Enhancing Warfighter Marksmanship Performance using Motion Tape Elastic Fabric Sensors

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ABSTRACT

Physical, tactical, and field training are critical for improving warfighter physical performance and capabilities. Exercises and training events are typically supervised; however, group/team training lacks personalized supervision, which is even more difficult during field events and war-gaming. While technologies such as optical motion capture (mocap) can capture detailed biomechanics, they are most conveniently used in indoor laboratory settings or in a pre-staged outdoor area. Commercial wearable sensors are readily available, but the data typically correspond to a discrete bodily location and only provide limited information about whether someone is moving, as opposed to how movements are being performed. To fill this gap, a self-adhesive, elastic fabric, nanocomposite skin-strain sensor was developed, tested in controlled environments, and validated through human participant studies. It was found that these “Motion Tape” sensors were not only able to measure skin-strains during functional movements, but its measurements were also correlated with how muscles engage. In this study, Motion Tapes were worn at major joints and muscle groups, and subjects performed exercises that simulated military marksmanship training. Individuals (civilians) were first asked to perform a functional task, before being asked to repeat the task after specific instructions that targeted improved performance. Then, a machine learning model was implemented and trained to classify movement sequences that resulted in positive versus negative task outcomes (*i.e.*, to classify correct versus incorrect movement sequences). The remaining datasets that were not used for model training were used for validation tests. Furthermore, the Motion Tape datasets that led to positive outcomes were further analyzed to reveal the primary movement and muscle engagement schemes that resulted in higher performance. The vision is that such “Warfighter Digital Twins” can one day be used for assessing the physical performance, health, and capabilities development of military service members.

ABOUT THE AUTHORS

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Yun-An Lin is a PhD student in the Department of Structural Engineering at UC San Diego. She is originally from Taiwan and graduated from National Chiao Tung University with a B.S. in Civil Engineering. She joined the ARMOR Lab to work with Prof. Ken Loh shortly after starting her graduate studies at UC San Diego. Her research interests are in designing next-generation thin film sensors for structural and human health monitoring applications. The long-term goal of her research is to leverage wearable physiological sensors as a platform for integrating other functionalities for broad uses in healthcare, military, the entertainment industry, and consumer sectors.

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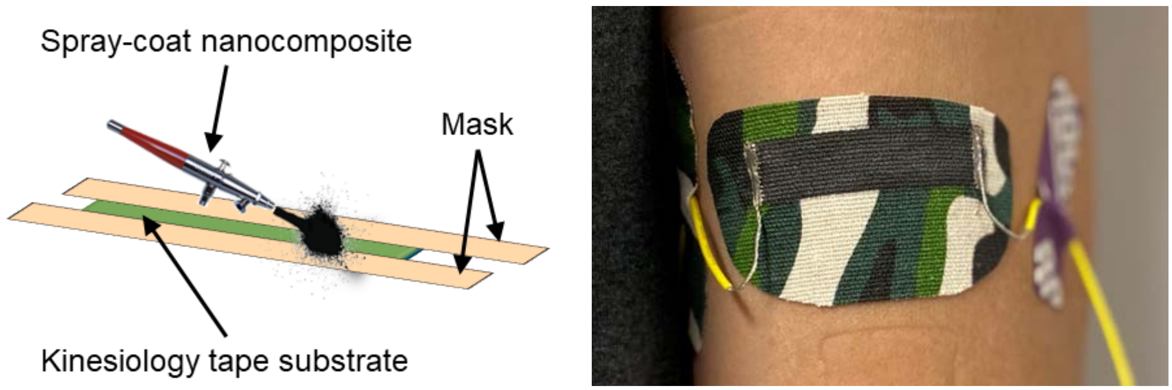
INTRODUCTION

