Measuring the Golf Swing Pattern Using Motion Tape for Feedback and Fault Detection

SHIH-CHAO HUANG, YUN-AN LIN, TAYLOR PIERCE, ELIJAH WYCKOFF and KENNETH J. LOH*

ABSTRACT

Golfers must hone the sequence of the golf swing for consistent and efficient results, where a good golf shot is both precise and accurate. It takes countless hours of practice to develop the skill, and methods such as video feedback and coaching serve as aids to the process. However, few methods outside of visual observations exist to identify factors in the swing that cause a poor shot. Most golf analysis equipment is expensive and requires extensive setup time. Some systems only measure the physics of the ball and are limited to the practice range, whereas wearable sensors for golf are limited to specific motions such as the wrist. To address these challenges, a fabric-based, on-body sensor was developed and investigated to assess biomechanical movements during the swing. The wearable sensor, herein referred to as Motion Tape (MT), is a low-profile, disposable, self-adhesive, skin-strain sensor formed by spray-coating piezoresistive graphene nanocomposites directly onto kinesiology tape (K-tape). The objective of this study is to use MT to identify key movements in the swing sequence at four body locations: wrist, flexor carpi, anterior deltoid, and torso. First, MT sensors were fabricated for testing. Second, a human subject test protocol recording the golf swing of an experienced golfer was designed and conducted with participants wearing four MT sensors at the aforementioned locations. Last, the test data were processed, and the results showed that MT was able to identify unique movements during the swing. The MT data was analyzed using machine learning algorithms to identify movement abnormalities associated with poor swings. This allows for analysis of swing tempo for direct feedback to the golfer for improved performance.

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INTRODUCTION

The golf swing is a dynamically complex movement that requires balance and coordination from head to toe while controlling the trajectory of the club for ideal distance and direction. The swing requires precise execution of numerous sequential elements where minor deviations can result in a poor shot [1]. The golf industry is heavily invested in equipment to measure both the metrics of the golf swing and the result of the shot. For example, the Trackman portable launch monitor has become a popular tool of assessment and feedback among elite golfers [2]. Although it provides instant feedback, its limitation is that it only tracks swing metrics like clubhead speed, which cannot provide the golfer with information on where the swing sequence went wrong in the case of a bad shot. Optical motion capture (mocap), with golfers wearing retroreflective markers over their entire body, can capture the full biomechanics of the golf swing [3]. However, the need for multiple, expensive, high-performance cameras means that mocap is only used by professional golfers and in specialized facilities.

To address these limitations, wearable sensors have been explored for measuring the golf swing, where wrist movement is most tracked because of its high influence on the outcome of the shot [4]. The wrist is a significant movement to capture as several measures were found to clearly indicate a difference between expert and amateur golfers [3]. These sensors are integrated as a watch worn on the wrist but are limited to this area. Therefore, they cannot determine if swing abnormalities occur at other locations such as the waist. To form a system that encompasses more body movements in the swing, accelerometer loggers have been attached to the left wrist, solar plexus, right knee, and head [5] and inertial measurement units (IMUs) have been explored to measure movement at the golfer's head, wrist, and waist [6]. Unfortunately, these sensors can be bulky, uncomfortable, and require trained professionals for setup.

Therefore, the objective of this study is to demonstrate that the sensing streams from a fabric-based, user-friendly, wearable sensor, which can accurately measure fine motor movements, can be used to analyze key movements during the golf swing. The wearable sensor, herein referred to as Motion Tape (MT), is a low-profile, disposable, self-adhesive, skin-strain sensor formed by spray-coating piezoresistive graphene nanocomposites directly onto kinesiology tape (K-tape). Individuals were recruited to hit golf balls while wearing four MT sensors, specifically, on the wrist, flexor carpi, anterior deltoid, and torso. The MT sensing streams from multiple golf swings were used to train a machine learning algorithm. The algorithm was then used to identify movement abnormalities that resulted in poor swings and bad shots.

