signals later on a computer. The microcontroller is also used to implement the second function of the system, namely performing calibration, which aims to reduce the measurement error due to environmental changes (e.g., temperature). Feature extraction, is performed using MATLAB software (Math-

Works, Natick, Mass.) to extract physiologically-relevant information from the calibrated data stored on a microSD.

Analogue Front-End

Comprising resistive body fluids (e.g., blood, intra-cellular fluid) and capacitive cell-walls, the EBI of a local joint body region can be modeled, to the first order, as a single RC network. It should be noted that the RC network has a static component related to the total fluid-volume and a dynamic component related to the time-dependent fluid-volume changes (e.g., blood flow periodic with the heart beat). The analog front-end was designed to perform a single-frequency bioimpedance analysis to extract both static and dynamic components of the RC network (block diagram of front-end shown in FIG. 9).

In FIG. 9, E1-E4 represent the four electrodes on the body used for impedance measurement; $i(t)$ and $q(t)$ represent the static (slowly varying on the order of hours to days), and $\Delta i(t)$ and $\Delta q(t)$ represent the dynamic (rapidly varying on the order of milli-seconds) bioimpedance components; $A(t)$ is the sensed electrical current delivery to the body being monitored in real-time to ensure safety and enable real-time calibration of the measured data on-board the microcontroller (μC).

The circuit excites the body with a sine wave current at $f_0 = 50$ kHz, a frequency that enables current to flow through both extracellular and intracellular fluid paths and therefore is widely used in single-frequency bioimpedance analysis systems. The design incorporates a diode-stabilized Wien-Bridge oscillator generating an 800 mV_{pp} sinusoidal signal at 50 kHz. The voltage output of the oscillator is converted to current by a high output-impedance, high-bandwidth, voltage-controlled current source (VCCS). The VCCS delivers the current to the series combination of the body-load, Z_{Body} , and a small and pure resistive load of $R_{sense} = 100 \Omega$.

To cancel out the effects of non-ideal skin-electrode interfaces on the measurements, current is injected to the joint through a quadripolar electrode configuration formed by E1-E4 in FIG. 9, where E1 and E4 are current injection and E2 and E3 are voltage measurement electrodes. Voltage measurements across Z_{Body} and R_{sense} are made by means of two separate instrumentation amplifier (IA) stages, IA_{body} and IA_{sense} .

The signal at the output of the IA_{body} , namely $v_{Body}(t)$ is used to extract voltage measurements corresponding to both resistive and reactive components of the Z_{Body} through phase-sensitive detection circuitry. A differential high-pass filter (HPF) with a cut off frequency of 7.2 kHz reduces any electromyogram (EMG) bleed-through from the surrounding muscles. The signal at the output of the IA_{sense} , namely $v_{sense}(t)$, is used for (i) generating the clocks that drive the phase-sensitive detection circuitry using comparators, and (ii) monitoring the magnitude of the current delivered to the body, namely I_{PP} , through an envelope detector formed by a diode and RC network, the output of which is the current monitoring signal $A(t)$ in FIG. 9. The clocks for the in-phase and quadrature-phase sensitive detection are generated from the $v_{sense}(t)$ and a 90° phase shifted version of the $v_{sense}(t)$ obtained using an all-pass-filter, respectively. Both clocks are used to alternate analog switches between $v_{Body}(t)$ and $-v_{Body}(t)$.

The signal from each phase-sensitive detector is filtered to give the final output signals. For the very slowly-varying static in-phase and quadrature signals, namely $i(t)$ and $q(t)$, the outputs of phase-sensitive detectors are each filtered with a low-pass filter (LPF) having a cutoff frequency of $f_{-3dB} = 2$ Hz. To extract the small-magnitude and more rapidly-varying dynamic in-phase and quadrature signals, namely $\Delta i(t)$ and

$\Delta q(t)$, the signals from the phase sensitive detector are filtered by band-pass filters (BPF) with bandwidths of 0.1 Hz-20 Hz and gains of 51 V/V.

It should be noted that the sinusoidal voltage signal from the oscillator is amplified through the VCCS and the IA_{body} stages, which set the mid-band gain, namely A_{MB}. When determining A_{MB}, both noise and dynamic range considerations have been taken into account. For improved noise performance, A_{MB} needs to be sufficiently high. On the other hand, to obtain a large dynamic range that satisfies the linear operation of the circuit, A_{MB} cannot be arbitrarily large.

For a typical knee impedance value of R_{body}=80Ω, high signal-to-noise ratio (SNR) signals can be obtained by setting I_{PP}≈2 mA, which is well below the safety threshold. However, it should be noted that Z_{body} will vary among different subjects. Therefore, the VCCS is designed as a variable-gain stage that can be tuned to ensure linear operation while not compromising the noise performance. For instance, to obtain high SNR signals from small impedance loads, I_{PP} can be increased. On the other hand, for measurements from larger impedance loads, to keep the circuit in the linear region, I_{PP} can be reduced. The maximum and minimum possible values of I_{PP} are 3.3 mA_{pp} and 0.6 mA_{pp}, respectively. The gain of the IA_{body}, namely A_{IA,body}, is determined based on the dynamic range constraints. Setting A_{IA,body}=10.67 V/V, a dynamic range of ~300Ω, which exceeds the typical maximum bioimpedance values from the knee, is achieved. The gain of the IA_{sense}, is set to A_{IA,sense}=3.47 V/V, which is sufficiently high for generating clocks at the comparator outputs.

The measurements from the analog front-end are converted to resistance and reactance values by following an automatic calibration procedure. During a measurement period, to compensate for the effects of environmental changes on the measurements, calibration is automatically repeated.

Calibration

As with any bioimpedance measurement system, a calibration procedure is necessary to map the static and dynamic voltage signals—namely i(t), q(t), Δi(t), Δq(t)—into static and dynamic impedance signals; namely static resistance r(t), static reactance x(t), dynamic resistance Δr(t) and dynamic reactance Δx(t). In an ideal synchronous demodulation scheme, i(t) and q(t) would be proportional to r(t) and x(t) respectively, where the impedance being measured is r(t)+jx(t). Therefore, ideally a one-time calibration of the circuitry would be sufficient to map the measured signals to impedance values. However, changes in environmental parameters (e.g., temperature, humidity), and circuit non-idealities, adversely affect the measurement consistency along the course of a measurement. To correct measurement errors caused by changes in the excitation current, I_{PP}, and therefore increase the robustness of the wearable system, the impedance measurements can be scaled by a correction factor of c_r=2 mA/I_{PP} (amplitude correction), where I_{PP} is monitored by A(t). Furthermore, temperature variations also create phase delays at the clocks of the phase-sensitive detection circuitry switches, which affects both magnitude and phase of an impedance measurement. To further rule out those variations, calibration can be performed in an intermittent manner (real-time calibration) by a low-power TI MSP430 series microcontroller.

As an effort to reduce the calculation burden that real-time calibration could potentially place on the microcontroller, a computationally-efficient two-step calibration procedure is followed: (i) phase correction and (ii) ordinary least squares linear regression.

The first calibration step is correcting the phase error. The non-ideal switching time, namely t_{sw}>0, of the demodulator switches in phase-sensitive detection circuitry results in rotation of the measurement vector [i(t) q(t)]^T by φ radians, where φ=2πt_{sw}f₀. Therefore, the phase error is corrected by rotating the vector by φ radians clockwise to obtain the corrected measurement vector:

$$\begin{bmatrix} \tilde{i}(t) \\ \tilde{q}(t) \end{bmatrix} = \begin{bmatrix} \cos\phi & \sin\phi \\ -\sin\phi & \cos\phi \end{bmatrix} \begin{bmatrix} i(t) \\ q(t) \end{bmatrix}, \quad (3)$$

where $\tilde{i}(t)$ and $\tilde{q}(t)$ are proportional to r(t) and x(t), respectively.

