Textile-Based Inductive Soft Strain Sensors for Fast Frequency Movement and Their Application in Wearable Devices Measuring Multiaxial Hip Joint Angles during Running

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Wearable multiaxes motion tracking with inductive sensors and machine learning is presented. The production, characterization, and use of a modular and size-adjustable inductive sensor for kinematic motion tracking are introduced. The sensor is highly stable and able to track high-frequency (>15 Hz) and high strain rates (>450% s⁻¹). Four sensors are used to fabricate a pair of motion capture shorts. A random forest machine learning algorithm is used to predict the sagittal, transverse, and frontal hip joint angle, using the raw signals from sport shorts during running with a cohort of 12 participants against a gold standard optical motion capture system to an accuracy as high as $R^2 = 0.98$ and root mean squared error of $2°$ in all three planes. Herein, an alternative strain sensor is provided to those typically used (piezoresistive/capacitive) for soft wearable motion capture devices with distinct advantages that can find applications in smart wearable devices, robotics, or direct integration into textiles.

1. Introduction

Wearable electronics have been increasing in popularity—including both commercial products and peer-reviewed reports—as the advancement of materials, electronics, and printed circuit boards (PCBs) allows a decrease in size, seamless integration, and improvements in performance. Wearable electronics can provide useful data such as pressure, biosignals and biochemical markers, and strain that can be used to provide users a variety of metrics. Optoelectric motion capture (OMC) systems are capable of providing accurate kinematic human motion data, which may be used to prevent injury and enhance performance. For example, runners—spanning professional athletes to those that run for casual exercise—utilize wearable devices to track a variety of metrics; various kinematic variables have been correlated with running economy and performance and systems that are able to provide these data are valuable. The spatial limitation of OMC systems reduces the ability to use these systems to track everyday activities where they could be highly useful for sports (such as our running example), rehabilitation, and occupational settings. Other factors such as marker influence on user movement, requirement for expensive sophisticated hardware, precise marker placement, and marker movement during use can decrease the accuracy of the OMC systems. Two alternatives to OMC systems include inertial measurement units (IMUs) and flexible strain sensors, both of which are not spatially limited. Textile-based sensors have previously been developed to track strain and pressure which can be correlated to user movement.

IMUs have been used frequently to provide orientation, angular velocity, and acceleration data in different axes with gyroscopes, magnetometers, and accelerometers, respectively. IMUs have been used previously to measure gait parameters of the lower extremities; however, significant performance limitations have been reported when using IMUs during long, fast, and complex movements. In addition, magnetometer components are very sensitive to environmental ferromagnetic disturbances, which may cause a considerable amount of inaccuracy in IMU heading measurements. The definition of local coordinate systems, when comparing IMU-based systems with OMC systems (considered as the gold standard), can carry influential biomechanical model differences which contribute into the poor estimation of lower hip joint angles in frontal and transverse planes compared with the sagittal plane. Furthermore, gyroscopes are sensitive to vibration shocks—typically occurring when feet hit the ground—and can affect the accuracy of tracking certain joints.
Flexible fiber-based textile-incorporated strain sensors come in three sensing types: resistive, capacitive, and inductive. Piezoresistive strain sensors—commonly composed of composites combining thermoplastic elastomers or elastic thermosets and conductive materials such as carbon nanotubes or filled tubes of conductive liquids such as room-temperature liquid metals or ionic liquids—are fairly common and the simplest systems for signal analysis (voltage reading).

Alternative morphologies have also been explored using painting and printing techniques to produce wearable patches. Capacitive sensors are less common, more complex to fabricate, and require more advanced readout circuitry but are advantageous as they rely on geometric changes to modulate the capacitance signal. Consequently, inductive sensors do not require specialized materials or synthesis and can be produced with conductive wire or thread. The sensing mechanism of an inductive sensor relies on a change of geometry of an enclosed area by a conductive material. To achieve a sufficient signal with good sensitivity, inductive sensors can encompass a larger area, use multiple perimeter coils, and use higher magnetic permeable materials.

Textile-based inductive sensor technology is under-represented compared with piezoresistive and capacitive sensors and is yet to be used for multiaxial kinematic motion tracking.

Previously, wearable inductive-based motion tracking sensors have been developed by enclosing an area with conductive thread or wire and have been used to track single-axis motion including joints such as the elbow or knee, body posture, and skin deformation. There has also been recent interest in utilizing analogous soft-sensors for robotic perception, an area that could benefit from inductive sensing capabilities.