EXPERIMENT DETAILS

Motion Tape Fabrication

The process of creating MT involves four steps: (1) ink preparation, (2) substrate preparation, (3) graphene deposition, and (4) electrical contacts. First, the ink was prepared by dispersing, by bath sonication, graphene nanosheets (GNS) in an ethyl cellulose (EC) in ethyl alcohol (EtOH) solution. GNS used in this work was synthesized using a water-assisted liquid-phase exfoliation process [7, 8, 9]. Second, the substrate was prepared by sectioning off 6 cm segments of K-tape from Rock Tape®. The non-

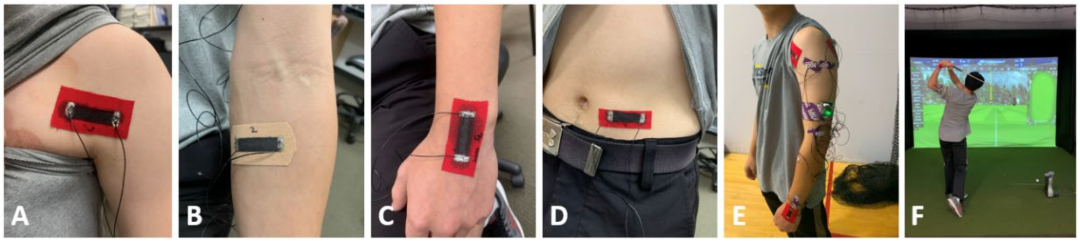

Figure 1. Motion Tape was affixed near the (a) anterior deltoid, (b) flexor carpi, (c) wrist, and (d) torso, (e) which were connected to a portable sensing node that collected data during golf swing tests.

adhesive side of the fabric tape was covered by a mask with a 4×1 cm^2 rectangular cutout to define the sensing region. Third, a Paasche airbrush was used to spray-coat and deposit the GNS-EC ink onto K-Tape. Spray-coating was repeated three times before a final layer was drop-casted to enhance film conductivity. Last, two-point probe electrodes were formed on opposite ends of the film by spreading a thin strip of colloidal silver paste before soldering thin multi-strand wires to each contact.

Human Participant Testing Protocol

An experiment that involved a participant hitting 52 golf shots in an indoor golf simulator facility was designed and conducted. The human subject study was approved by the University of California San Diego, Institutional Review Boards, Human Research Protection Program, under Project No. 191806, and informed written consent was obtained from all participants. First, four MT sensors were affixed at the anterior deltoid, wrist, flexor carpi, and torso of the participant for capturing golf swing movements (Figure 1). Second, all four MT were connected to a customized, portable, wireless sensing node that recorded the electrical resistance of each channel at 60 Hz and streamed the raw data to a wireless base station connected to a personal computer.

During each shot, MT sensing streams were recorded. In addition, the Foresight GC Quad launch monitor tracked club head metrics and ball launch to estimate the distance and trajectory of each shot. An additional shot metric that was estimated is offline distance. Offline distance is defined as the left and right deviation from the target line. In this experiment, a shot was considered good if the offline distance was less than 5 yd (4.57 m). The subject was performed good and bad golf shots while being captured by mocap; bad golf swings were performed intentionally by inducing excessive wrist movement. A total of 18 good and 34 bad golf swings were recorded.

DATA PROCESSING

The proposed deep learning model for processing MT data was a deep convolutional autoencoder (CAE), which was initially proposed by Kwak and Kim [10] for detecting anomalies in multi-channel automobile signals. The CAE model consists of an encoder, which extracts and compresses essential information and features from input signals to form a representation of the input data. The model also has a decoder, which reconstructs the input signals by converting the low dimensional representation formed by the encoder [10]. The loss function of CAE is formulated to minimize the discrepancy between the input and output data, which can be described as:

$$\mathcal{L}(x) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \widehat{x_i})^2 \tag{1}$$

where x_i denotes the input data, and $\widehat{x_i}$ denotes the output obtained from the model of the i^{th} observation among a total of N observations.