The second step aims to map the corrected measurement vector to the impedance vector:

$$\begin{bmatrix} r(t) \\ x(t) \end{bmatrix} = \begin{bmatrix} m_R \\ m_X \end{bmatrix} \begin{bmatrix} \cos\phi & \sin\phi \\ -\sin\phi & \cos\phi \end{bmatrix} \begin{bmatrix} \tilde{i}(t) \\ \tilde{q}(t) \end{bmatrix} + \begin{bmatrix} c_R \\ c_X \end{bmatrix}, \quad (4)$$

where m_R and c_R are the coefficients of linear regression between $\tilde{i}(t)$ and r(t). Similarly, m_X and c_X are regression coefficients for the quadrature channel.

Finding the calibration coefficients in Equation 4—namely m_R, c_R, m_X, c_X, and φ—requires a series of static in-phase and quadrature measurements on test loads of known values. Four series RC test loads, which span the impedance dynamic range, with impedances R₁=23.8Ω, C₁=47 nF; R₂=98.2Ω; R₃=56.4Ω, C₃=94 nF; R₄=75.4Ω, C₄=68 nF are selected. The loads are connected to the analog front-end successively by means of a multiplexer controlled by the microcontroller. The phase correction step is performed by calculating φ=arctan q₂i₂ using measurements from the purely resistive R₂. Then, linear regression is performed using the measurements from all four test loads to calculate the remaining calibration coefficients. The same coefficients are used to perform the mapping for the dynamic measurements:

$$\begin{bmatrix} \Delta r(t) \\ \Delta x(t) \end{bmatrix} = \frac{1}{G} \begin{bmatrix} m_R \\ m_X \end{bmatrix} \begin{bmatrix} \cos\phi & \sin\phi \\ -\sin\phi & \cos\phi \end{bmatrix} \begin{bmatrix} \Delta i(t) \\ \Delta q(t) \end{bmatrix}, \quad (5)$$

where the factor 1/G is introduced to divide out the dynamic channel output gain. The offset vector [c_R c_X]^T in Equation 4 is filtered out by the dynamic channel output stages.

The mapped signals are then used to extract musculoskeletal and cardiovascular features from the knee joints.

Preprocessing and Feature Extraction Algorithms

The preprocessing and feature extraction is separately done for static and dynamic signals. The musculoskeletal features of tissue resistance and reactance are extracted from the static signals and the cardiovascular features of heart rate, local pulsatile blood volume and flow rate are extracted from the dynamic signals.

The preprocessing of the static signals i[n] and q[n] involves conversion to impedance signals r[n] and x[n] using Equation 4. Then, the static signals and the current monitoring signal A[n] are averaged in a 60 second window, to get r_{avg}, x_{avg}, and A_{avg}, respectively. The final joint resistance and reactance measurements of R_{measured} and X_{measured} are obtained by performing the amplitude correction explained in the calibration section on r_{avg} and x_{avg} using A_{avg}.

The signal processing performed on the dynamic signals involves calibration/filtering and ensemble averaging as shown in FIG. 10. FIG. 10 is a physiology-driven algorithm design for extracting cardiovascular parameters automatically from the dynamic component (i.e. IPG) of the bio-impedance signals. First, the signals are pre-processed to reduce noise and detect heartbeats; then heartbeat segmentation is used to enable ensemble averaging to further improve the signal quality; finally, features of blood volume pulse and blood flow are then extracted from these ensemble averaged vector IPG traces.

The dynamic signals, $\Delta i[n]$ and $\Delta q[n]$, are first converted to impedance signals via calibration using Equation 5. The dynamic impedance signals are then amplitude corrected using A_{avg} which is followed by band-pass filtering by an FIR (finite impulse response) filter with bandwidth 0.1 Hz to 20 Hz to obtain $\widehat{\Delta r}[n]$ and $\widehat{\Delta x}[n]$. This step completes the calibration/filtering of the impedance signals before they are ensemble averaged.

Heartbeats from the knee are detected using $\Delta i[n]$. This signal is first smoothed using a Savitzky-Golay filter of 4th order and 21 taps, then filtered using a matched filtering approach. The matched filter impulse response (kernel) is a clean, smoothed dynamic in-phase bioimpedance signal, also acquired from the knee previously. This kernel is stored for use and is not adaptive. The matched filtered signal is then differentiated using a Savitzky-Golay Filter of the same kind as used for the smoothing, to form the signal

$$\frac{d}{dt}i_m[n].$$

The signal

$$\frac{d}{dt}i_m[n]$$

is fed to a peak detection algorithm to detect heart beats. Peaks in the waveform are searched window-by-window. When a peak is found within the given window, the window size is updated using previous heartbeat intervals. The window is then moved to its next location. To make sure the heartbeats are detected precisely, the window is relocated such that the peak is around the mid-point of the given window. The peak times found are stored in a vector τ'_k . The number of peaks detected per minute gives the heart rate (HR) in bpm.

The signal $\Delta i[n]$ is segmented using the peak times τ'_k . The segments of $\Delta i[n]$ ($\Delta i_k[n]$) are stored in each row of the matrix ΔI . The cross correlation of each segment $\Delta i_k[n]$, with the kernel is calculated. The maximum of this cross correlation is used to correct the peak times τ'_k such that each $\Delta i_k[n]$ is aligned with the kernel. The corrected peak times are stored in the vector τ_k .

The peak times τ_k are used to segment $\widehat{\Delta r}[n]$ and $\widehat{\Delta x}[n]$. The segments $\widehat{\Delta r}_k[n]$ and $\widehat{\Delta x}_k[n]$ are stored in rows of the matrices $\widehat{\Delta R}$ and $\widehat{\Delta X}$ respectively. The ensemble average of $\widehat{\Delta r}[n]$ is calculated by averaging the segments $\widehat{\Delta r}_k[n]$ on a sample by sample basis equation:

$$\Delta r_{EA}[n] = \sum_{k=1}^N \widehat{\Delta r}_k[n]. \quad (6)$$

The ensemble average of $\widehat{\Delta x}[n]$ ($\Delta x_{EA}[n]$) is then calculated in an analogous manner. The ensemble averaged signals $\Delta r_{EA}[n]$ and $\Delta x_{EA}[n]$ are used for feature extraction. The peak-to-peak amplitudes of these waveforms, Δr_{pp} and Δx_{pp} , are extracted as they might show differences in injured and healthy knees.

The signal $\Delta r_{EA}[n]$ is differentiated using the same Savitzky-Golay filter mentioned before, to obtain

$$\frac{d}{dt}\Delta r_{EA}[n].$$

On the waveforms, the B, C and X points are identified. The amplitude difference between the points B and

$$C\left(\frac{d}{dt}\Delta r_{MAX} \text{ in } \Omega/s\right),$$

the timing difference between B and X (ejection time, T_{ET} in s) are used to calculate the local pulsatile blood volume ΔV_{blood} (in ml) using:

$$\Delta V_{blood} = \rho \left(\frac{L}{R_{measured}}\right)^2 T_{ER} \frac{d}{dt}\Delta r_{MAX}, \quad (7)$$

where ρ is the resistivity of blood which is taken as 135 Ω cm, L (cm) is the distance between the voltage electrodes and $R_{measured}$ (Ω), is the measured resistance of the joint. The local blood flow rate \overline{Q}_{local} (in ml/min) is calculated using the equation $\overline{Q}_{local} = \Delta V_{blood} \text{HR}$. The cardiovascular features HR, ΔV_{blood} and \overline{Q}_{local} will be used in injury assessment as discussed previously.

