

# Augmented Reality Visualization of Wearable Strain Sensor Data for Monitoring Low Back Activation During Weightlifting

---

ELIJAH WYCKOFF, TAYLOR PIERCE, DAVID STEN  
and KENNETH J. LOH\*

## ABSTRACT

Resistance training is a widely practiced method for building strength, endurance, and muscle definition across various muscle groups. Certain weightlifting exercises are designed to isolate specific muscles. However, unintentional lower back engagement during these movements can reduce the effectiveness of the exercise and increase the risk of muscle strains that can lead to injury. Addressing incorrect form in weightlifting has been accomplished by a variety of methods, including wearable sensors, but there exists a need for a real-time, noninvasive solution to correct weightlifting form on-the-fly. To address these challenges, an augmented reality (AR) interface was developed to directly provide form feedback to the weightlifter based on wearable sensor skin-strain measurements from Motion Tape (MT), which is a self-adhesive skin-strain sensor formed by drop-coating piezoresistive carbon nanomaterial solutions directly onto kinesiology tape. Participants performed sets of 10 repetitions of biceps curls (where low back activation is undesirable), with and without the aid of AR feedback. During testing, each participant wore a pair of MT sensors on their lower back at the left and right sides of the pelvis. These MT low-back strains were displayed in real-time during exercise in the Microsoft HoloLens 2 headset. Analysis of the test data showed that MT recorded lower levels of low-back engagement across three sets of each exercise when the subject was aware of the strains visualized in AR.

## INTRODUCTION

Progressive overload is a fundamental principle in weight training for developing muscular strength. This involves gradually increasing the intensity, volume, and frequency of strength training. In isolation exercises like biceps curls, which target a single joint or muscle group, progressive overload can effectively build strength. However, this also means that poor form can limit training efficacy, stunt the progression of an individual's training program, and increase risk of injury if left uncorrected. In a weightlifting study comprising of 560 injury cases, the low back

---

Elijah Wyckoff, Taylor Pierce, and Kenneth J. Loh\*, Active, Responsive, Multifunctional, and Ordered-materials Research (ARMOR) Lab, University of California San Diego, 9500 Gilman Dr MC 0085, La Jolla, CA 92093-0085, USA

\* Corresponding author e-mail: kenloh@ucsd.edu

David Sten, S10 Fitness, 3810 Rosecrans St, San Diego, CA 92110, USA

accounted for 130 injuries (23.1%), with most injuries reported as strain [1]. An updated study with 676 injury cases since 2011 confirms the prevalence of low back injuries with 152 (22.5%) occurrences among powerlifters and Olympic weightlifters [2].

Augmenting training with quantitative data from wearable sensors enables detailed form analysis. Wearables have transformed personal fitness and rehabilitation by offering cost-effective, portable solutions for capturing real-time biomechanical data during activities such as weightlifting [3]. For example, surface electromyography (sEMG) sensors measure muscle activation by detecting the electrical signals generated by contracting fibers, which can detect undesirable muscle compensation in biceps curls [4]. In the same study, optical motion capture (mocap) also demonstrated high accuracy in tracking joint kinematics, including upper limb movements during biceps curls. Inertial measurement units (IMUs) can track body segment orientation and movement dynamics in biceps curls as well [5]. These methods are well-suited for analyzing lifting form, but movement artifacts and latency can hinder immediate form correction during exercise. There exists a need for a method of delivering simple, interpretable real-time feedback to allow lifters to adjust their technique during the movement itself.

Augmented Reality (AR) enables the overlay of relevant information directly into the user's field of view, enhancing decision-making by providing data that would otherwise be inaccessible in real-time. New advances in noncontact computer vision-based systems have been shown to measure and correct weightlifting form using high-resolution cameras and advanced algorithms [6]. However, this may divert user visual attention away from natural gaze patterns crucial for safe and effective lifting. Feedback is also based on multiple screen-based visual cues, whereas cognitive load has been shown to decrease when information is augmented directly into the user's environment with AR [7]. Visual cues in AR have been implemented in a game-like manner for motivating rehabilitation patients [8-10]. Augmenting real-time data has the potential to promote weightlifting posture by leveraging the same gamified motivational effects.