The channel-wise reconstruction error vector ε containing the reconstruction errors of a total number of K channels was calculated to represent the discrepancy between each channel of the input data and the output data, which can be described as:

$$\varepsilon_k = \frac{1}{T}\sum_{t=1}^{T}\left(x_{t,k} - \widehat{x_{t,k}}\right)^2 \tag{2}$$

where $\varepsilon = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_k) \in \mathbb{R}^K$ denotes the channel-wise reconstruction error vector that calculates the discrepancy between input data and the output of CAE over a time window containing a total of T observations. To identify the abnormal data stream based on the reconstruction error ε, the Local Outlier Factor (LOF) was adopted in this study. LOF identifies outliers by comparing the data distribution of reconstruction error of each channel between normal data streams (*i.e.*, correct or good movements) and abnormal data streams (*i.e.*, incorrect or bad movements) [11].

Dataset Construction

The normalized change in resistance (R_n) of MT were calculated using Equation 3.

$$R_n = \frac{R_i - R_0}{R_0} \tag{3}$$

where R_i is the resistance of MT at each time step, and R_0 is its baseline or nominal resistance (*i.e.*, when the participant was standing in a neutral position and relaxed). The sensing streams for each golf swing were split into 0.3 s time windows (with 20 time frames) with a 1 time frame stride; stride controls the number of time frames overlapped for adjacent time windows. In this study, 70% of good golf swing datasets were used for training, while 30% of good golf swings were used for validation. All the good and bad golf swing datasets were employed for testing the CAE model.

Model Architecture and Hyperparameters

The architecture of the proposed CAE, as shown in Figure 2, was implemented and adopted following a previous study on marksmanship training [12, 13]. It was shown that using a deep neural network may lead to gradient vanishing. Therefore, a technique called skip-connection was used to alleviate this issue by simply adding the feature map of the current layer with that of the previous layer before passing the feature map to the next layer. This not only prevented updates of the gradient from gradually becoming negligible but also facilitated the search of the optimal set of parameters [14]. In addition, the identical CAE model architecture was run 10 times to account for the randomness of the adopted deep learning approach. Therefore, the result of the anomaly signal detection was finalized by combining the predictions from 10 different CAE models (but with identical architecture).

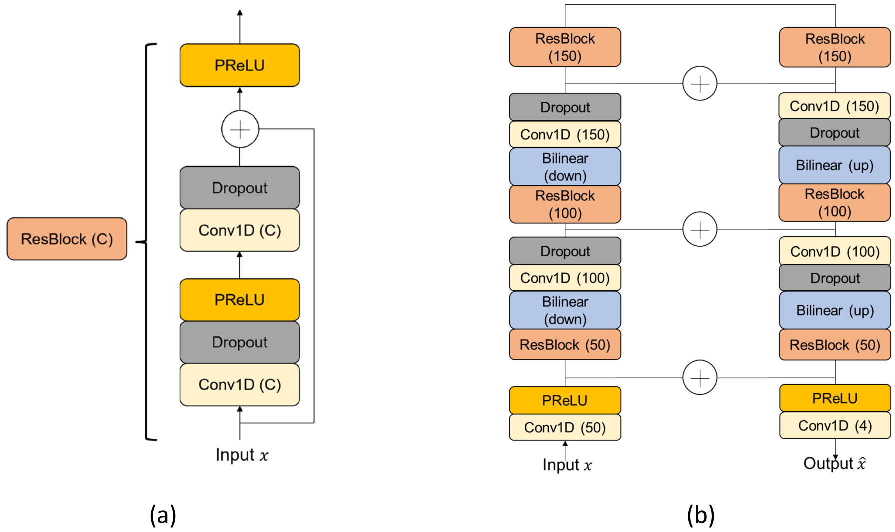

Figure 2. (a) A "ResBlock (C)" layer consists of the dropout layer, PReLU layer, and two one-dimension convolutional layers with *C* kernel. (b) The proposed CAE architecture consists of an encoder and decoder that reconstructs the input signal.