Results and Discussion

Circuit Verification

The designed analog front-end was fabricated on a 64 mm \times 48 mm PCB (FIG. 11(a)). On-board potentiometers were used such that the circuit can also be tuned for other excitation frequencies (7.5 kHz-100 kHz) and current amplitudes (0.6 mA_{pp}-3.3 mA_{pp}) as well.

To verify the calibration procedure, the measurements i_k and q_k were acquired from the four calibration loads mentioned previously using a 3024 A oscilloscope (Keysight, Santa Rosa, Calif., US). The calibration parameters were calculated using MATLAB. Static measurements $i(t)$ and $q(t)$ were acquired from the same loads, 10 times within a day.

From Equation 4, the acquired voltage measurements were converted to impedance measurements using the calculated calibration parameters. The measured versus actual resistance (R) and reactance (X) of the loads are shown in FIG. 11(b). The actual load impedances were measured using an Agilent 34410 A 6 $\frac{1}{2}$ digit multimeter. A line was fitted for the R and the X measurements separately (red lines in FIG. 11(b)). The impedance measurements made by the custom analog front-end were linear and consistent within the range $0\Omega < R < 100\Omega$ and $0\Omega < -X < 70\Omega$ ($R^2 \approx 1$ for both R and X).

To measure the relative error, four impedances, different than the calibration impedances but within the same impedance range, were used. The measured impedances were compared to those measured using the multimeter. The mean relative measurement errors were 3.9% for R, 5.9% for X, 1.4% for $|Z|$ and 1.8% for $\angle Z$.

Connecting a potentiometer to the circuit as a load, the dynamic range of the front-end was tested. The resistance at which the IA measuring across the potentiometer saturates, was defined as the dynamic range and was measured as 345Ω. The measured dynamic range covers the expected knee impedance values varying between 40Ω and 80Ω for R and -20Ω and -10Ω for X.

To calculate the noise floor of the measured dynamic impedances, the noise spectral densities of Δi(t) and Δq(t) were acquired using an SR785 signal analyzer (Stanford Research Systems, Sunnyvale, Calif., US) with a 0Ω load across the analog front-end. The cross spectra of Δi(t) and Δq(t) were also acquired. The voltage noise spectral densities were mapped to the noise spectral densities of Δr(t) and Δx(t) using Equations 4 and 5. The resulting noise spectral densities are shown in FIG. 11(c). The noise floor was calculated for a bandwidth of 0.1-20 Hz. The resulting noise floors were 0.018 mΩ_{rms} for Δr(t) and 0.055 mΩ_{rms} for Δx(t).

The current consumption of the front-end was measured as 132 mA when supplied by ±5 V regulated from two 9 V batteries, leading to 0.66 W power consumption. The micro-

controller power consumption was measured as 150 mW when writing data to the SD card, and 33 mW when sampling with the clock frequency set to 25 MHz. Thus, the overall power consumption for the system was 0.81 W.

To evaluate the system performance, the electronic and system specifications were compared against numerous bio-impedance measurement systems (see TABLE II). The architectures used for these systems can be categorized as (i) computer assisted designs, (ii) application specific integrated circuits (ASICs), (iii) field programmable gate array (FPGA) designs, and (iv) discrete designs. Computer-assisted systems such as [1-3] cannot be classified as wearable. ASIC systems such as [4-9] are advantageous due to their small size and low power consumption but are expensive to manufacture and limited in terms of programmability. FPGA based systems such as [10, 11] require high current levels, limiting their feasibility for wearable, continuous monitoring applications. Discrete designs such as [12-16] can provide an inexpensive, programmable alternative to existing approaches, can be rapidly prototyped and evaluated in human subjects testing, and with the design described in this paper can achieve sufficiently small size and low power consumption for wearable joint health monitoring systems.

TABLE II

| Reference(s) | Power Cons. (W) ^a | Noise (RTI, mΩ _{rms}) | Measurement Error | Dynamic Range (Ω) | Size | Architecture ^b | Functions |
|-------------------|------------------------------|---------------------------------|---|-------------------------------------|---|----------------------------------|--|
| [1, 2] | — | — | Z : 0.05Ω ∠Z: 0.003° | 100Ω < R < 1.1 kΩ | Non-wearable, PXI based | (i) PXI based synth. and demod. | Static/Dynamic Z and ∠Z, spectro. |
| [3] | — | — | R: 0.02Ω | 100Ω < R < 1 kΩ | Large, rack mounted modules | (i) Analog front end + computer | Static Z and ∠Z, spectro. |
| [4] | 0.0016 (FE) | — | — | 1Ω < Z < 3.5 kΩ 0° < ∠Z < 90° | 8 cm ² including antenna, wearable | (ii) ASIC | Static Z and ∠Z, spectro. |
| [5] | 0.0024 (FS) | 100 | — | — | 5 mm ² | (ii) ASIC | Dynamic Z |
| [6] | 0.0144 (FS) | — | R: 0.2Ω X: 0.2Ω | R < 54Ω 0.7 Ω < X < 15Ω | 4.8 × 3 cm ² | (ii) ASIC | Static R and X, spectro. |
| [7] | 0.0021 (FE) | — | — | 100Ω < Z < 10 kΩ 0° < ∠Z < 30° | 6.95 mm ² | (ii) ASIC | Static R and X, multi-freq. |
| [8] | 0.0034 (FS) | — | R, X: 5% | 32Ω < Z < 5.3 kΩ | 1.52 mm ² | (ii) ASIC | Static R and X, multi-freq. |
| [9] | 58μ (FE) 345μ (FS) | 438 | * | — | 7 × 7 mm ² | (ii) ASIC | Static R |
| [10] | 3.7 (FS) | 5 | — | R < 3.2 kΩ | 136 × 145 mm ² | (iii) FPGA based | Static/Dynamic Z and ∠Z, spectro. |
| [11] | — | — | Z : 1.2% ∠Z: 0.18° | Z > 2 kΩ | — | (iii) FPGA based | Static Z and ∠Z |
| [12] | — | — | Z : 1.1% ∠Z: 1% | R > 10 kΩ | — | (iv) AD5933 controlled by μC | Static Z and ∠Z, spectro. |
| [13] | — | — | R: 1% | 50Ω < R < 1.6 kΩ | Wearable | (iv) AD5933 based | Static R and X, spectro. |
| [14] | — | — | — | Z < 1 kΩ | Portable | (iv) Discrete with sync. demod. | Static Z , Dynamic Z |
| [15] | — | — | Z : 0.36Ω ∠Z: 0.0049° | 9Ω < Z < 5.7 kΩ 0° < ∠Z < 180° | Handheld, 0.5 kg | (iv) AD8302 controlled by μC | Static Z and ∠Z, spectro. |
| [16] | 0.546 (FS) | — | R: 0.4Ω X: 0.3Ω | — | 145 × 40 × 4 mm ³ , 30 g | (iv) AD5933 based | Static R and X, spectro. |
| Present Invention | 0.66 (FE) 0.81 (FS) | 0.018 | R: 3.9% X: 5.9% Z : 1.4%, ∠Z: 1.8% | Z < 345Ω | 64 × 48 mm ² (FE) | (iv) Discrete with, sync. demod. | Static and Dynamic R, Static and Dynamic X |

^aFS = Full system, FE = Front-end only; Noise RTI in [5] was calculated for a bandwidth of 20 Hz using the noise spectral density reported.

^bArchitecture sorted into four groups: (i) Computer-assisted architecture; (ii) ASIC; (iii) FPGA; (iv) Discrete design.