Thus, the objective of this study was to develop an AR system that could visualize, in real-time, skin-strain measurements (from a textile-based wearable sensor called Motion Tape (MT) [11-13]) for detecting and directly conveying deviations in weightlifting. A custom-built *Unity* application was developed, and the Microsoft HoloLens 2 (HL2) was employed to stream and project MT resistance data into the user's visual field. Participants performed weightlifting exercises while MT on the left and right sides of the spine measured low-back engagement. The AR user could look at the MT measurements in real-time while attempting to minimize deviations in movements associated with poor performance. MT data was stored and analyzed to determine the level of form improvement accomplished with the AR tool.

## **EXPERIMENT DETAILS**

### **Motion Tape Fabrication**

MT piezoresistive sensors were fabricated following previous work that leveraged graphene nanosheets (GNS) [13]. In this study, GNS ink was replaced with a 2% multi-walled carbon nanotube (MWCNT) aqueous suspension. The sensor was fabricated by coating a 7.5×40 mm<sup>2</sup> masked area of commercial kinesiology tape (k-tape) with four layers of MWCNT solution, followed by painting conductive silver electrodes at

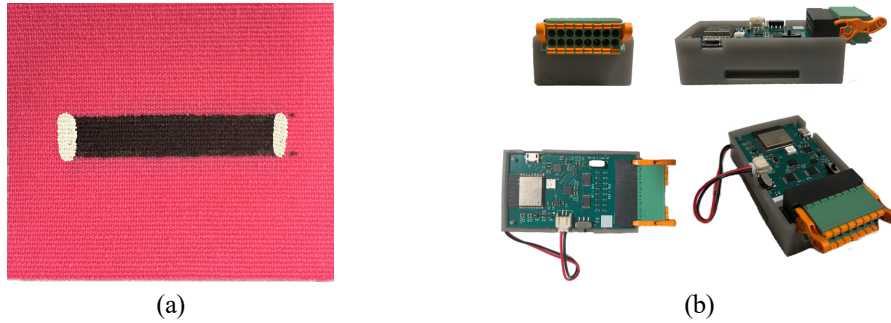


Figure 1. Components of the MT-DAQ platform, including (a) the MT wearable sensor and (b) the fully assembled wireless sensing node for multi-channel MT data acquisition.

opposite ends of the rectangular film. After drying, multi-strand wires were soldered to the electrodes for ease of electrical resistance measurements. The MT sensor had a baseline or unstrained resistance ( $R_0$ ) of  $\sim 1$  k $\Omega$ . A MT specimen is shown in Figure 1a.

### Wireless Sensing Node

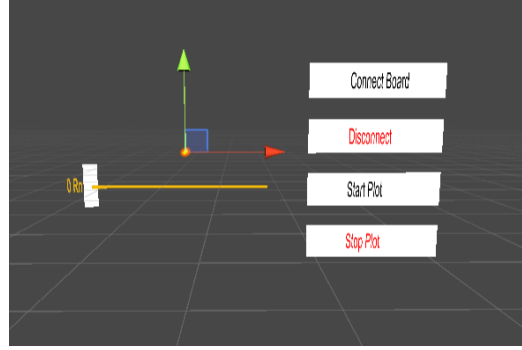
Data collection was accomplished using a custom-designed data acquisition (DAQ) board. This board was designed and built around an ESP32-C3 (Espressif Systems) microcontroller. The sensing streams were collected using a voltage divider network and the Analog Devices AD7689 analog-to-digital converter (ADC). This 16-bit Successive Approximation Register (SAR) ADC includes a buffered reference voltage for low-noise and power supply isolation alongside an eight-channel multiplexer and sequencer for simultaneous sampling across up to eight sensors. These components, along with supporting hardware (*i.e.*, power regulation, LED indicators, programming interface, and additional sensors), were assembled onto a custom printed circuit board (PCB) and housed in a 3D-printed enclosure, as depicted in Figure 1b. Collected data points are posted as resistance data to a pre-defined IP address, where it is then copied and saved to comma-separated value (csv) format. For data communicated directly to the AR headset, a C# script was written to save to csv in the headset's local file directory.