RESULTS AND DISCUSSION

Analysis of Golf Swing Using Mocap

The golf swings of a subject were analyzed in an experimentally controlled environment using both MT sensors and mocap. Representative MT time histories of different phases of a golf swing are shown in Figures 3 and 4. The distinct phases of the golf swing were identified by manually inspecting the subject's movements from mocap results. In Figures 3 and 4, it can be observed that the incorrect wrist

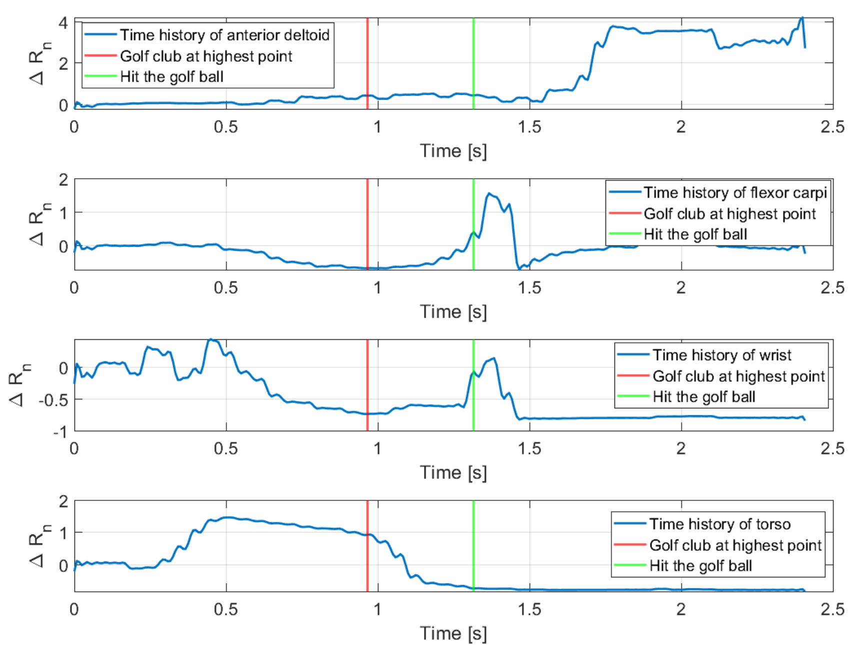

Figure 3. Different phases of a golf swing were identified and overlaid with Motion Tape normalized change in resistance time histories for an exemplary good golf swing.

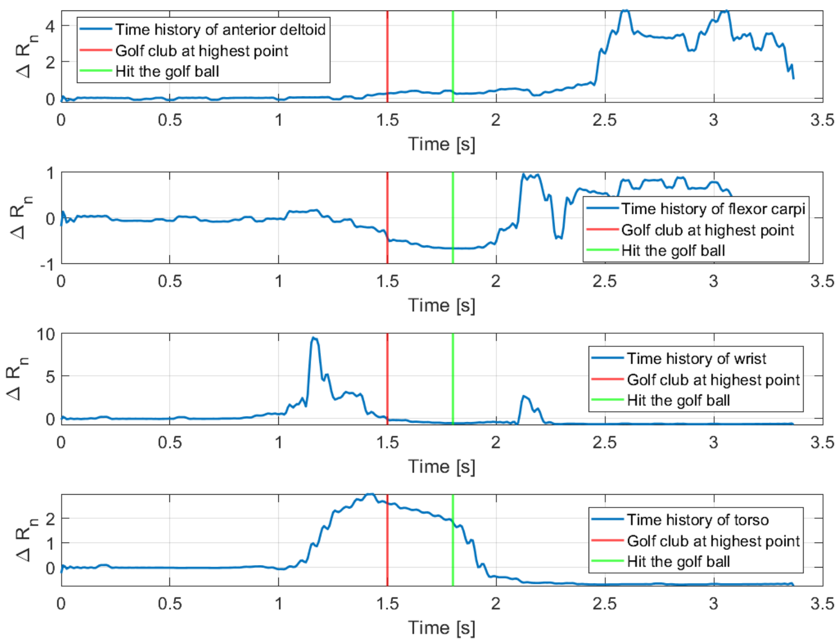

Figure 4. Different phases of a golf swing were identified and overlaid with Motion Tape normalized change in resistance time histories for an exemplary bad golf swing .