The ability to track kinematics—complex body movements typically reserved for motion capture systems—with soft sensors has been growing with the development of both hardware (i.e., sensors, electronics, and wireless systems) and software (i.e., apps and neural networks) and has become increasingly accurate for complex movements. Tracking lower body movements requires sensors to track at high frequency and speeds, upward of 5 Hz for a sprinter’s gait, although the body can move at a frequency beyond 10 Hz in certain circumstances such as seizures. Strain sensors that rely on geometric changes are attractive for high-frequency applications (which would currently be reserved for OMCs and IMUs) as these sensors can be produced with highly elastic and resilient materials that are not as susceptible to hysteresis. A further consideration for designing high-frequency strain sensors is to ensure that the electronics are capable of sampling data at a frequency well above the intended application frequency to ensure accuracy.

Herein, we outline the fabrication, characterization, and application-based performance analysis of textile-based inductive sensors with readily available materials. The sensor was fabricated using a simple procedure of wrapping a conductive but nonelastic wire around nonconductive elastic thread. This system could be produced and used as a patch or stitched directly onto textiles/fabrics. The basic characteristics of the sensor was analyzed for comparison with other fiber-based textile sensing systems. A prototype device was created with four of our inductive sensors to track multiaxial kinematic movement of the hip. We utilized a previously determined sensor pattern such that strain from each sensor was attributable to movement in multiple axis and through the use of machine learning, predict each plane—flexion/extension, abduction/adduction, and rotation of the hips—with accuracy to within 2°. This is the first inductive sensor to be used in multiaxes kinematic monitoring of the lower body and highlights the benefits of the inductive sensing system.

2. Experimental Section

2.1. The Sensor

2.1.1. Sensor and Device Fabrication

The stretchable conductive copper-coiled elastic thread (CCET)—which was used to produce the inductive strain sensor—was fabricated using an in-house-built spur machine (Figure S1, Supporting Information). The fabrication machine consisted of four rotary actuators, three pulling the stretchable wire through a guided path and another rotary actuator spurring the copper wire around the elastic thread (Figure 1, wrapping moment). The elastic thread had a diameter of 850 μm, and the wound copper wire had a spacing of 672 ± 119 μm between coils (Figure 1).

2.1.2. CCET Sensor-Integrated Sport Shorts

The CCET was then used to form rectangular loops (three loops/sensor) using a zigzag sewing stitch to create a patch on an elastic textile (Figure 2). The sensor batches used in the prototype consisted of three loops in a rectangle, 8 cm in length and a width of 2 cm for a total starting area of 16 cm². The sensors were attached to stretchy sports shorts using a zigzag sewing stitch and were labeled from 1 to 4 for reference to the discussion in the following sections (Figure 2).

2.1.3. Sensor Placement

Sensor placement and orientation and the number of sensors can play a major role in improving the accuracy of the multiaxes body motion tracking systems. In this study, sensor locations were used from our previous work that identified optimal sensor orientations for multiaxes hip angle tracking with piezoresistive sensors. The sensors were connected to an LDC1614 chip (see Supporting Information for details, Figure 2).

![Figure 1. Illustration of the fabrication of the copper-wound elastic thread.](image-url)
2.1.4. Method for Real Application Strain Range Calculation and Sensing Range

The prestrain (the strain when the garment is worn in a static standing position) and maximum strain define the sensing range during running and were analyzed using an OMC system. Two optical markers were attached using a fabric fusion tape at each end of each sensor to measure the strain applied to each sensor for 1 min of a participant’s running at a speed of 2.0 m s⁻¹. The analysis determined that maximum prestrain applied to the four sensors present in the prototype was 10%. The maximum strain applied to any of the sensors did not exceed a further 18% for 1 min of running. Therefore, the sensor’s sensing range was defined as less than 30% strain and was subsequently used during the sensor’s basic performance testing to ensure that the sensor characterization was within expected strain from different participants’ body shapes and gaits. This test was intended only to determine the sensing range of the strain sensors and independent from the test protocol.

2.1.5. Read-Out Circuit for Sensor’s Signal Data Acquisition

With the exception of Figure 3 (which measured inductance directly with an inductance–capacitance–resistance [LCR] meter), all work presented here used a Texas Instruments LDC1614 four-channel, 28-bit inductance-to-digital converter for inductive measurements. The LDC1614 chip was interfaced via an I2C protocol using a STM Nucleo-F401RE, which was programmed to set proper register values at the beginning of each trial, read the corresponding registers, and convert the sensor’s raw output from bits to decimal values for each sensor. According to the LDC1614 datasheet, the decimal values obtained for each sensor can be used to calculate the frequency of the current generated in the inductance–capacitance (LC) circuit, which can then be converted to inductance. For simplicity, the decimal values of each sensor’s raw signal were used throughout this investigation.

\[
f_{\text{sensor}}(t) = \frac{\text{DATA}x f_{\text{REF}x}}{2^{28}}
\]

\[
L(t) = \frac{1}{(2\pi \cdot f_{\text{sensor}}(t))^2 \cdot C}
\]