### Augmented Reality Platform

AR integrates digital content into the user's physical surroundings, enabling real-time interaction with a combined virtual-physical environment. In this study, holograms were overlaid onto the real world using an optical see-through display. The AR system employed a head-mounted display (HMD) that supports hands-free operation via gesture recognition. Sensor capabilities, interface, and practical factors such as weight, battery life, cost, and market availability were considered when selecting an HMD. The device manufacturer was also considered because application development varies depending on the platform. Based on the selection criteria, the Microsoft HL2 headset (Figure 2a) was selected for development and application deployment in this project because Universal Windows Platform (UWP) development is supported in the *Unity* game engine platform (Figure 2b).



(a)



(b)

Figure 2. AR development components include (a) the Microsoft HoloLens 2 AR headset and (b) the MT plot interface and menu in the *Unity* application.

## Software Development

The software development for the live data plot centers around a custom *Arduino* program written for the ESP32-C3 microcontroller. The program initializes and configures the DAQ during setup, then establishes a WiFi connection with a static IP. A simple HTTP server streams sensor data to a connected client. Resistance values ( $R$ ) were calculated from raw ADC readings and normalized against baseline measurements according to Equation 1.

$$R_n = (R - R_0) / R_0 \quad (1)$$

$R_0$ , which is MT baseline resistance, was recorded as the average of the initial 60 samples ( $\sim 0.5$  s) when the internet connection was first established and when the subject was standing upright in a neutral posture. All subsequent resistance values ( $R_n$ ) were computed in real-time and normalized against  $R_0$  to yield strain estimates. Data from up to four channels were transmitted over WiFi at a sampling rate of 10 Hz.

The software development of the live MT data visualization system was conducted using *Unity* version 2019.4.17f1 with Microsoft's *Mixed Reality Toolkit (MRTK)* for deployment to HL2. The *MRTK* input system was used to implement gesture-based controls for interaction with buttons floating in 3D space. These buttons include (1) connection to the DAQ server, (2) server disconnection, (3) initiation of the live normalized resistance plot, and (4) option to stop the data feed as shown in Figure 2b. Development was performed in *C#* in *Visual Studio 2022*. A transmission control protocol (TCP) client was implemented within *Unity* to establish a network connection to the DAQ, which acts as a TCP server and transmits data. Upon connection, the application continuously receives the data streams and parses each channel of MT.

Each data point was instantiated as a point in *Unity* using the *Transform* component to encode its position in space. *LineRenderer* was used to connect these points into a continuous, color-coded scatter plot (*i.e.*, red and yellow for channels 1 and 2, respectively) while a sliding window of 100 data points was maintained. The position of the graph remained anchored relative to the user's head position, thereby maintaining a fixed distance in the user's central field of view, even as they move. The data plotted in the live graph were  $R_n$  values, where each plot began at 0 (*i.e.*, with the subject

starting in a neutral position) and movements thereafter visualized as relative changes in strain. Precise value labeling is not required at this stage, as the primary goal was either to verify that minimal or uniform signal fluctuations occurred during weightlifting movements. Thus, the augmented baseline axis shown in Figure 2b was labeled as  $0R_n$ , where any positive values represented low-back tension.

## Human Participant Test Protocol

This human subject study was approved by the University of California San Diego, Institutional Review Boards, Human Research Protection Program, under Project No. 191806X. This study focused on a single participant to evaluate the feasibility and usability of the live data plot as a pilot investigation. A previous study showed that the electrical resistance amplitude of MT, when placed on the lower back during deadlift exercises, was correlated to sEMG measurements [14]. An increase in MT electrical resistance corresponds to tension, while a decrease is due to compression.

This study tested the hypothesis that reacting to visualized changes in MT resistance could bring awareness to a weightlifter's form. A pair of MT were placed at the posterior superior iliac spine (PSIS) to monitor low back activation during biceps curls (Figure 3a). The left sensor was channel 1 on the DAQ, and the right sensor was channel 2. The PSIS serves as a consistent and anatomically meaningful landmark for capturing strains in the lumbopelvic region. While some lumbar activation is necessary for stabilization, excessive or asymmetrical recruitment during upper-limb isolation exercises suggests a breakdown in midline control [15]. This reduces the effectiveness of biceps contraction and may contribute to strain-related injury over time. Selecting the biceps curl focused analysis on a movement where the trunk should remain relatively stable, thus making deviations in postural control more apparent and easier to quantify.