Physical, tactical, and field training are critical for developing and improving warfighter physical performance and capabilities, especially to prepare these tactical athletes for a broad spectrum of operations and the theater of war (Scofield & Kardouni, 2015). The suite of training activities extends beyond strength and conditioning exercises such as push-ups, sit-ups, and endurance runs and includes close quarter combat, casualty extraction, marksmanship, performing various functional tasks while carrying an external load, and war-gaming (Clemente-Suárez, 2022; Öberg, 2020). Exercises and training events are typically supervised; however, group/team training, field exercises, and war-gaming lack personalized supervision. On the other hand, individual training such as marksmanship is time-consuming, dangerous, and demanding for the trainer (Brown, Villa, Hussey, Ramsay, & Mitchell, 2020), since each trainee can exhibit unique deficiencies (*i.e.*, associated with how they move and perform those tasks) that impact performance. Furthermore, in both military and sports sectors, trainer assessments are usually performed by visual observations (Jones, 2006), which can be subjective and inaccurate at times.

To address these gaps in providing more personalized, effective, and accurate training feedback, the objective of this study was to test whether a prototype, self-adhesive, elastic fabric sensor, called Motion Tape (Lin, Zhao, Wang, et al., 2021), could differentiate between correct and incorrect postures during simulated marksmanship training exercises. Motion Tape was directly affixed onto the skin and could measure skin-strains associated with how muscles engage during movement. The direct skin attachment eliminated the issue of movement artifacts, which could be an issue for electronic textiles and compression garments (Yang, Isaia, Brown, & Beeby, 2019). In addition, Motion Tape was designed for assessing functional movements and human performance/limits with military-relevant training and applications in mind, which is in stark contrast to most commercial wearables that are geared towards consumer applications that only provide a general sense of physical activity (Friedl, 2018). Regardless, two human participant test protocols were designed and conducted to emulate marksmanship training. During the tests, Motion Tape measurements were acquired, as well as a full-body optical motion capture (mocap), to record the different postures and movement sequences. A machine learning algorithm was trained using Motion Tape data and validated using different datasets to show that incorrect movements at specific times during a movement sequence could be identified.

The vision is that Motion Tape, and the unique muscle engagement and movement sensing streams that it provides, will be crucial for developing "Warfighter Digital Twins", which is an individualized cyber representation of the "Human Warfighter." With this added capability, the warfighter and its corresponding Warfighter Digital Twin will constitute a mutually interacting cyber-physical-human system that can assess tactical performance and provide individualized feedback to augment training activities that support improved performance. In relation to this work, the Warfighter Digital Twin can potentially and automatically identify movement deficiencies and relay detailed movement analysis that can be corrected or improved to achieve higher performance (*e.g.*, marksmanship). In addition, future implementations of the Warfighter Digital Twin can acquire, aggregate, fuse, and analyze relevant sensing streams to minimize the risk of physical injuries and enable rapid and active rehabilitation, among many others.

This paper begins with an overview and description of Motion Tape elastic fabric sensors and how they work. The human subject test protocols that emulated marksmanship training exercises are then described in detail, along with the different sensors that were used during the tests. Next, the machine learning algorithm that was implemented for analyzing Motion Tape data streams is explained. Then, the results from the two human subject test protocols are presented and discussed. The paper concludes with a summary and discussion of planned future work.



(a) **(b)**

Figure 1. (a) Fabrication of Motion Tape by spray-coating a graphene nanosheet ink and (b) Motion Tape specimen affixed onto skin for human subject testing