TABLE II is a comparison of electrical and system specifications for EBI circuits and systems sorted by architecture. The references include:

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- [9] N. Van Helleputte, M. Konijnenburg, J. Pettine, J. Dong-Woo, K. Hyejung, A. Morgado, R. Van Wegberg, T. Torfs, R. Mohan, A. Breeschoten, H. de Groot, C. Van Hoof, and R. F. Yazicioglu, "A 345 uW Multi-Sensor Biomedical SoC With Bio-Impedance, 3-Channel ECG, Motion Artifact Reduction, and Integrated DSP," *Solid-State Circuits, IEEE Journal of*, vol. 50, pp. 230-244, 2015.
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- [16] T. Schlebusch, Ro, x, thlingsho, x. L. fer, K. Saim, Ko, x, M. ny, and S. Leonhardt, "On the Road to a Textile Integrated Bioimpedance Early Warning System for Lung Edema," in *Body Sensor Networks (BSN), 2010 International Conference on*, 2010, pp. 302-307.

As seen from TABLE II, the present invention has higher resolution in impedance measurements than all the similar conventional systems shown. This enables the present invention to sense blood-flow-related impedance changes from the knee. This high measurement resolution is achieved in an energy-efficient manner with a small footprint. Furthermore, compared with other systems in TABLE II, the present invention is the only one (that can be deployed in a wearable device) enabling real-time calibration to minimize measurement errors due to environmental changes.

Physiological Measurement Results and Discussion

Human subject testing was performed on nine subjects; seven control subjects with no recent history of injuries to the knees and two injured subjects with recent unilateral knee injuries (ACL or meniscal tear). The studies were approved by the Georgia Institute of Technology IRB as well as the AHRPO. The circuit was interfaced to the body via Ag/AgCl gel electrodes, positioned as shown in FIG. 12(a). The proximal current electrode was placed three inches above the crease on the quadriceps tendon, towards the inner side of the knee. The distal current electrode was placed three inches below the crease on the popliteal fossa, towards the outer side of the knee. The voltage electrodes were placed adjacent to the current electrodes. To evaluate the ensemble averaging algorithm, ECG signals from the control group were acquired using a BioNomadix (Biopac Systems Inc, Goleta, Calif., US) wireless ECG acquisition module.

All signals acquired were recorded on Biopac data acquisition hardware and processed on MATLAB. For the human subject studies, a one-time calibration followed by amplitude correction was performed.

During the testing protocol, each subject sat upright with his/her back resting against the wall and legs extended forward. While the subject was still, 90 seconds of the signals $i(t)$, $q(t)$, $\Delta i(t)$, $\Delta q(t)$, $A(t)$ and the ECG (for the control group) were acquired from both knees separately. The data between 20 s and 80 s were processed to rule out any motion artifacts at the beginning and the end of the measurement cycle (from initial positioning of the body). For pulsatile blood volume calculations, the distance between the voltage electrodes on each knee were measured.

The resulting static impedances for each knee from each subject are plotted in FIG. 12(b), and the differences between the magnitude of resistance and reactance in left versus right knee are shown in FIG. 13. The left versus the right knee impedances of nearly all control subjects were within 12Ω from each other in the R and 3.2Ω from each other in the X axes. The difference between the resistance and reactance of the left and the right knees had no statistical significance for the control group. However, even for the

small feasibility study sample size of two injured subjects, there was a significant difference ($p < 0.01$) in the impedances of the involved and contralateral knee compared to the control group. The injured side on both subjects had lower resistance, R , by an average of 13.7Ω and negative reactance, $-X$, by an average of 5.25Ω . These results are consistent with physiological expectations (reduced resistance due to increased edema, reduced negative reactance associated with damaged cell membranes).

The pre-processing and feature extraction algorithms described were used to calculate the cardiovascular features HR, ΔV_{blood} and Q_{local} for the control group. The signals obtained at intermediate and final steps of the ensemble averaging algorithm are presented in FIG. 12(c). The accurate detection of heart beats enabled the dynamic (IPG) impedance signals to be segmented accurately. Therefore, high SNR waveforms were obtained after ensemble averaging leading to clear detection of B, C, and X points.

These features were also calculated using an ECG-assisted ensemble averaging algorithm for comparison. It was observed that the cardiovascular features calculated with and without the ECG were consistent (FIG. 12(d)) with no statistically significant differences observed. Furthermore, no significant differences were observed in the cardiovascular features on the injured side compared to the contralateral side.

For one of the control subjects, a separate experiment was performed to examine the effects of vasoconstriction on the dynamic impedance signal measured from one knee. Specifically, the methodology was analogous to a cold pressor test, with the subject's bare foot being submerged in ice water while the IPG signal was measured across the knee (not submerged) to increase downstream peripheral vascular resistance (PVR). The purpose of this experiment was to evaluate the sensitivity with which the system developed in this work could detect minute changes in knee joint blood flow associated with modified downstream PVR.

The subject's skin temperature was measured on the bare foot prior to submerging and found to be 30°C . The impedance signals were acquired from the knee for 60 seconds while the subject was seated, with the tested leg extended and resting on a support. The foot of the same side was immersed into ice water until the foot skin temperature dropped to 17°C . The foot was taken out of the cold water and impedance signals were again recorded for 60 seconds from the knee in the same position as before.

A plot of the resistance signal ensemble averaged using the algorithm described above ($\Delta r_{EA}(t)$) and its derivative

$$\left(\frac{d}{dt}\Delta r_{EA}(t)\right)$$

taken using a Savitzky-Golay filter are shown in FIG. 12(e). The minute changes in this IPG signal associated with downstream vasoconstriction can be observed on both waveforms as a significant drop in amplitude ($20\text{ m}\Omega$ decrease for the resistance, and $0.2\Omega/\text{s}$ decrease for the time derivative of resistance). Accordingly, the system was sufficiently sensitive to detect both the reduction in local blood volume pulse and blood flow with increased PVR, consistent with physiological expectations.

Assessing Joint Physiology or Structure in A Manner Relevant to Assessing Overuse of The Joint

In an exemplary embodiment related to assessing overuse of the joint, vector EBI measurements are taken from the

joint using a tetrapolar electrode configuration before, after, and/or at different intervals during, the training session or competition. Changes in the resistive and/or reactive components of the EBI measurements are quantified. Simultaneously obtained inertial measures such as joint angle and body posture/position are taken to ensure that the physical conditions of the user during the EBI measurements were the same for each usage. These changes in EBI characteristics are then outputted to the user as a score indicative of joint swelling/tissue damage.

In another exemplary embodiment, joint acoustical emission measurements are taken using contact microphones (e.g., piezoelectric based acceleration or velocity sensors) placed around the joint. Inertial measures are simultaneously obtained such as joint angle, velocity, and/or position of the limbs or limb segments. The user performs several prescribed movements while wearing the sensors, and the acoustical emissions are measured in the context of particular activities. These measurements are obtained before, after, and/or at various intervals during the training session or competition. Algorithms, such as graph mining in conjunction with graph community factor quantification, are used to derive quantitative characteristics from the acoustical emission signals for each usage. Changes in these characteristics throughout the training session or competition are quantified and outputted to the user as a score indicative of joint inflammation/structural disruption.

In another exemplary embodiment, vector EBI, joint acoustical emission, and inertial measures are obtained simultaneously from the joint before, after, and/or at different intervals during, the training session or competition. Changes in the characteristics of all three measures are extracted and fused together to provide a single score indicative of overall joint health. This score is then outputted to the user.

In another exemplary embodiment, the EBI measurements are taken together with local measurements of skin temperature such that the changes in skin temperature are used to correct the EBI characteristics, since changes in skin temperature can modulate the filtration/absorption of fluid from the capillaries into the interstitial space and thus confound the measurement of local swelling.