The participant was asked to perform biceps curls for 10 repetitions at a rate of perceived exertion (RPE) of 5 [16]. A non-recorded trial was used to determine the appropriate weight such that RPE would begin at 5 and increase slightly by the 10<sup>th</sup> repetition, introducing mild fatigue and increasing the likelihood of compensation. The first set was performed without AR, and  $R_0$  was recorded before beginning the set. The second set was performed using the same weight while wearing the HL2, as shown in Figure 3b. In both conditions, the participant was instructed to maintain a stable posture to the best of his or her ability. The participant was already familiar with the live MT line plot and was instructed to minimize peaks by keeping their back as stable as possible during biceps curls. MT data were recorded for both sets for comparison. The user's AR view of the plot is shown in Figure 3c.

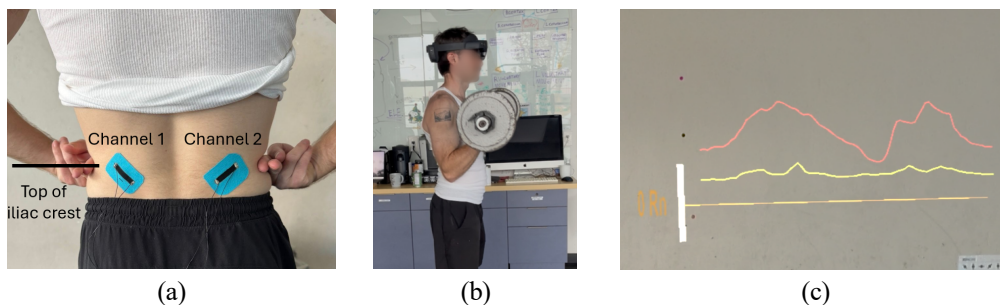


Figure 3. (a) The participant wore a pair of MT on the back and (b) performed biceps curls while wearing the HL2, and (c) MT  $R_n$  was displayed in real-time in the Microsoft HL2.

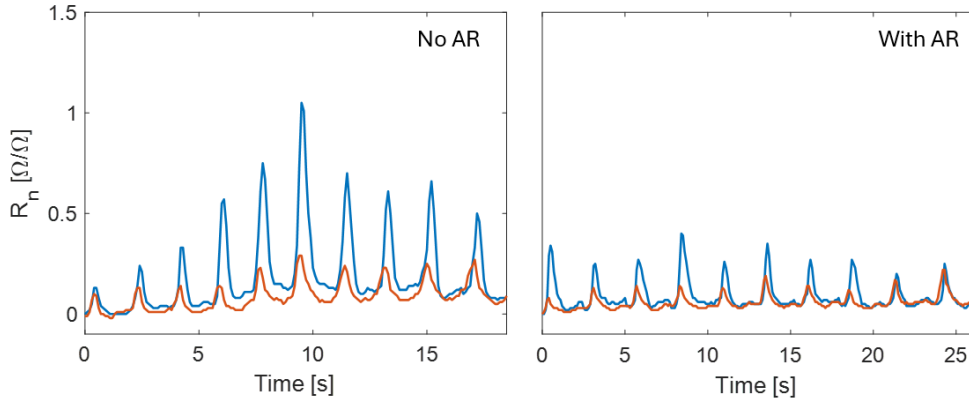


Figure 4. Normalized resistance plots recorded by MT during biceps curls without and with AR.

## RESULTS AND DISCUSSION

This pilot study examined whether real-time MT resistance data could help the participant modulate low-back engagement during biceps curl exercises. In the example in Figure 3c, the left MT sensor (red line) exhibited distinct fluctuations in resistance with each repetition, indicating low-back engagement. The right sensor (yellow line) remained relatively stable, consistent with the subject's right-hand dominance. These observations from the AR plot were confirmed by the recorded MT data, which is reported in Figure 4. Data was manually cropped to the start of the first repetition.

Without the AR tool, the left MT exhibited increasing peak resistance across the first six repetitions most noticeably (Figure 4 left plot), likely indicating progressive compensation through greater spinal extension. In contrast, when biceps curls were performed with AR feedback, there were reduced peak MT strain amplitude and more consistent resistance values (Figure 4 right plot), suggesting improved postural stability. The nervous system can react more quickly to visual cues than to auditory feedback [17]. By engaging both visual and proprioceptive systems, the AR interface can help the brain form a more accurate representation of movement, allowing for rapid, subtle adjustments. A slight upward baseline drift in the first trial also suggested cumulative forward lean or fatigue over the set, which was not as apparent with AR.