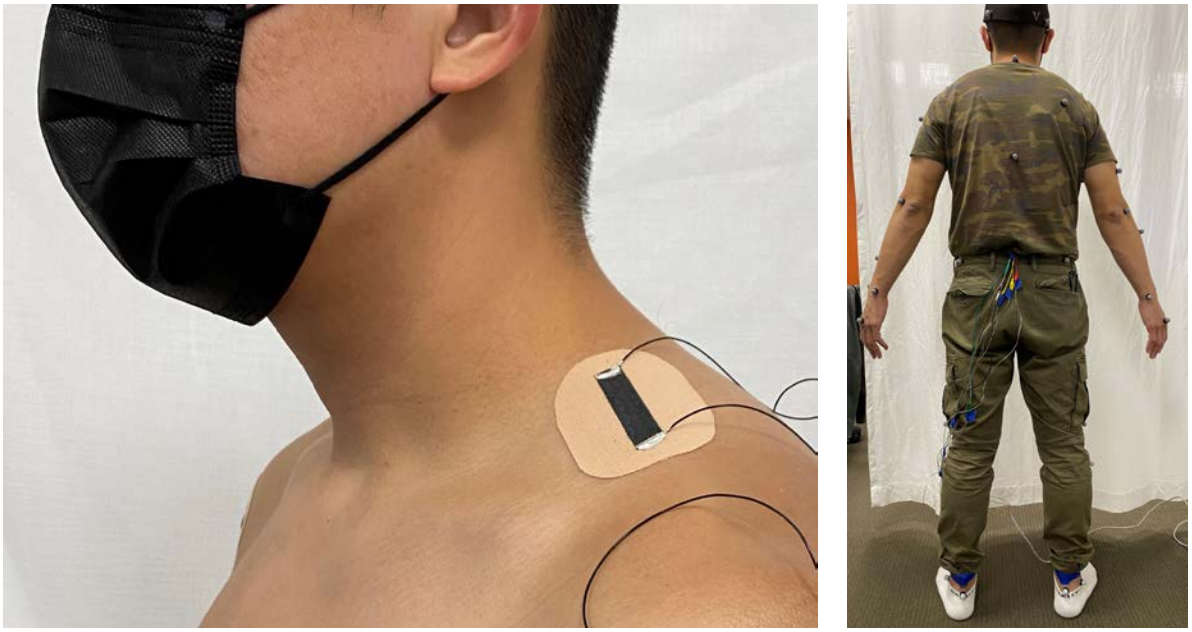
MOTION TAPE ELASTIC FABRIC SENSORS

Motion Tape is a self-adhesive, elastic fabric, skin-strain sensor that was designed for functional movement assessment and muscle engagement monitoring. The wearable sensor was created by integrating strain-sensitive nanocomposite films with commercially available athletic or kinesiology tape (K-Tape). Its fabrication process is illustrated in Figure 1(a) and was described in detail by Lin *et al.* (Lin, Zhao, Wang, et al., 2021) but is summarized here for completeness. In short, graphene nanosheets (GNS) were dispersed in an ethyl cellulose (EC) solution in ethyl alcohol. Upon adjusting the viscosity of the GNS-EC solution, an airbrush was used to spray-coat and deposit strain-sensitive nanocomposites onto masked K-Tape substrates. Electrodes were formed at opposite ends of the GNS-EC strain sensing element by soldering multi-strand wires onto conductive silver traces. These Motion Tape specimens could then be used as is by peeling off the adhesive backing and affixing them anywhere on the skin but typically over major muscle groups or joints, as shown in Figure 1(b).

Extensive Motion Tape laboratory load frame and human participant tests were conducted in previous studies to verify their skin-strain sensing performance. First, tensile cyclic electromechanical tests conducted by mounting Motion Tape in a load frame confirmed their linear, repeatable, and low-hysteresis strain sensing properties (Lin, Zhao, Wang, et al., 2021). Their strain sensitivity (or gage factor) could be varied between 10 to 100 depending on the GNS-EC solution formulation and fabrication parameters. Second, human subject tests were also performed by affixing Motion Tape over major muscle groups (*e.g.*, deltoids, triceps, and biceps) to show that unique skin-strain waveforms corresponding to different muscle groups could be observed when subjects performed different exercise movements (*e.g.*, pushups and triceps dips) (Lin, Zhao, Wang, et al., 2021). Its sensing response is also sensitive to the effort or amount of weight being lifted, for instance, in the case of a subject performing biceps curls (Lin, schraefl, Chiang, & Loh, 2021). Third, Motion Tape could also be affixed at the wrist and ankle joints for capturing joint rotations, and the results were verified by comparing them to reference video and mocap kinematic measurements (Lin, Zhao, Silder, et al., 2021; Lin, Zhao, Wang, et al., 2021). Last, a more recent study by Lin *et al*. (Lin, Noble, Loh, & Loh, 2022) also showed that Motion Tape could be integrated with other elastic fabrics, such as a chest band, for measuring physiological parameters such as respiration. Overall, these previous studies not only demonstrated their versatility and diverse use cases but also verified skin-strain sensing on human participants undergoing typical daily-life and exercise movements.