According to LDC1614 Datasheet, formula (1) shows the relationship between the measured frequency of the sensor and the raw signal in bits, where DATAx is the raw signals in bits of each sensor (x). \( f_{\text{sensor}} \) is the sensor oscillation frequency in Hz, \( f_{\text{REF}x} \) is the reference frequency in the chip, which was set to 40 MHz, \( L(t) \) is inductance in Henries, and \( C \) is the sum of sensor’s capacitance and parasitic capacitance. The parasitic capacitance of the coil is negligible in comparison with the selected chip capacitance—which was 330 pF and chosen to match the inductance—which was constant.[27]

During LCR meter use, the device was set at a reference frequency of 100 MHz and 5 mV, which were empirically found to be the best fitting parameters. The parameters included reference frequency of 1 MHz, level (voltage) of 0.5 V, and “auto” range mode.

2.1.6. Sensor Characterization Signal Processing

The data acquisition system for the linear stage testing recorded displacement of the actuator with respect to its original position in one axis. Displacement was converted to strain at each moment in time using formula (3). Python 3.6 and the
formulas (4) and (5) were used to normalize strain and the sensor’s raw signals.

\[
S(t) = \frac{\text{displacement}(t)}{l} \\
S(t)_{\text{normalized}} = \frac{(S(t) - S_{\text{min}})}{S_{\text{max}} - S_{\text{min}}} \\
f_{\text{bits}}(t)_{\text{normalized}} = \frac{(f_{\text{bits}}(t) - f_{\text{bits max}})}{f_{\text{bit min}} - f_{\text{bits max}}}
\]

where \(f(t)\) and \(S(t)\) are the signal value and strain value at time \(t\), respectively; \(f_{\text{min}}\) and \(S_{\text{min}}\) are the minimum values of that raw signal and strain in each trial, respectively; \(f_{\text{max}}\) and \(S_{\text{max}}\) are the maximum values of the raw signal and strain, respectively; and \(S(t)_{\text{normalized}}\) and \(f_{\text{bits}}(t)_{\text{normalized}}\) are the normalized value of the strain and raw signal in time \(t\), respectively.

Gauge factor (GF) was calculated by the following formula

\[
\text{GF} = \frac{\Delta f / f_0}{\Delta l/l_0}
\]

where \(\Delta f\) was the change in frequency of the current generated in the LC circuit, \(f_0\) was the initial frequency of the current in the LC circuit at 0% strain, \(\Delta l\) was the change in length, and \(l_0\) was the initial length of the sensor.

2.2. Components for the Analysis of the Motion Tracking Sport Shorts

2.2.1. Optical Motion Capture Setup for Standard Comparison

Six high-speed motion tracking cameras collected pelvis and right thigh kinematic data (and subsequently used as the standard for joint angles) from eight retroreflective tracking markers using a modified lower extremity marker set. Prior to dynamic trials, a static calibration trial was captured using additional six static/calibration markers. This trial was used to construct the pelvis and right thigh model of each participant in Visual3D software.

A signal from the motion tracking system was used to synchronize the sensors and motion capture data. Data from the sensors were collected at a frequency of 125 Hz and motion tracking system at 100 Hz. The sensor data were interpolated and down sampled to the sampling rate of the motion tracking system (100 Hz) to match the number of samples in each trial.

We chose to describe angles using clinical terms as we were conducting this study within a clinic setting. Clinical (or orthopedic) angles are analogous to Euler angles in this study and are described as flexion/extension (sagittal plane), abduction/adduction (frontal plane), and rotation (transverse plane).

The 3D kinematic data were analyzed using Visual3D software and passed through a sixth-order Butterworth low-pass filter to remove low-frequency noise. Reference angles were extracted from the filtered data.

2.2.2. Machine Learning Inductive Sensor Raw Signal Processing

To extract useful features for the machine learning model, the sensor’s raw data were processed before being used in the machine learning model for training. To extract features useful for the random forest regressor, each pair of sensor signal values were numerically added together, deducted, divided, and multiplied by each other. A first-order derivative of each sensor’s signal was added to the list of features and finally, a sliding window of ten previous data points was added to the features to smooth the output signal. Using the aforementioned method, an input array size of \((n \times 720)\) was achieved for each participant, where \(n\) is the number of data points for each trial, and 720 is the total number of features for each model.

A second model was trained without the numerically modified signal values and only contained the previous ten data points to determine the effects of adding these additional features.

2.2.3. Participants

To evaluate the performance of the prototype, 12 participants—2 females and 10 males—between the ages of 22 and 31 were recruited. The experimental protocol was approved by the Office of Research Ethics at Simon Fraser University. Prior to any data collection, written informed consent was obtained from all participants (details of participants in Table 1).