Analysis was conducted to quantify asymmetry in low-back engagement, evaluate the effectiveness of real-time feedback in reducing unnecessary trunk activation, and investigate how well the subject maintained their posture as fatigue increased. First, mean absolute error (MAE) was calculated as a ratio between the left and right sensor signals. MAE has previously been shown to effectively evaluate asymmetry in muscle engagement in weightlifting [14].

$$MAE = \frac{R_{L,peak-avg}}{R_{R,peak-avg}} \quad (2)$$

Normalized resistance values were calculated, then the mean of the peak values for the two sets was computed for the left ( $R_{L,peak-avg}$ ) and right ( $R_{R,peak-avg}$ ) sensors. These peak amplitudes were then sorted to represent the magnitude of spinal engagement. Finally, maximum baseline drift across repetitions was extracted to assess postural consistency and potential fatigue-related compensation. These results are summarized in Table 1.

TABLE I. QUANTITATIVE COMPARISON OF MT RESISTANCE SIGNALS WITH AND WITHOUT AR

MAE Left vs Right MT [ $\Omega/\Omega$ ]		Mean Peaks [ $\Omega/\Omega$ ]				Max Baseline Drift [ $\Omega/\Omega$ ]			
No AR	With AR	No AR		With AR		No AR		With AR	
		MT1	MT2	MT1	MT2	MT1	MT2	MT1	MT2
2.564	1.621	0.403	0.157	0.166	0.098	0.120	0.070	0.050	0.050

Normalized resistance values were used instead of raw values to account for differences in sensor placement and fabrication variability. This allowed for more meaningful comparisons between trials and by expressing changes relative to each sensor's own baseline. The MAE between the left and right MT sensors was notably reduced with AR (1.621  $\Omega/\Omega$ ) as compared to no AR (2.564  $\Omega/\Omega$ ). More stable and symmetric strain profiles suggest improved postural control and reduced reliance on the lumbar spine. Similarly, the mean peak values were lower in both MT1 and MT2 with AR. A 61% decrease in mean peak amplitude in the left MT suggests visual feedback helped the subject stabilize their posture. The maximum baseline drift, which may reflect cumulative forward lean or fatigue, was also reduced when using AR. The left side demonstrated a more pronounced change, possibly reflecting its role as the more actively compensating side during the movement. AR visual feedback appeared to help balance strains between both sides, promoting better symmetry and control across the lumbopelvic region. Overall, this integration of PSIS-based strain monitoring with real-time visual feedback provides a precise and ecologically valid method to enhance motor learning and minimize unnecessary activation during resistance training.

Future applications of this tool may include integration into stretching routines, where real-time feedback could help users identify their maximum range of motion and ensure proper muscle activation. The system can also be adapted for trainers, allowing them to observe live MT data as an extra layer of interpretable information to provide verbal cues to the trainee. Beyond biceps curls, this approach holds promise for other exercises and even more complex compound movements. The scalable framework will be explored across other training techniques for efficiency and injury prevention.

## CONCLUSIONS

The objective of this study was to develop an AR system that could visualize, in real-time, skin-strain measurements from a textile-based wearable sensor called Motion Tape for detecting and directly conveying movement deviations during weightlifting. A custom-built *Unity* application was developed to stream and project MT low-back strain data into the user's visual field using a head mounted device. By leveraging the speed and influence of the human visual system, users can quickly adjust their posture while performing an exercise like biceps curls. MT on the left and right sides of the spine were used to measure low-back engagement, which the AR user attempted to minimize with and without the aid of the live plot representing muscle engagement and movement. The observed decrease in asymmetry and compensatory trunk activation when using AR feedback supports the potential of this approach for enhancing exercise form, warranting further investigation in larger and more diverse populations of weightlifters.

## ACKNOWLEDGEMENTS

This research was partially supported by the U.S. National Science Foundation (NSF) under grant no. IIS-2205093 (principal investigator: Dr. Emilia Farcas, University of California San Diego) and the U.S. Office of Naval Research (ONR) under grant no. N00014-23-1-2647 (principal investigator: Prof. Kenneth Loh).