SIMULATED MARKSMANSHIP PARTICIPANT STUDY AND EXPERIMENTAL DETAILS

Two human participant test protocols were designed and conducted to test the hypothesis that Motion Tape, as well as the machine learning algorithm, could differentiate between correct and incorrect postures when operating a rifle. In that regard, each test included movement sequences that were deemed "correct" and "incorrect." Measurements



(a) **(b)**

Figure 2. (a) Two Motion Tapes affixed to the neck-shoulder region along with (b) a full body marker set for mocap

from mocap and Motion Tape sensors were simultaneously acquired during all the tests, and the datasets were processed accordingly. The human subject study protocol was approved by the University of California San Diego, Institutional Review Board (Project No. 191806X) in compliance with all applicable federal regulations governing the protection of human subjects. Informed written consent was obtained from every participant.

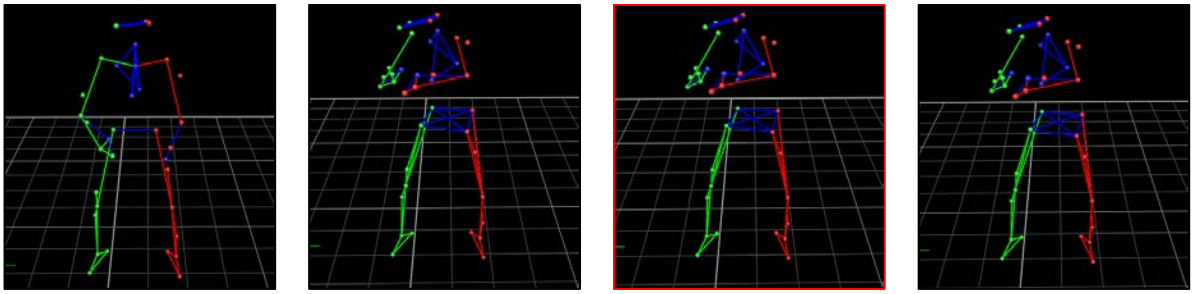
Sensors and Motion Capture Measurements

Each participant wore two separate Motion Tapes, one on each side of the body, over the trapezius muscles between the neck and shoulders as shown in Figure 2(a). The Motion Tapes were connected to the Vicon Lock Lab analog interface for acquiring their electrical resistance measurements through the use of a voltage divider. The voltages were conditioned and filtered using a low-pass fourth-order Butterworth filter with a cut-off frequency of 60 Hz. In addition, retroreflective markers were also placed on each subject for full-body optical motion capture using a 12-camera Vicon system, as is shown in Figure 2(b). The Vicon mocap system measured the absolute 3D positions of all retroreflective markers at 100 Hz. It should be mentioned that the Vicon Lock Lab enabled time-synchronized Motion Tape resistance measurements with mocap.

Rifle Shooting Human Participant Experiments

Two sets of human participant tests that emulated incorrect and correct rifle shooting postures were performed. For both tests, each subject held an M4/M16 rifle replica (*i.e.*, a CYMA XM177E2 full metal airsoft rifle) that weighed ~ 7 lb (3.2 kg) while standing in a comfortable position. Each set of tests consisted of two cases, specifically, a correct as well as an incorrect movement sequence or posture. All subjects repeated each case (*i.e.*, correct and incorrect) 25 times, while Motion Tape and mocap measurements were simultaneously recorded during every test.

For Test #1, the subjects were asked to aim the rifle at a target directly in front and then fire (*i.e.*, to pull the trigger without actually firing any rounds), before returning to the neutral (starting) position. Subjects were instructed to vary the position of the stock on the side of the chest in order to produce the correct and incorrect posture cases. For the correct posture, the position of the rifle (and stock) should be such that the head remained leveled with respect to the ground, and the subject could easily aim using the front and rear sights. Figure 3(a) shows a series of full-body mocap measurements corresponding to this correct rifle shooting posture. On the other hand, subjects were also asked to purposely position the rifle stock farther out towards the shoulder for the incorrect posture case. In doing so, once the