2.2.4. Study Protocol

The participants were asked to wear the tight-fitting prototype sport shorts, and the OMC markers were affixed directly to the shorts. After collecting the static calibration, each participant...
was asked to run at a speed of 2.0 m s⁻¹ on a treadmill. This speed was chosen to ensure all participants could complete the entire testing protocol without breaks. The data collection for each participant involved one trial of 10 min of running.

2.2.5. Evaluation of Strain Signals from Inductive Sensors

The performance of the joint angle measurement by the machine learning algorithm was assessed by comparing the predicted angle from the algorithm with the reference angle measured by the motion capture system. The coefficient of determination ($R^2$), root mean squared error (RMSE), and the normalized root mean squared error (NRMSE) were used as metrics for comparison.

Using these metrics, we validated the performance of the machine learning algorithm in an intraparticipant analysis. In this evaluation approach, one separate model was trained and tested for each participant. A tenfold cross-validation method was used to evaluate the performance of the model. Each fold comprised all the movement conditions with the same speed. In this tenfold cross-validation approach, the model was trained using the data from ninefolds (equivalent to 9 min of running) and tested on the remaining fold (equivalent to 1 min of running). This was repeated until all the tenfolds were selected as the test set. The accuracy of the model was determined by averaging the results of all tenfolds.

To understand the temporal order inherent in the data, the participant’s data were analyzed using a tenfold forward-chaining technique. The forward-chaining technique splits the participants’ data into ten parts, then a separate model was trained using all possible splits, whereas one future split was used for testing. For instance: 1) first split was used in training, second as testing; 2) first and second split as training, third split on testing; etc. This was repeated for all participants and averaged.

3. Results

3.1. Sensor’s Principal of Operation and Basic Properties

Inductance of a polygon made of a conductive material with circular cross section can be approximated by the following formula:

$$L \approx \frac{\mu_0 P}{2\pi} \left[ \ln \left( \frac{2P}{r} \right) + 0.25 - \ln \left( \frac{P^2}{A} \right) \right]$$  (7)

where $L$ is inductance (Henries), $P$ is perimeter (meter) of the loop, $A$ is the area (m$^2$) circumscribed by the loop, $r$ is the radius of the conductive material’s cross section, and $\mu_0$ is relative magnetic permeability ($4\pi \times 10^{-7}$ H m⁻¹). The area can be approximated by a rectangle with length $l$ and width $w$ ($A_{sensor} = l \times w$). Considering the spring as a constructing element of the rectangle, as shown in Figure 2D, the perimeter of the sensor’s loop ($P_{sensor}$) can be approximated by

Number of turns in the spring $= \frac{l}{\text{pitch}}$

Perimeter of the spring with 1 turn $= \pi \times d_{elas}$  

$P_{spring} = \frac{l}{\text{pitch}} (\pi \times d_{elas})$

where $d_{elas}$ is diameter of elastic thread, and pitch is the distance between each coil (within each segment of each loop, Figure 1). Therefore, the perimeter of the sensor—or length of the copper wire present—would be

$$P_{sensor} = 2 \cdot \left( \frac{l}{\text{pitch}} \times \pi \times d_{elas} + \frac{w}{\text{pitch}} \times \pi \times d_{elas} \right)$$

$$= \frac{2 \times \pi \times d_{elas}}{\text{pitch}} \times (l + w)$$  (9)

This formula was used for approximating the inductance of the sensor based on its geometric parameters. Finally, the formula for calculating inductance as a function of its length can be derived as follows, assuming that the strain was applied in the direction of the length of the sensor according to

$$\ln \left( \frac{P^2}{A} \right) = \ln \left( \frac{P_{sensor}^2}{l \times w} \right) = \ln \left( \frac{P_{sensor}^2}{l \times w} \right) - \ln(l)$$  (10)

$$L \approx \frac{\mu_0 P_{sensor}}{2\pi} \left[ \ln \left( \frac{2P_{sensor}}{r} \right) + 0.25 - \ln \left( \frac{P_{sensor}^2}{w} \right) \right] + \frac{\mu_0 P_{sensor}}{2\pi} (\ln(l))$$  (11)

Given that all parameters are constant except $l$ in formula (11), the sensor’s inductance correlation is nonlinear with a changing length of the sensor defined by the natural logarithm function. Similarly, when having a multiloop sensor with $N$ as the number of loops, the perimeter of the sensor or the amount of copper wire present in the loop is multiplied by $N$. Finally, the area bounded by the loop is multiplied by the number of loops which results in the following

$$L_{\text{multiloop}} \approx \frac{N \mu_0 P_{sensor}}{2\pi} \left[ \ln \left( \frac{2NP_{sensor}}{r} \right) + 0.25 \right] - \ln \left( \frac{\left( NP_{sensor} \right)^2}{\pi \Delta} \right) + \frac{N \mu_0 P_{sensor}}{2\pi} (\ln(l))$$  (12)

Using formula (12), it was possible to calculate the expected change in inductance of a sensor when strained length wise—assuming a constant value for the number of loops, pitch value, and width of the loops. Calculations for strain up to 100% are shown in Figure 3A,B. The width of the sensor was held constant during strain (no expected Poisson effect) as the CCET was not attached to a textile/fabric for these tests.