## REFERENCES

1. Calhoon, G. and A. C. Fry. 1999. "Injury Rates and Profiles of Elite Competitive Weightlifters," *J. Athl. Train.*, 34(3), pp. 232-238.
2. Tung, M. J.-Y., G. A. Lantz, A. D. Lopes and L. Berglund. 2024. "Injuries in Weightlifting and Powerlifting: An Updated Systematic Review," *BMJ Open Sport Exerc. Med.*, 10(4), p. e001884.
3. De Beukelaar, T. T. and D. Mantini. 2023. "Monitoring Resistance Training in Real Time with Wearable Technology: Current Applications and Future Directions," *Bioengineering*, 10(9), p. 1085.
4. Xuan Chua, M., Y. Okubo, S. Peng, T. Nho Do, C. Hui Wang and L. Wu. 2024. "Analysis of Fatigue-Induced Compensatory Movements in Bicep Curls: Gaining Insights for the Deployment of Wearable Sensors," *IEEE Trans. Med. Robot. Bionics*, 6(3), pp. 1147-1157.
5. Elshafei, M. and E. Shihab. 2021. "Towards Detecting Biceps Muscle Fatigue in Gym Activity Using Wearables," *Sensors*, 21(3), p. 759.
6. Conner, C. and G. M. Poor. 2016. "Correcting Exercise Form Using Body Tracking," *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, ACM, San Jose California USA, pp. 3028-3034.
7. Wyckoff, E., M. Ball and F. Moreu. 2022. "Reducing Gaze Distraction for Real-time Vibration Monitoring Using Augmented Reality," *Struct. Control Health Monit.*, 29(10).
8. Viglialoro, R. M., S. Condino, G. Turini, M. Carbone, V. Ferrari and M. Gesi. 2019. "Review of the Augmented Reality Systems for Shoulder Rehabilitation," *Information*, 10(5), p. 154.
9. Aung, Y. M. and A. A. Jumaily. 2014. "Augmented Reality-Based RehaBio System for Shoulder Rehabilitation," *Int. J. Mechatron. Autom.*, 4(1), p. 52.
10. Leon, N. I. D., S. K. Bhatt and A. Al-Jumaily. 2022. "Augmented Reality Game Based Multi-Usage Rehabilitation Therapist For Stroke Patients," *Int. J. Smart Sens. Intell. Syst.*, 7(3), pp. 1044-1058.
11. Lin, Y.-A., M. C. Schraefel, W.-H. Chiang and K. J. Loh. 2021. "Wearable Nanocomposite Kinesiology Tape for Distributed Muscle Engagement Monitoring," *MRS Adv.*, 6(1), pp. 6-13.
12. Lin, Y.-A., Y. Mhaskar, A. Silder, P. H. Sessoms, J. J. Fraser and K. J. Loh. 2022. "Muscle Engagement Monitoring Using Self-Adhesive Elastic Nanocomposite Fabrics," *Sensors*, 22(18), p. 6768.
13. Lin, Y., Y. Zhao, L. Wang, Y. Park, Y. Yeh, W. Chiang and K. J. Loh. 2021. "Graphene K-Tape Meshes for Densely Distributed Human Motion Monitoring," *Adv. Mater. Technol.*, 6(1), p. 2000861.
14. Wyckoff, E., D. Sten, R. Wareham and K. J. Loh. 2024. "Progressive and Asymmetrical Deadlift Loads Captured by Wearable Motion Tape Sensors," *Sensors*, 24(23), p. 7700.
15. De Souza Castelo Oliveira, A. and M. Gonçalves. 2009. "Lumbar Muscles Recruitment during Resistance Exercise for Upper Limbs," *J. Electromyogr. Kinesiol.*, 19(5), pp. 737-745.
16. Williams, N. 2017. "The Borg Rating of Perceived Exertion (RPE) Scale," *Occup. Med.*, 67(5), pp. 404-405.
17. Jain, A., R. Bansal, A. Kumar and K. Singh. 2015. "A Comparative Study of Visual and Auditory Reaction Times on the Basis of Gender and Physical Activity Levels of Medical First Year Students," *Int. J. Appl. Basic Med. Res.*, 5(2), p. 124.