In another exemplary embodiment, the joint acoustical emissions are measured with a combination of electret or microelectromechanical systems (MEMS) microphones (which capture airborne sounds) and contact microphones. The two measurement modalities are fused, for example by determining which signal has more interference and extracting characteristics only from the other signal. Since microphones capturing airborne sounds are more susceptible to background noise than contact microphones, while contact microphones are more susceptible to rubbing noise from contact with skin or clothing, the interferences are distinctly different and thus the fusion results in improved signal quality overall.

In another exemplary embodiment, the sensors are attached to the elbow and/or shoulder of a user's throwing arm and contralateral arm to compare the sensed parameters on both sides such that the characteristics on one side versus the other can be quantified. Thus, the user's contralateral arm is used as a control, and a more sensitive and accurate joint health or use score can be outputted to the user to direct further training, competition, or rehabilitation regimens.

In another exemplary embodiment, sensor data can be obtained from the joint before and after treatments, such as in the training room. For example, data can be obtained before and after ice is applied to the joint, to assess the

differential effects of the treatment on the joint and improve the sensitivity and accuracy with which the joint health or use score derived from the sensor data.

In an exemplary embodiment, the sensor data can be processed locally on the device using a microprocessor such that the indication can be provided directly to the user.

In another exemplary embodiment, the sensor data can be transmitted wirelessly to a phone, tablet, laptop, or other computing device for remotely processing the data and providing an indication to the user.

In another exemplary embodiment, the sensor data can be used to quantify inflammation non-invasively (without the need for obtaining blood from the subject) in tracking progression after muscle injury resulting from eccentric loading. For example, the characteristics of the joint acoustic emission and bioimpedance measurements can be fused for serial measurements taken periodically—or continuously—throughout training/eccentric loading exercises.

FIG. 14 illustrates the concept of acquiring two sets of recordings with the system, the first taken as a baseline recording, and the second taken following a perturbation. The first recording can include a combination of multiple modalities of sensors, and the second recording would typically include the same combination of sensors. The perturbation can comprise any set of activities performed by the user (e.g., exercise), changes to the environment or joint conditions enforced externally (e.g., changing skin temperature or joint stiffness conditions), or a combination of both (e.g., running on a treadmill while the stiffness is being changed locally). The perturbation can be applied artificially for the purposes of enhancing the information extracted for measurement purposes or can be an activity that the user was planning to perform anyway (e.g., activities performed by an athlete during a normal practice or training workout). The data taken following the perturbation (in the second recording) can then be compared against the data taken during the baseline recording using a variety of algorithms, such as clustering analysis and graph mining techniques.

Whether the characteristics of acoustical emissions from the joint change in a quantifiable and monotonic manner in response to increased vertical loading forces for a standardized movement is herein evaluated. It is assumed that increased vertical loading forces will lead to more interactions between internal surfaces of the knee and thus will increase the complexity of the emitted sounds. The reason for this variability in the signal could be the increased number of surfaces interacting, and increased friction between surfaces causing more complex interactions and ensuing acoustic emissions.

FIG. 15 provides an illustration of the assumption, and FIG. 16 shows the measurement setup used for assessing loading effects, based on a vertical leg press with varying weight and the measurement of acoustical emissions from the knee.

Graph mining algorithms were leveraged to quantify this complexity and evaluated the approach in a study of able-bodied subjects. This is believed the first-time the effects of joint loading forces on acoustical emissions is quantified. Quantifying loading based on wearable measurements of joint acoustical emissions throughout activities of daily living and in a broader range of movements and exercises presents continued avenues for research.

Human Subjects Study and Measurement Protocol

Twelve healthy subjects with no prior injuries were recruited for the study which was approved by the Georgia Institute of Technology Institutional Review Board (IRB). Subject demographics are described in TABLE III.

TABLE III

DEMOGRAPHIC DATA FOR STUDY PARTICIPANTS

| | Male | Female |
|--------------------------------------|-----------------|----------------|
| Number of Subjects | 9 | 3 |
| Age (mean \pm σ , in years) | 24.3 \pm 1.9 | 25.3 \pm 2.1 |
| Height (mean \pm σ , in cm) | 175.1 \pm 3.5 | 155 \pm 2.7 |
| Weight (mean \pm σ , in kg) | 74.3 \pm 9.9 | 50.7 \pm 7.2 |

For each subject, four miniature (7.9 \times 5.5 \times 4.1 mm) contact microphones (BU-23173-000, Knowles Electronics LLC., USA) were attached to the medial and lateral sides of the patella and superficial to the lateral and medial meniscus using Kinesio Tex tape (see FIG. 16). These microphone, which are piezoelectric sensors with broad bandwidth (>20 kHz) and low output noise (7 μ Vrms “A” weighted), were selected as they provide high quality acoustical pick-up from the body while maintaining a small footprint amenable for wearable use. The subjects were then asked to perform ten repetitions of vertical leg press with different loading conditions. Vertical leg press was selected as the exercise for this study since it allows for vertical loading at the knee joint to be varied in a controlled manner up to a sufficiently large load (i.e. body weight) to notice effects on the acoustical emissions. There was a total of four loading conditions, starting with zero load (no weights), and increasing by a third of the subject’s body weight up to the full weight of the subject. The audio signals from each microphone were pre-amplified using a custom analog front-end comprising a voltage regulator, setting a 3V supply used for powering the microphones and amplifiers, a low noise amplifier with a voltage gain of 100, and 180 kHz bandwidth, and a bandpass filter (bandwidth: 16 Hz-20 kHz, Butterworth). The amplified signals were then sampled at 50 kHz (16 bits/sample) using NI USB-6225 data acquisition hardware (NI, Austin, Tex., USA). All signals were recorded on a laptop using LabVIEW System Design Software (NI, Austin, Tex., USA) and were processed using MATLAB (The Mathworks, Naticks, Mass., USA) and RStudio (RStudio, Boston, Mass., USA).

Joint Sound Pre-Processing and Feature Extraction

The overall signal processing and feature extraction steps are illustrated in FIG. 18. The acoustical signals were acquired during ten repetitions of vertical leg press cycles on the dominant leg of the subject. The signals were digitally filtered using a Kaiser-window finite impulse response band-pass filter with a bandwidth of 400 Hz-20 kHz to remove the low-frequency interface noise between the tape and the microphone. The filtered signals were standardized with zero mean and unity variance to balance out any variations in the signal amplitude among sensors that could result from differences in contact pressure against the skin.

The normalized signals were then divided into segments (windows) with a duration of 200 ms and 90% overlap between successive segments. This segment duration and the overlap allowed multiple joint sound signatures to be present within a given frame. The features derived from each segment are summarized in TABLE IV. The features were

selected empirically and are commonly used in other audio signal processing applications. For example, the mel-frequency cepstrum coefficient (MFCC) is prevalent in speech recognition analysis, for discriminating speech, music, and background noise.

From each windowed segment of each microphone, a total of 69 features were extracted and stored in a matrix. For each loading condition, the features were vertically concatenated extracted from all four microphones into one single matrix. Based on common statistical learning rules, the number of features acquired for the dataset is a reasonable value.