The comparison of calculated and actual inductance changes with strain (Figure 3A) is not in agreement with respect to the
expected GF. Most likely, the reason for this disagreement lies in neglecting the self-inductance of each loop’s segments and the mutual inductance of each pair of segments. Upon increasing the length of a solenoid, its self-inductance would decrease, affecting the resulting signal. Normalization of the sensor’s signal and strain resulted in an $R^2 = 0.985$ (Figure 3B).

3.2. Sensor Testing: Step Test

To achieve a better understanding of the sensor’s performance, the electromechanical properties of the sensor were investigated with respect to different strain profiles. The sensor was initially analyzed by completing strain-inductance measurements to determine the signal quality and accuracy within our desired sensing range (<30% strain, see Experimental section and Supporting Information for the determination of sensing range). The sensor was able to track steps in 5% increment strain (5–10–15–20–25–30–25–20–15–10–5%) at 1% s$^{-1}$ with 10 s holds at each step and resulted in an NRMSE = 2.83% (Figure 5A). The step holds did not show any signal drift/relaxation.

3.3. Sensor Testing: Hysteresis and GF

To analyze any hysteresis and time-dependent effects, a triangular wave pattern with increasing strain (0–1–0–2–0–3–0... 30–0% strain at 5 mm s$^{-1}$ ≈4.7 strain%/s$^{-1}$) was completed. The sensor was able to track with an NRMSE = 1.43% (Figure 5B). There was no change/drift in the baseline and/or peak values, and the sensor displayed no hysteresis—displayed as an inductance versus strain overlay plot in Figure 5D for 0–10–0%, 0–20–0%, and 0–30–0% strain. The sensor displayed a consistent GF of $-0.055 ± 0.002$ from 0% to 30% strain (Figure 5C).

3.4. Sensor Testing: Signal Drift and Noise

The sensor stability was analyzed over a period of 10 000 s (2.7 h) with a minimal constant strain (0.1%). The sensor signal had a maximum signal drift of 0.48% (0.00077 MHz, Figure 5E, largest signal deviation) and a signal noise calculated at three separate 1 min intervals of 0.05% (0.00016 ± 0.0001 MHz, Figure 5E, green boxes left to right).

3.5. Sensor Testing: Random Wave Pattern Tracking

During a random wave pattern from 0% to 6% strain for 60 s, the inductive sensor was able to track with an NRMSE = 2.43% (Figure 5F). The range and rate were chosen because of the limit of our custom linear stage. This test mimics what is expected for motion tracking movement and can give an indication on sensor performance prior to installation in a wearable device.

3.6. Accurate Tracking of High-Frequency Strain

The sample sensor was stretched from 15% prestrain up to 30% at a variety of frequencies expected during prototype use and included 0.1, 1, 2, 4, 8, 10 Hz (where 10 Hz equates to 453% s$^{-1}$, Figure 6A). Strain and the sensor’s raw signal were normalized for comparison. A subsequent test was completed from 15% to 22% strain to increase the range of frequencies (to the tensile testers limit) up to 20 Hz (Figure 6B). The strain ranges were chosen to enable the Instron tensile testing instrument to strain at the desired frequencies with our sensor dimensions. The sensor accurately tracked the strain to 20 Hz and only started to show a small inability for consistent peak/valley—maximum/minimums at 20 Hz. Compared with data obtained by optical motion tracking (Figure 6C), the majority of motion is expected to be below 100% s$^{-1}$ (2 Hz in the previous test equates to a

Figure 5. A) Step test from 0% to 30% strain in 5% steps. B) Triangular wave pattern from 0% to 30% strain in 1% increments. C) The linear relation of $\Delta f/f_0$ and $\Delta l/l_0$ and the GF up to 30% strain. D) Hysteresis plot between 0–10–0%, 0–20–0%, and 0–30–0% strain. E) Signal variation over 2.7 h. Green boxes represent instantaneous noise. F) Normalized 60 s random wave pattern tracking.
maximum of 95\% \text{s}^{-1} strain rate, Figure 6D), with a maximum of 150\% \text{s}^{-1}—well within the ability of the inductive sensors capabilities. Hysteresis was analyzed by plotting the signal versus strain (Figure 6E) and showed an increasing hysteresis loop at frequencies greater than 4 Hz (Figure 6F).