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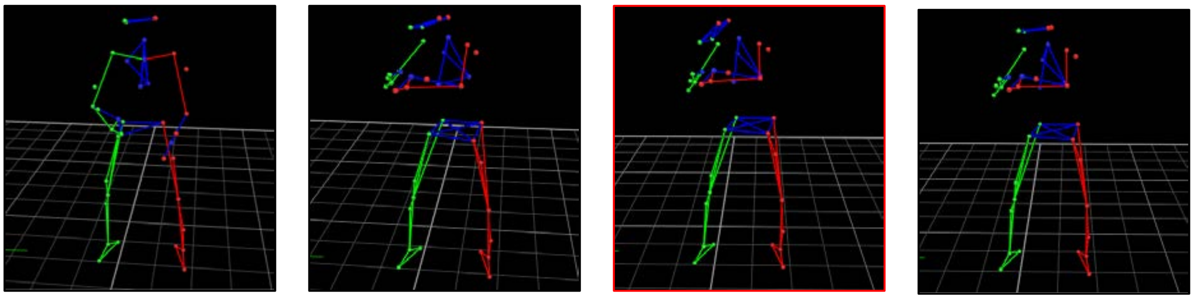
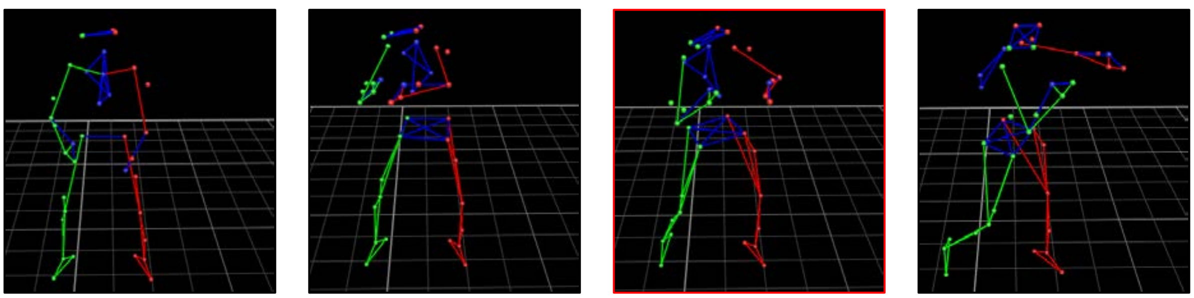
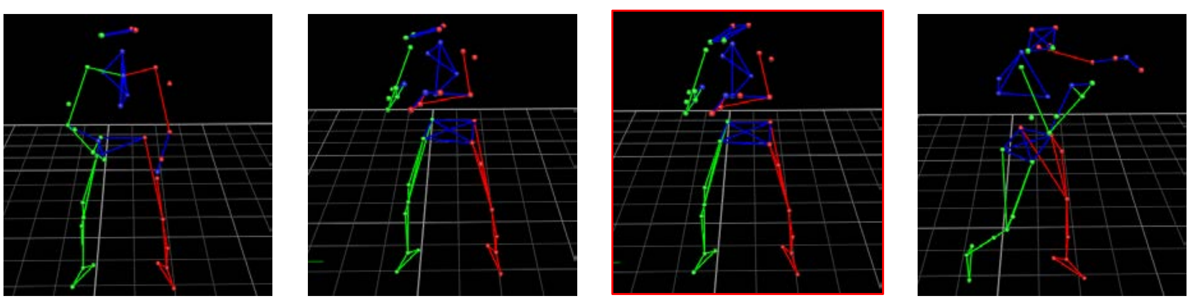


(b)

Figure 3. Test #1 – forward shooting posture: optical motion capture image frames of (a) correct rifle shooting posture (*i.e.*, head in leveled position) versus (b) incorrect shooting posture (*i.e.*, with head tilted to align eyes with rifle sights)



(a)



(b)