TABLE IV

| AUDIO FEATURES FOR KNEE JOINT SOUNDS | | |
|--|---|--|
| Feature Name | General Description | Significance |
| Energy | Total signal energy | Short term energy is expected to exhibit high variation over successive speech frame |
| Zero Crossing Rate | Rate of sign changes | Exhibit higher values in the case of noisy signals (i.e. noisier if there is higher loading forced on the knee joints) |
| Energy Entropy | Measure of abrupt changes in the energy level | Low value in abrupt energy changes (i.e. low peaks if there are higher loads affecting the joints) |
| Spectral Centroid and Spread | Center of gravity of spectrum/ second central moment of spectrum | Higher values correspond to brighter sounds (i.e. brighter sounds if higher loads are endured on the joints) |
| Spectral Entropy | Like entropy but in frequency domain | Higher value in sounds for more loads on the joints |
| Spectral Flux | Measure of spectral change between two successive frames | Lower value if the signals are more consistent (i.e. lower the values will be as more loads affect the joint sounds) |
| Spectral Rolloff | Frequency below which 90% of the signal energy (magnitude) is concentrated | Higher value for wider spectrum (i.e. higher in joint sounds with more loads are enforced) |
| MFCCs | Coefficients that make up a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency. | First 13 MFCCs carry enough discriminative information to compare joint sounds with different loading conditions |
| Band Powers | Power of the signal in 29 distinct frequency bands, between 30 logarithmically spaced frequencies in the range of 1 kHz-15 kHz | Higher frequency band powers will exhibit high values at frames where joint sounds are most abrupt. (i.e. joints affected by more loads will have higher values) |
| Chroma Vector, Fundamental Frequency, and Harmonic Ratio | Features widely used in music-related applications | These features could indicate which segments contain high values (i.e. joint sounds affected by higher loads) |
| Standard deviation, mean, median, minimum, maximum | Basic features for signal processing | Higher values for noisy signals (i.e. noisier if there is higher loading enforced on the joints) |

signals captured by the microphones. To investigate this, the concept in graph theory of quantifying heterogeneity by locating, and computing the number of, communities within the graph were used. The combined features from microphones for a single loading condition as a data matrix X was considered.

It is assumed that more loads should increase the number of sound sources in the knee and this would increase the heterogeneity within the captured signals by different microphones. Accordingly, the distribution of X should be modeled. Although this can be done using some statistical models such as Gaussian or student t-distributions, these

Proof-of-Concept Study of Loading Effects during Walking

An alternative exercise was considered using an Alter-G (AlterG, Inc., Ferment Calif., USA), an anti-gravity treadmill that assists patients with fast recovery. Illustrations for the measurement setup and the exercise movement are depicted in FIGS. 19-20. The microphone placements were the same as the locations for the vertical leg press. As a proof-of-concept, one subject was recruited, approved by the IRB, to perform 20 seconds of walking on the treadmill with two different weight conditions: 20% of the body weight (minimum), and 100% of the body weight (maximum). The same signal processing and feature extraction methods were used.

Graph Mining Algorithm

It was believed that increasing the vertical loading forces on the knee would increase heterogeneity among acoustical

techniques require strong assumptions about the high-dimensional shape of the data (e.g., ellipsoid versus convex) and model parameters (e.g. mean and standard deviation) which can cause many problems, such as unreliable bandwidth estimation for applied kernel density function.

To overcome these challenges, a k-Nearest Neighbor graph (kNN) from graph theory was reconstructed that previously has been successfully used by researchers to model and cluster high dimensional bioinformatics data. The constructed graph from a knee which experienced smaller loads should be less heterogeneous than the one that experiences higher loads. This heterogeneity can be modeled with the number of complex communities in the related graph: a greater number of graph "communities" should be needed to describe sounds emitted from a knee which is loaded with higher forces.

In this work, a kNN graph is defined for each dataset X. Let $KG = \{V, E\}$ indicate the kNN graph corresponding to X

where $V = \{v_1, v_2, \dots, v_N\}$ is the set of vertices and $E \subseteq V \times V$ represents the set of edges among v_i . In this graph, each vertex v_i indicates one row (acoustical window) in X . To model the local neighbor of each window x_i in X , the corresponding vertex v_i is connected to its k nearest neighbors using Euclidean distance. In this work, k was chosen to be 10 empirically. Other values were also investigated (e.g. 5-15) and similar results were obtained.

If only the Euclidean distance values are considered to assign related weights of edges between v_i with its nearest neighbors, noisy data points would engender many problems. If there are some v_i s expanding the dispersed zones between two different communities, it may not distinguish these two communities and merge them as one single community incorrectly. Hence, weights are reassigned to each graph edge using dice similarity, such that we incorporate the properties of each point's neighborhood rather than relying on Euclidean distance alone in attributing points to clusters or communities. The dice similarity of v_i and v_j means twice the number of common neighbors divided by the sum of the degrees of v_i and v_j . Assuming v_i and v_j indicate two connected vertices within the kNN graph, the assigned weight for the edge between these two vertices is defined as:

$$w_{ij} = \frac{2 * |A_i \cap B_j|}{(|D_i| + |D_j|)}, \quad (8)$$

where A_i and B_j denotes the set of the neighbors of v_i and v_j , respectively. Also, the degree of v_i and v_j are represented as D_i and D_j , respectively and finally, the notation $|*|$ is the number of elements in a set.

Once the weighted kNN graph is extracted, a community detection algorithm is applied to extract all the potential communities (clusters) within the kNN graph. There are several community detection algorithms studied in graph theory that could be applied. In this work, the Infomap community detection algorithm is employed to quantify the communities of the kNN graph, since Infomap has been applied successfully in various areas of graph mining in different fields such as bioinformatics.

Infomap uses the probability flow of random walks on the network as a proxy for information flows and clusters the graph into multiple communities. The algorithm searches for a partitioning of the kNN graph to minimize the expected description length of a random walk and seeks to compress the description of information flow visited by a random walker on the network. Using Huffman code, all v_i visited by a walker are recorded and coded. The walker takes a reasonable amount of time within the same community which results in longer walking process. The computational complexity of this algorithm is approximately $O(|E|)$. In this work, the number of detected communities is shown with "GCF" (Graph Community Factor) which represents the heterogeneity of extracted kNN graph from the data matrix X .

One important note is that discovering of the potential communities in the kNN graph is tantamount to finding the number of clusters (dense areas) in a high dimensional dataset X . Applying regular clustering methodologies such as K-means and Gaussian Mixture Models are not possible in this problem, as these methods require the knowledge of the number of clusters (dense populations of acoustical windows) within the data matrix. It is further noted that applying a kernel-based density clustering algorithm (as it

automatically estimates the number of dense areas in data) on a 69-dimensional dataset X to find the clusters is challenging and is not practical. The difficulty is that the curse of dimensionality causes the density detection in high dimensions (in this problem 69) to be very time consuming and statistically not robust.

Results and Discussion

Changes in the GCF with Loading for All Microphones

The use of the graph mining algorithm was evaluated to quantify the changes of acoustical emissions from the knee joints with respect to different vertical loading forces on twelve subjects. Four contact microphones were used to collect the joint sounds from various locations on the knee (medial and lateral of patella and meniscus). FIG. 21 illustrates the increasing trend of heterogeneity and the calculated GCF value with respect to different loading conditions for one representative subject. The knee graph is constructed from the individual loading data matrix where each data point (vertex in the graph) represents all the time and frequency domain features for one windowed frame of the acoustical emissions and different colors characterize different communities. The GCF values for no loading, one-third body weight (BW), two-thirds BW, and BW were 26, 34, 38, 40, respectively.

FIG. 22 provides a boxplot of the GCF values calculated for all subjects for each loading condition. The mean values for no load, one-third BW, two-thirds BW, and BW were 30, 32, 36, and 39. Since the sample size is not large, the non-parametric paired Kolmogorov-Smirnov test was used to calculate the p-value ($p < 0.01$). For twelve subjects, we demonstrated the increase in GCF of the acoustic emissions from the joints with respect to the increasing load level on the knee.

Changes in GCF Across Microphone Locations

The characteristics of the acoustical signals were also evaluated across four different microphone locations to determine which locations had the most heterogeneity. Each microphone data matrix consists of all the segments and the features for the four loading conditions. FIG. 23 shows the boxplot of average GCF value for all subjects with respect to the microphone locations (numbers). Microphones 1, 2, 3, and 4 have mean GCF values of 26.4, 32.6, 33.5, and 23.8 respectively.