3.7. Dynamic and Repeated Cyclic Test

An important factor in sensor performance is the stability of the signal over time. To analyze the CCET sensor, we subjected a nontextile-supported CCET three-loop sensor to 300 trapezoidal cycles from 5\% to 30\% strain at a strain rate of 10\% \text{s}^{-1} (Figure 7A). The stress and sensor signals both shifted to lower values, indicating some mechanical relaxation within the sensor. The signal frequency shifted to lower values with a consistent GF (Figure 7B).

3.8. Smart Tight-Fitting Sport Shorts Cohort Kinematic Motion Tracking Testing

For each of the 12 participants (Table 1), 10 min of running data were collected. The random forest regressor estimated...
the sagittal plane (flexion/extension, Figure 8A) angle with an $R^2 = 0.98 \pm 0.01$, RMSE = 1.63 ± 0.32°, and NRMSE = 3.45 ± 0.56%; the frontal plane (abduction/adduction, Figure 8B) angle with an $R^2 = 0.93 \pm 0.04$, RMSE = 1.09 ± 0.22°, and NRMSE = 5.31 ± 0.96%; and the transverse plane (rotation, Figure 8C) angle with an $R^2 = 0.80 \pm 0.09$, RMSE = 1.17 ± 0.25°, and NRMSE = 7.35 ± 1.20% averaged over all participants. Among the three angles, the sagittal plane angle estimation had the highest accuracy, whereas the transverse plane angle estimation had the lowest accuracy (Table 2 and Figure 8A–C).

3.9. Machine Learning Training and Evaluation

Three separate machine learning methods were used—tenfold cross validation with 720 features, 10-split forward chaining with 40 features, and 10-split forward chaining with 720 features. The ten-split forward chaining technique had slightly lower average values compared to the tenfold cross-validation method (Table S2, Supporting Information). Including numerical-modified signal values (720 total features) resulted in an increase in the average accuracy in all planes in comparison with the method using only the previous ten data points (on each of the four sensors) using a sliding window function (Table S2, Supporting Information).

3.10. Electromagnetic Interference

To gauge the effects of external electromagnetic field (EMF) disturbances, common sources of interference were brought to within ≈2 cm of the sensors. All of the sources of EMF resulted in noise of the sensor; the phone and circuit board caused the largest amounts of noise. The effect of distance with the phone and circuit board was analyzed and resulted in noise, starting at 5 cm and increased with closer proximity (Figure S7, Supporting Information).

4. Discussion

4.1. Inductive Sensor Design

There have been two approaches for inducing an inductive change during strain: bending the inductive loop, without necessarily a change in the area encircled by the loop, and a quantitative change of area enclosed by the inductive loop.\[26,29,45,46\] The fabrication method for our CCET sensor required only a spur machine to coil the copper wire around an elastic thread. The materials are commercially available, and the production method would be easily scalable. The sensors used in all of the sensor characterization tests and those fabricated for the smart compression shorts consisted of three perimeter loops; this was considerably lower than other examples that have required from 20 to 65 loops.\[26\]

It was possible to calculate the inductance of a nonstretched sensor before choosing the geometric parameters (width, length, number of loops, and pitch) using formula (12). The geometric parameters of the sensors were chosen such that the inductance of the sensor in the non-stretched state was a minimum of 2 μH. Three enclosed loops were empirically found to achieve at least 2 μH and was insensitive to most of the EMF disturbances of the surrounding environment—including our own bodies. The sensors were sensitive to a variety of devices at proximities of less than 5 cm, although we did not observe any noise during our cohort testing, nor would we expect to have a device within that distance during regular use (see Figure S7, Supporting Information).

![Figure 8. Comparison of kinematic tracking for different planes (shown in each graph) during running. This includes A) flexion–extension (sagittal plane); B) abduction–adduction (frontal plane); and C) rotation (transverse plane).](#)

| Plane | $R^2$ | RMSE [°] | NRMSE [%] | $R^2$ | RMSE [°] | NRMSE [%] | $R^2$ | RMSE [°] | NRMSE [%] |
|-------|-------|----------|------------|-------|----------|------------|-------|----------|------------|
| Average (std dev) | 0.98 (0.01) | 1.63 (0.32) | 3.45 (0.56) | 0.93 (0.04) | 1.09 (0.22) | 5.31 (0.96) | 0.80 (0.09) | 1.17 (0.25) | 7.35 (1.2) |

Table 2. Performance results of the algorithm in the estimation of three angles in sagittal ($\psi$), frontal ($\theta$), and transverse ($\phi$) planes, averaged across all participants.
Information, for EMF disturbances of different objects). Using fewer loops (e.g., 1 or 2) resulted in insufficient signal variation as well as having high sensitivity toward other EMFs in the surrounding environment. Others have used lower base inductance values, starting from a few hundreds of nH to 1–3 μH.\[10,45\]

As shown in Figure 3, using formula (12) resulted in an underestimation of the base inductance value but overestimation of the GF. The relationship of what affects the inductance change will be discussed as follows. The small GF of the sensor is offset by a stable signal with low noise.