movements could be successfully captured by MT. An abnormal peak normalized resistance with a value of around 10 occurred during the bad golf swing. In addition, the time intervals and the trend of the data streams between the red and green lines also changed slightly. Although those features are not chosen for training the machine learning model in this study, they may be useful candidate features for assessing the quality of golf swings and detecting if undesirable muscle activity occurs during the golf swing.

Fault Detection of Golf Swings using Machine Learning Algorithm

The effectiveness of the proposed CAE model was also evaluated using MT golf swing datasets. As mentioned earlier, the quality of each golf swing was determined based on the golf simulator data, specifically, whether the offline distance was less or greater than 5 yd (4.57 m). Figure 5 shows exemplary classification results made by the proposed CAE model. For the bad golf swing shown in Figure 5, the proposed CAE model successfully identified anomalies occurring during the golf swing. The subject also confirmed that the wrist movement was anomalous for this specific golf swing, which was correctly detected by the proposed CAE model. However, it was not clear what caused those anomalies even if they were identified. Therefore, an explainable anomaly detection algorithm may be required to address this issue to provide more values in the scenario when a professional golf trainer is not available. Apart from the exemplary results, the overall performance of the proposed CAE model is summarized in Table I, which shows the reconstruction error of each muscle group. It can be observed that Table I demonstrates the effectiveness of the proposed CAE model.

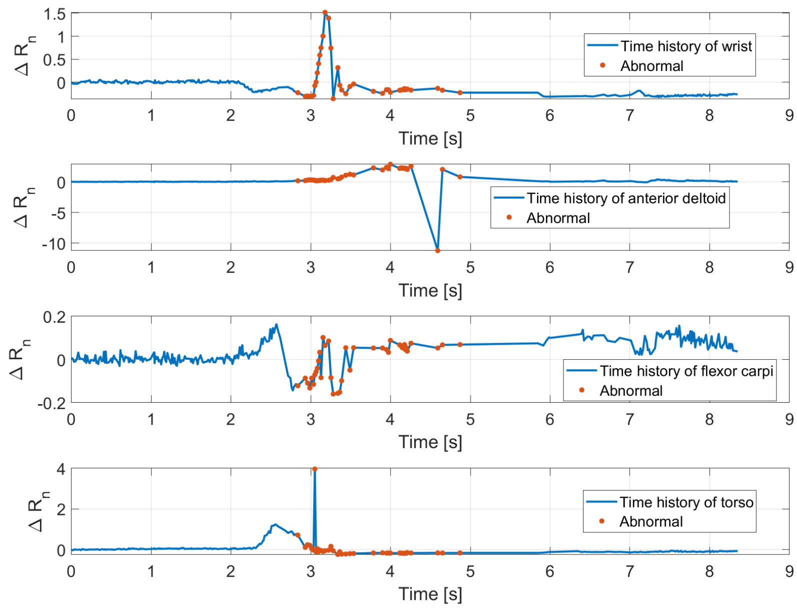

Figure 5. The proposed CAE model successfully identified anomalies of an exemplary bad golf swing.

TABLE I. OVERALL RECONSTRUCTION ERROR

Muscle Group	**Good Shots**		**Bad Shots**	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Wrist	8.851×10^{-5}	5.181×10^{-4}	4.237×10^{-4}	5.300×10^{-3}
Anterior Deltoid	8.238×10^{-5}	4.967×10^{-4}	2.330×10^{-4}	1.700×10^{-3}
Flexor Carpi	6.325×10^{-5}	1.979×10^{-4}	2.996×10^{-4}	2.600×10^{-3}
Torso	6.995×10^{-5}	1.736×10^{-4}	3.292×10^{-4}	2.600×10^{-3}