The same non-parametric paired Kolmogorov-Smirnov test was used to calculate the p-value ($p < 0.01$). Referring to FIG. 17, the results showed that locations 2 and 3 (medial side of the patella and superficial to the lateral meniscus, respectively) seem to show higher variation than the microphones placed on 1 and 4 (lateral side of the patella and superficial to the medial meniscus, respectively). The underlying anatomical sources of this variation are hypothesized as follows: microphone 1 is located on the superior lateral aspect of the knee which is principally superficial to the femur, quadriceps tendons, muscle, and fat. Microphone 3 placement includes the tibia collateral ligament, muscles, and the semi-membranous bursae, a jelly filled sacs in between ligament and bone, along with the previously mentioned lateral meniscus and associated connective tissue. In addition, the fibula connects to the tibia on this side of the leg, which could cause considerable differences from the sounds produced on the opposite side. The fibular collateral ligaments are located on the lateral side, close to microphone 3, which could contribute to more heterogeneity in that location since it is another source of tension on the joint when load is applied. Locations 1 to 4 (lower hetero-

geneity) and locations 2 to 3 (higher heterogeneity) makes an 'X' through the knee. There are several anatomical structures that follow a similar course through the region, and as such may be particularly potent contributors to the variations and heterogeneity seen. These structures include the two proximal heads of the gastrocnemius, the popliteus muscle/ligaments, and the anterior cruciate ligament (ACL) and posterior cruciate ligament (PCL).

Changes in GCF during Walking with Loading

Using the graph mining technique from the acoustical signal obtained from one subject, it could be evaluated that the GCF value increased from 28 to 36 as the body weight changed from 20% (minimum) to 100% (maximum), respectively (see FIG. 24). This showed that changing the loading on the knee while walking could have similar impact on the knee joint acoustical emissions as for the vertical leg press exercise.

Wearable Sensor System to Evaluate and Manage Throwing Arm Health

In yet a further embodiment, developing wearable technology that can quantify significant changes in joint (shoulder and elbow) health status for pitchers that could inform sports medicine practitioners and aid in the prevention of overuse injuries could be beneficial. Recovery training and rehabilitation decisions (e.g., continued need for modalities and/or recovery pitch counts or velocities) before the next hard practice or game can be made with quantitative, objective, joint health data complementing current approaches.

The collection of key joint health parameters using our present sound, swelling, and activity context measurements can be developed and validated on the knee joint, and be translated to the elbow and shoulder.

FIG. 25 illustrates a timeline for a pitcher's training/competition schedule, and how physiological-data-driven recovery schedules can potentially be used to avoid overuse injury. Major League Baseball (MLB) has an interest in preventing overuse injuries and managing recovery from arm (elbow/shoulder) injuries in pitchers. Current approaches employ self-reported discomfort/pain, physical examination and pitch count metrics, which are either subjective or based on performance indicators and not biomarkers. Quantitative biomarkers sensitive to worsening or improving subclinical and clinical injuries are needed to manage throwing arm health in pitchers.

FIGS. 26(a)-(d) illustrate an overview of the present wearable sensor system to evaluate and manage throwing arm health.

A wearable physiological monitoring system to assess knee health that incorporates measures of acoustical emissions (i.e., joint sounds), swelling based on electrical bioimpedance (EBI), and joint angle and kinematics with advanced machine-learning algorithms for an individualized joint health score is disclosed herein. Acoustics capture information regarding alignments of articulating surfaces while EBI can detect extremely small differences in tissue edema due to heating and/or cooling the limb. These have been applied these measures to discriminate healthy from injured knees and quantify post-surgery recovery. This same approach potentially can be applied to the arm (elbow and shoulder) to provide quantitative biomarkers of injury and recovery during directed movements in pitchers.

It is assumed that an elbow and shoulder health score—derived from sounds, swelling, and activity context metrics—will detect subtle biological changes, which can then be used to manage recovery in pitchers and thus reduce the potential risk of arm injuries. A decrement in passive glenohumeral external rotation (lying supine) was over two

times more likely for pitchers to be placed on the disabled list with a throwing arm injury.

Here, the measurement of joint angles achieved during an active throwing motion are coupled simultaneously with joint sounds during the motion. Swelling in the joint picked up by electrical bioimpedance in the present sensor system might also explain decreased range of motion that occurs intermittently throughout the season. Collectively, these signals can be used as a gauge to evaluate each pitcher's individual response to treatment or previous pitching practices as an objective recovery signal. The sensing modalities that are quantifying represent the same aspects (sounds, swelling, and activity context) that are qualitatively evaluated in physical exams, and thus should provide sufficiently rich information to more comprehensively assess changing throwing arm health.

One first obtains measurements of acoustical emissions, EBI, and activity context (inertial measurement) data from pitchers to optimize the location of the sensors, and the types of movements, to facilitate the highest quality of data acquisition. The present invention includes methods that determine what constitutes a high-quality signal for each of these modalities. For example, for measurement of acoustical emissions, we have developed algorithms for quantifying the signal to interference and noise ratio (SNIR), which can then be compared for different measurement locations for the sensors. Similarly, for the EBI measurements, measurement repeatability and variability in the resistance and reactance measurements across the recording time have been used as an index of quality.

It is assumed that the locations across the elbow will be analogous to placements used at the knee, since many of the characteristics of this hinge joint—such as range of movement, internal bone structure, etc.—are similar. It is assumed that the shoulder might require more in-depth studies and envision requiring minor changes to the sensor packaging and adhesion approaches. In terms of activities used to generate acoustical emissions, it is anticipated that the activities for the elbow to closely mirror our approach for the knee—unloaded elbow flexion/extension exercises will be used, combined with pronation/supination which is an important motion for pitching and putting spin on the ball. For the shoulder, movements that are typically used in the physical exam currently will be used to evaluate crepitus such as internal and external rotation, shoulder flexion, and shoulder internal rotation in 90 degrees of abduction (90-90).

After optimizing sensor placement, packaging, and activities for the elbow and shoulder, measurements of acoustical emissions, EBI, and joint angle baseball players, for example (5 pitchers, and 5 infielders), will be obtained. The measurements will be obtained at three time points throughout the season (to assess cumulative "wear-and-tear" on the joints). At each time point, sensor data will be measured (a) before, (b) immediately after, (c) 24 hours after, and (d) 48 hours after an exhaustive pitching session (to assess acute effects of a fatiguing workout on the joints, and delayed onset inflammatory effects such as edema).

Signals from both arms will be measured, such that the contralateral side can provide a "control" for each subject that can then be used to normalize inter-subject differences in the data. If any of the pitchers are injured during the season, we will take recordings at two-week intervals throughout the rehabilitation period following the injury. This will allow the data analytics efforts to both focus on pre-injury (prediction) and post-injury (rehabilitation status) quantification of joint health/risk.

The data analytics efforts will then have two focuses: (1) using unsupervised machine learning (i.e., graph mining) to facilitate clustering of the measured data to determine which signals, and features of signals, provide the best capability in detecting fatigue and “wear-and-tear” (cumulative throughout the season, incorporating metrics such as the number of pitches throughout the season) for the joints, and (2) using supervised machine learning (i.e., support vector machines) to provide preliminary approaches for quantifying the risk of acute overuse injury throughout the season by mapping sensor data to physical exam, symptoms, and other reference standard clinical data regarding the status of the players. These reference standard measures can include player-reported symptoms/pain, athletic trainer evaluations, and functional surveys.