### 4.2. Inductive Sensor Characterization

To better assess the sensors properties, we initially wanted to understand the effect of strain on inductance (or indirectly using frequency), and completed tests were performed on a displacement-controlled linear stage/tensile tester. The step and hold test indicated consistent values on the increasing and decreasing steps and did not show any signal drift/relaxation typical of piezoresistive sensors.\[47\]

An important aspect of accurate sensing is the ability for the sensor to be unaffected by previous or preceding events.\[47\] As our inductive sensor relies on the area enclosed by the elastic CCET, there was no discernable hysteresis within our sensing range of <30% strain at a strain rate of 1% s\(^{-1}\) (Figure 5D).

The relationship of inductance to area is not formally linear (see formula (7)) although the small changes in area of the sensor result in a pseudolinear relationship (according to formula (12), inductance is correlated to strain with a natural logarithm function, although the small changes in values of length result in a linear sensing range) within the expected sensing range of <30% strain (Figure 5D). The inductance of the sensor is a combination of (see Supporting Information for a further discussion): 1) self-inductance of each consisting segments, i.e., each solenoid side of the rectangular loop; 2) mutual inductance of neighboring segments, i.e., a pair of parallel/adjacent solenoid-like sides of rectangular loop; and 3) mutual inductance of neighboring loop if \(N > 1\).

Comparing the calculated and experimental inductive signals for up to 100% strain—excluding the GF by normalization—resulted in an \(R^2 = 0.985\). Although the predicted GF did not agree with the experimental data (Figure 3A), the inductance–strain relationship with normalization was in agreement (Figure 3B). In the future, a more accurate calculation of signal variation with strain would be advantageous for computational modeling of the ideal sensor size/area and position for motion tracking devices.

Drift of a sensors baseline signal over a period of time can be detrimental when attempting to accurately track kinematic movement over longer periods of time. The CCET inductive sensor was stable over a period of 2.7 h to within 0.48% with minimal noise equal to \(\approx 0.05\%\) change under static conditions (Figure 5E). The 0.48% change was likely from external EMFs, such as computers, antennas, and other ferromagnetic objects. Under dynamic conditions (cyclic strain from 5% to 30%), the sensor underwent a small amount of mechanical relaxation, resulting in a decrease in force and an analogous decrease in inductance (Figure 7). The decrease in inductance and consistent GF suggests that the length of the sensor did not increase—as we would expect an increase in inductance. We reasoned that from our understanding of the inductive-producing components of the CCET-based sensor (discussed earlier), an increase in pitch would result in a decrease in the self-inductance of the individual CCET filaments and mutual inductance of neighboring CCET filaments.

Once the CCET sensor is installed in the sport shorts, determining sensor performance with respect to tracking random movements is difficult to analyze and troubleshoot without knowing how the sensor responds to random movement in a controlled environment. Subjecting the sensor to a random waveform strain profile can give an indication of the expected accuracy of the sensor for motion tracking. A random waveform was produced with a maximum strain rate of 4.6% s\(^{-1}\) (5 mm s\(^{-1}\)) within a strain range of 0–6%. The inductive sensor was able to accurately track strain with an NRMSE of 2.43% (Figure 5F). This test was limited in its strain rate and in comparison with the motion capture data of the intended application (Figure 6C), the actual frequency and strain rate required to track running was much higher—often upward of 100% s\(^{-1}\) (Figure 6C)—with a stride frequency as high as 5 Hz for a sprinter.\[15,30,38\] To analyze the ability of the sensor to track fast movements, the sensor was strained at frequencies from 0.1 to 20 Hz using a sine wave pattern (Figure 6A,B). The sensor was able to track up to 20 Hz and 450% s\(^{-1}\) (Figure 6A,B,D). The fastest human motion is \(\approx 10\) Hz, typical of seizures—which could be a suitable alternative application for these sensors—along with robotics applications that may require tracking strain at high frequencies/strain rates not capable in human motion.\[19\] At frequencies greater than 4 Hz (186% s\(^{-1}\) strain rate), signal hysteresis was observed as a result of the mechanical lag of the CCET sensor components—likely caused by an increase in the dissipation of energy by the elastic thread (Figure 7).\[48\] The sensor was still able to track minimum/maximum values effectively but exhibited an increasing lag with increasing frequency and strain rate above 4 Hz (186% s\(^{-1}\), Figure S5 and S6, Supporting Information).