CONCLUSIONS

The objective of this study was to identify key movements in the golf swing sequence at four body locations (*i.e.*, wrist, flexor carpi, anterior deltoid, and torso) using Motion Tape elastic fabric skin-strain sensors. Analysis of the MT data using a machine learning technique identified abnormalities in poor swings and determined the locations at which the key swing movements are captured most effectively. It was found that three out of four locations were capable of capturing the golf swing sequence effectively. The preliminary results presented in this work validated that MT and the machine learning algorithm, as a system, could provide direct feedback to golfers for improved training and performance. Future work is planned to identify an explainable anomaly detection algorithm to address the issue of determining anomaly causations with the goal of providing more value in golf performance and training.

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REFERENCES

1. Mather, S. J. 2004. "Physics and Mechanics of the Golf Swing," *Biomedical Engineering Principles in Sports*, 47-73.
2. Fisher, K. 2019. "A Repeated-measures Assessment of Golf Shot Performance at Varying Distances in Collegiate Female Golfers Using the Trackman Portable Launch Monitor," *Journal of Advanced Sport Technology*, 3(1):1-7.
3. Fedorcik, G. G., R. M. Queen, A. N. Abbey, C. T. Moorman III, and D. S. Ruch. 2012. "Differences in Wrist Mechanics During the Golf Swing Based on Golf Handicap," *Journal of Science and Medicine in Sport*, 15(3):250-254.
4. Ghasemzadeh, H., V. Loseu, and R. Jafari. 2009. "Wearable Coach for Sport Training: A Quantitative Model to Evaluate Wrist-Rotation in Golf," *Journal of Ambient Intelligence and Smart Environments*, 1(2):173-184.
5. Mitsui, T., Tang, S., & Obana, S. (2015, January). Support System for Improving Golf Swing by Using Wearable Sensors. In *2015 Eighth International Conference on Mobile Computing and Ubiquitous Networking (ICMU)* (pp. 100-101). IEEE.
6. Kim, M., & Park, S. (2020). Golf Swing Segmentation from a Single IMU Using Machine Learning. *Sensors*, *20*(16), 4466.
7. Lin, Y.-A., m. c. schraefel, W.-H. Chiang, and K. J. Loh. 2020. "Wearable Nanocomposite Kinesiology Tape for Distributed Muscle Engagement Monitoring," *MRS Advances,* 6(1):6–13.
8. Lin, Y-A., Y. Zhao, L. Wang, Y. Park, Y-J. Yeh, W-H. Chiang, and K. J. Loh. 2021. "Graphene K-Tape Meshes for Densely Distributed Human Motion Monitoring," *Advanced Materials Technologies (2365-709X)*, 6(1):2000861.
9. Loh, K. J. and Y-A. Lin. July 2021. "Smart Elastic Fabric Tape for Distributed Skin Strain, Movement, and Muscle Engagement Monitoring," U.S. Patent Application 17/379,522.
10. Kwak, M., and S. B. Kim. 2021. "Unsupervised Abnormal Sensor Signal Detection with Channelwise Reconstruction Errors," *IEEE Access*, 9:39995-40007.
11. Breuniq, M. M., H. P. Kriegel, R. T. Ng, and J. Sander. 2000. "LOF: Identifying Density-Based Local Outliers," *ACM SIGMOD Record*, 29(2):93–104.
12. Loh, K. J., S.-C. Huang, and Y.-A. Lin. 2022. "Enhancing Warfighter Training and Performance using Motion Tape Elastic Fabric Sensors," presented at the 2022 Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC), November 28-December 2, 2022.
13. Lin, Y-A. and K. J. Loh. 2022. "Tactical Athlete Training and Performance Monitoring using Motion Tape Wearable Sensors," presented at the Materials Research Proceedings – Structural Health Monitoring, The 9th Asia-Pacific Workshop on Structural Health Monitoring, December 6-8, 2022.
14. Mao, X.-J., C. Shen, and Y.-B. Yang. 2016. "Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections," presented at the 29th Conference on Neural Information Processing Systems (NIPS 2016), December 5-10, 2016.