Evaluation will focus on assessing the following: (1) quantifying whether high-quality measurements are obtained in throwing and non-throwing arm, (2) the differences in the pre- and post-workout measures, (3) the differences across the short-term recovery phase following a typical, large-volume pitching effort, and (4) the differences throughout the course of a season. To quantify whether the high-quality measurements are obtained, first the EBI signals will be visualized and expect the resistance to be below 150Ω and negative reactance to be below 50Ω at a single frequency of 50 kHz. The Cole-Cole characteristic in the spectroscopy plots will also be reviewed, as these clearly will indicate a good signal quality.

In terms of the joint sounds, first the SNIR will be computed to determine the optimal location for the microphone placement. Then a plot of the signals and detect clicks that are in high amplitudes and in short duration will be made, and they will be analyzed in the spectroscopy to look for high energy and broad bandwidth. These high amplitude clicks could correlate to the popping or crunching sounds which may indicate the friction between the joints or soft tissue impingement. In terms of evaluating the differences in the pre- and post-workout, it is anticipated the EBI parameters at a single frequency (50 kHz) to slightly decrease and the absolute difference of these values between the throwing and the non-throwing arm to increase as there would be a minor effect of edema and a structural wear-and-tear.

As for the immediate recovery phase (24-48 hours) after a large pitching effort, it is hypothesized that the absolute differences between the two arms would eventually return to the normal state (i.e. pre-workout levels) over time (although the exact time course may differ for each individual and each session). For this longitudinal testing, it is predicted that throughout recovery, EBI parameters would decrease with variations to occur with an inflammatory flare up (potentially signaling inadequate recovery or overuse syndrome). As for the elbow and shoulder sounds, the frequency domain features and custom features related specific to the clicks will be extracted and analyzed, and then any changes that occur will be observed using an unsupervised machine learning algorithm (i.e. increase in the graph heterogeneity).

CONCLUSIONS

The present invention incorporates a discrete design for high resolution EBI measurements from the knee joint based on embedded systems concepts. The combined use of high performance analog front-end electronics and digital programmability using a microcontroller allow high quality static (slowly varying over the course of hours to days) and

dynamic (rapidly varying on the order of milli-seconds) impedance measurements on a platform that is appropriate for a wearable device.

The overall system was designed and demonstrated from end-to-end, including the design of the circuit, customized physiology-driven algorithms for detecting features from the measured signals, and human subject experiments to both evaluate the capabilities in detecting small changes in local bioimpedance due to edema and modified blood flow. The invention includes the mechanical packaging to encapsulate the electronics in a wearable sleeve around the knee joint and collect data serially during the recovery from acute knee joint injury. The present wearable system based on the engineering foundation herein presented enables high resolution, quantitative assessment of both the structural and hemodynamic characteristics of the knee joint longitudinally for the first time, paving the way to better understanding joint recovery physiology, and designing closed-loop personalized therapies to accelerate the recovery process.

Further, a method of using a graph mining algorithm to quantify the impact of loading on knee joint sounds is established. With increasing loading conditions, the acoustical emissions became more heterogeneous. Furthermore, there were more variations in microphone placement at the medial side of the patella and the lateral side of the meniscus.

Numerous characteristics and advantages have been set forth in the foregoing description, together with details of structure and function. While the invention has been disclosed in several forms, it will be apparent to those skilled in the art that many modifications, additions, and deletions, especially in matters of shape, size, and arrangement of parts, can be made therein without departing from the spirit and scope of the invention and its equivalents as set forth in the following claims. Therefore, other modifications or embodiments as may be suggested by the teachings herein are particularly reserved as they fall within the breadth and scope of the claims here appended.

What is claimed is:

1. A system for assessing joint health comprising:
 - a joint health sensing assembly configured for sensing characteristics related to joint health at a first time before a perturbation of the joint and a second time after the perturbation;
 - a bioimpedance sensing assembly comprising a source of current and a receiver and configured for sensing characteristics related to bioimpedance of joint structure at the first time and the second time; and
 - a health assessor configured to provide an assessment of joint health through interpretation of characteristics from the physiology and the bioimpedance sensing assemblies at the first time and at the second time;
 wherein the characteristics from the joint health and the bioimpedance sensing assemblies at the first time represent the joint pre-perturbation and the characteristics from the joint health and the bioimpedance sensing assemblies at the second time represent the joint post-perturbation, and the health assessor uses clustering analysis or graph mining techniques to compare the pre-perturbation and post-perturbation characteristics from the joint health and the bioimpedance sensing assemblies.
2. The system of claim 1, wherein the joint health sensing assembly comprises a first wearable sensor for placement proximate the joint; and

wherein the bioimpedance sensing assembly comprises a second wearable sensor for placement proximate the joint.

3. The system of claim 1, wherein the bioimpedance sensing assembly further comprises a processor;

wherein the source of current of the bioimpedance sensing assembly comprises two electrodes configured for current injection;

wherein the receiver of the bioimpedance sensing assembly comprises two electrodes configured for voltage measurement; and

wherein the processor is configured to measure a potential difference across the joint through amplification and phase-sensitive detection stages.

4. The system of claim 3, wherein the electrodes of the bioimpedance sensing assembly are in a quadripolar electrode configuration.

5. The system of claim 3, wherein the perturbation comprises an activity performed by the joint.

6. The system of claim 3, wherein the perturbation comprises changes to the environment of the joint enforced externally.

7. The system of claim 3, wherein the perturbation comprises changes to the environment of the joint enforced internally.

8. The system of claim 3, wherein the perturbation comprises changes to joint conditions enforced externally.

9. The system of claim 3, wherein the perturbation comprises changes to joint conditions enforced internally.

10. A system for predicting joint health comprising:
 a joint health sensing assembly comprising a joint health wearable sensor for placement proximate the joint and configured for sensing characteristics related to joint health at a first time before a perturbation of the joint and a second time after the perturbation;
 a bioimpedance sensing assembly comprising:
 a first bioimpedance wearable sensor comprising a source of current; and
 a second bioimpedance wearable sensor comprising a receiver;

wherein the bioimpedance sensing assembly is configured for sensing characteristics related to bioimpedance of joint structure at the first time and the second time;

a health assessor configured to provide a prediction of joint health through interpretation of characteristics from the joint health and the bioimpedance sensing assemblies at the first time and at the second time; and an output assembly configured to provide a prediction of joint health to a user of the system;

wherein the characteristics from the joint health and the bioimpedance sensing assemblies at the first time represent the joint pre-perturbation and the characteristics from the joint health and the bioimpedance sensing assemblies at the second time represent the joint post-perturbation, and the health assessor uses clustering analysis or graph mining techniques to compare the pre-perturbation and post-perturbation characteristics from the joint health and the bioimpedance sensing assemblies.

11. The system of claim 8, wherein the bioimpedance sensing assembly further comprises a processor;
 wherein the first bioimpedance wearable sensor comprises two electrodes configured for current injection;
 wherein the second bioimpedance wearable sensor comprises two electrodes configured for voltage measurement; and
 wherein the processor is configured to measure a potential difference across the joint through amplification and phase-sensitive detection stages.

12. The system of claim 11, wherein the electrodes of the bioimpedance sensing assembly are in a quadripolar electrode configuration.

13. The system of claim 11, wherein the joint health wearable sensor comprises a wearable acoustic sensor to measure acoustic emissions from the joint.

14. The system of claim 11, wherein the joint health wearable sensor comprises a wearable sensor to measure at least one non-acoustic characteristic of the joint.

15. The system of claim 11, wherein the bioimpedance sensing assembly is further configured to measure proximal electrical bioimpedance of tissue and blood in proximity of the joint.

16. The system of claim 11, wherein the perturbation is selected from the group consisting of exercise, changing skin temperature, changing joint stiffness conditions, and subjecting the joint to an electromagnetic wave.

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