Figure 4. Test #2 – 90° shooting posture: optical motion capture image frames of (a) correct rifle shooting posture (*i.e.*, head in leveled position) versus (b) incorrect shooting posture (*i.e.*, with head tilted to align eyes with rifle sights)

rifle was raised, the subject had to tilt their head in order to see the sights to aim at the target. Figure 3(b) shows the series of mocap snapshots acquired during an incorrect posture case. Therefore, the main difference between the two

posture cases is the degree of head tilt, which can also be seen by comparing the red-boxed images in Figure 3.
Test #2 considered a slightly more complicated marksmanship scenario, where the target was located 90° to the left of the subject. Figure 4 shows the series of mocap measurements obtained when a subject performed the correct and incorrect movement sequences for Test #2. Similar to Test #1, the goal was to move from the starting position to aim at the target and shoot, before returning to the neutral position. For the correct movement sequence, the subject was instructed to first position the rifle in the forward shooting posture as in Test #1. The rifle stock should rest on the chest so that the subject could see and aim through the sights without any significant head tilt. Then, because the target is located 90° away, the correct movement sequence entailed the subject rotating his or her body to aim and shoot the target. It should be emphasized that the subject's head would not turn or tilt during this movement, so the subject continues to look in the direction wherever the rifle is pointed, as can be seen from the mocap snapshots in Figure 4(a). In contrast, Figure 4(b) shows the mocap movement sequence for the incorrect case. The subject began by bringing the rifle to a forward shooting position similar to the correct case. The difference was in the next movement, where the subject would turn to look at the target, before swinging the rifle around to aim and then shoot. These movement differences were also captured by mocap and is highlighted in the red-boxed images in Figure 4. The remainder of the movement sequence was the same as the correct case to return to the neutral position. Similar to Test #1, no rounds were fired when the subject "shot" the target.

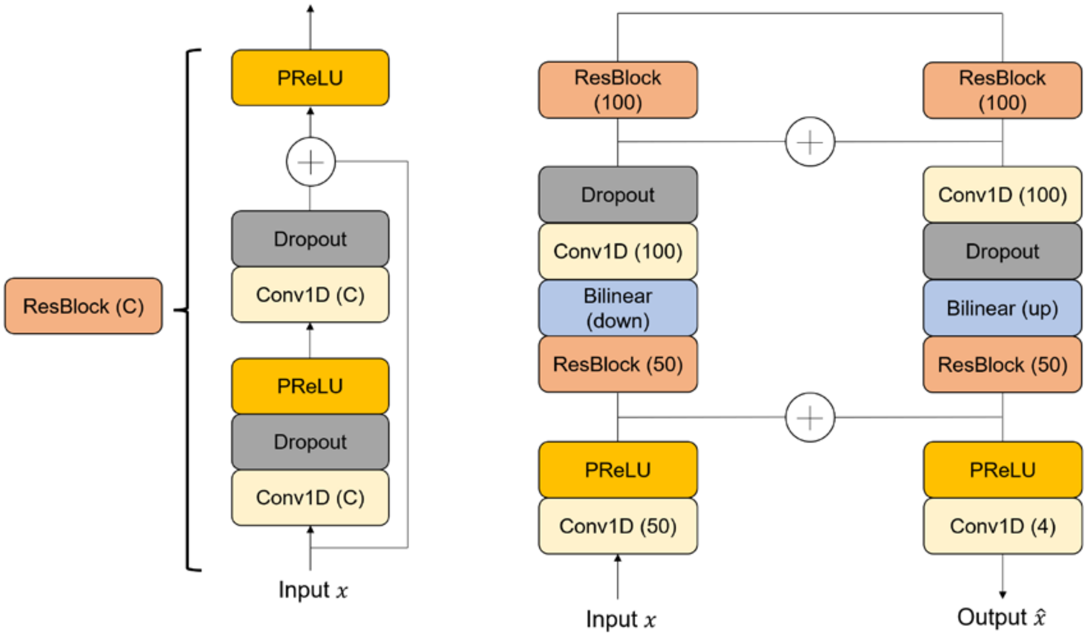
MACHINE LEARNING ALGORITHM BACKGROUND

In this section, a deep learning model that could discriminate the different patterns between correct and incorrect movements is introduced. The deep convolutional autoencoder (CAE), proposed by Kwak and Kim (M. Kwak & Kim, 2021), consists of an encoder, which extracts essential information from multiple channels of input signals to form the representation of data, and a decoder, which reconstructs the input signals by taking the low dimensional representation formed by the encoder as input. It has been shown that CAE can detect abnormal data streams across multiple channels in an unsupervised manner. Furthermore, this also means that only normal data streams are needed during the training process, and ground-truth values or data labels are not needed during training (M. Kwak & Kim, 2021). The architecture of the proposed CAE model is shown in Figure 5.