### 4.3. Prototype Fabrication

The number of sensors used in the prototype was limited by the LCD1614 chip capabilities of reading four sensors simultaneously. The sensors were connected to the LCD1614 chip which was attached to the waistband of the shorts (Figure 2C).

We utilized a previous approach developed in our group to maximize accuracy with four sensors in specific placements to monitor multiaxes hip kinematics.\[41\] Each sensor was placed in different orientations (horizontal/vertical/orthogonal, Figure 2A–C) which allowed the system to learn as many unique relationships between strain of each sensor and hip movement in different planes (sagittal, frontal, and transverse).

The choice of garment to attach the CCET sensors was a tight-fitting, stretchable sport short. The textile that the sensors are attached to or embedded into will affect the resulting performance of the sensor; the elasticity and resilience of the textile will directly affect the performance and response of the geometry-based CCET sensor. If the textile has lower elasticity, this would
limit the sensing range, whereas lower resilience would decrease the accuracy on increasing frequencies (or strain rates).

4.4. Cohort Testing and Application of Machine Learning for Multiaxes Kinematic Tracking

To our knowledge, there have been no previous reports of quantitative tracking of lower-body motion using inductive sensors and only one classification-based motion tracking and one regression-based single-axis angular motion. The smart compression shorts fabricated in this work captured motion in three dimensions during a running speed of 2.0 m s\(^{-1}\). Running speeds are variable and while this pace may have been slower than average, it was a speed that our participants could manage comfortably over the complete testing period. It was important for our participants to run at a speed that allowed them to maintain their normal running mechanics throughout the test. We expect the motion tracking to perform equally well at higher running speeds (upward of 5 Hz for a sprinter) as the inductive sensors were not susceptible to hysteresis at these strain rates or frequencies.

Machine learning was required to interpret and predict hip joint angles for our four sensors set-up. A random forest regressor was chosen, as in comparison with other popular supervised machine learning models, it can deliver similar performance to other algorithms with less computational effort, no requirements for hyperparameter optimization, or model-specific selections. The use of evaluation features with a k-fold cross-validation method produced the best results. The forward-chaining method with 720 features and the use of only the past ten data points on each of the four sensors resulted in slightly lower average values (Table S2, Supporting Information).

Hip angles were estimated for all participants with an average RMSE of less than 1.63°, 1.08°, and 1.15° in the sagittal, frontal, and transverse planes, respectively (Table 2). The random forest regressor was able to provide excellent estimation in the sagittal plane \(R^2 = 0.98\) and in the frontal plane \(R^2 = 0.93\) but the accuracy was much lower in the transverse plane \(R^2 = 0.80\). The larger range of motion in the sagittal and frontal planes \(45°\) and \(15°\), respectively compared with the transverse plane \(5°\) resulted in a larger relative error \(>1°\) of \(5°\) for the transverse plane and reduced accuracy as a direct result of the smaller range of motion. In addition, the kinematic profile of the transverse plane joint angle of the hip is a more complicated pattern during running in comparison with the sagittal plane and frontal plane. Further improvement of this accuracy would require the use of more sensors with high sensitivity to the transverse movement. Furthermore, while optical motion capture technology is considered the gold standard approach to measuring running biomechanics, it is also less accurate in the transverse plane compared with sagittal or frontal tracking and may be a source of error in our results.

CCET sensors show little drift and the ability to capture motion at a high frequency (>15 Hz) and strain rates (>450% s\(^{-1}\)), without any discernable hysteresis up to a frequency of 4 Hz and strain rate of 186% s\(^{-1}\). This shows great potential for inductive-based sensor smart textile systems to provide feedback useful for injury prevention, performance tracking and enhancement, or robotics. Future work will involve the incorporation of additional sensors and chips to improve the accuracy of the more difficult-to-track transverse and frontal planes, especially to enable tracking at faster running speeds. An improved calculation of inductance may also allow modeling and sensor optimization with respect to size and position to improve tracking further. Although we have shown the sensor is susceptible to external EMF, the EMF-producing objects must come to within 5 cm of the sensors, which was not an issue during out testing. If the CCET sensor technology was to be used in alternative motion tracking devices that may be in close proximity to EMF-producing objects, shielding to reduce or eliminate the effects would be important. Sweat did not adversely affect the inductive sensors performance, although further testing is required to ensure feasibility in different working environments (temperature and humidity) and repeated machine washing to ensure durability. Finally, to eliminate the requirement for joint angle-labeled data collection (using OMC systems for calibration) for each individual, alternative machine learning models and calibration protocols will be required to allow accurate hip joint angle prediction with interparticipant training.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

inductive sensors, kinematic tracking, smart sensors, soft sensors, wearable devices

5. Conclusions

Overall, our developed smart compression shorts system was able to track multiaxial thigh movements with respect to pelvis during running in three dimensions with errors less than 1.63°.
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