The core concept of CAE is identical to the one of a classical autoencoder. The only difference between CAE and the classical autoencoder is that convolutional layers are usually adopted to capture the temporal relationship of data across multiple channels. Convolutional neural networks (CNN) are one of the most frequently used artificial neural network (ANN) architectures for applications related to images or signal processing (Lecun, Bengio, & Hinton, 2015). The idea of CNN is that each neuron in each layer can be considered as a filter that detects unique features from the input data. Generally, the closer the convolutional layer is to the input layer, the easier the features detected can be interpreted. The overall training process of CAE is similar to training a typical deep learning model (*e.g.*, training a CNN model for image classification), where the only difference is the formulation of the loss function. To train a typical deep learning model, the loss function is usually defined as some metric that indicate the error between the ground-truth values and model predictions. Those metrics are then minimized by training the trainable parameters with algorithms (*e.g.*, "Adam", which is a popular gradient descent-based approach) (Kingma & Ba, 2015). However, the loss function of CAE is formulated to minimize the discrepancy between the input data and output data, which can be defined as:

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

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. In Equation (1), although the mean squared error (MSE) was used as a metric to represent the error between the input data and output data, the formulation of the loss function used during the training process should be chosen based on different tasks and domain knowledge (J. Kwak & Cho, 2005). After the input data was fed into the CAE and the output of CAE was obtained, the channel-wise reconstruction error vector ε, which contains the reconstruction errors of a total number of K channels, was then calculated to represent the discrepancy between the input and output data:



(a) **(b)**

Figure 5. (a) A "ResBlock (C)" layer consists of the dropout layer, PReLU layer, and two one-dimensional convolutional layers with *C* kernel. Skip-connection was implemented in each ResBlock. (b) The CAE architecture consists of the encoder and decoder that reconstructed the input signal.

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

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 the 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, an algorithm, namely, the Local Outlier Factor (LOF), was utilized in this study to identify outliers by comparing the data distribution of reconstruction errors of each channel between normal data streams (*i.e.*, good movements) and abnormal data streams (*i.e.*, incorrect movements) (Breuniq, Kriegel, Ng, & Sander, 2000).

Dataset Construction

Motion Tape resistance measurements from the human participant tests were used to the normalized change in resistance (ΔR_n) using Equation (3):

$$\boldsymbol{\Delta R_n = \frac{R_i - R_0}{R_0}} \qquad (3)$$

where R_i is the resistance of Motion Tapes at each time instance i, and R_0 is the nominal (baseline) resistance of Motion Tape. In this case, R_0 corresponds to the Motion Tape resistance when each subject was standing still prior to the beginning of each test.

The ΔR_n datasets from each trial were prepared for the CAE algorithm to perform unsupervised abnormal sensor signal detection. Instead of taking the entire time history of each trial as input, each trial was split into ~0.5 s time windows (*i.e.*, 600 frames) with a specific stride, which controls the percentage of data overlap of adjacent time windows. A stride of 10 frames was used to ensure that there were enough training samples for each trial and that the CAE model could capture spatial and temporal features of input data streams within a proper time interval. It should be mentioned

Table 1. Hyperparameters and Techniques Used for CAE Training

Hyperparameters/Techniques	Value/Method
Number of Epoch	400
Number of batch size	64
Optimizer	Adam
Learning rate	10^{-3}
Regularization coefficient	10^{-3}
Patience of early stopping	20
Loss function	Mean square error (MSE)
Activation function	PReLU
Kernel size of CNN layer	3
Dropout rate (probability of a neuron to be omitted)	0.2
Learning rate scheduler	ExponentialLR provided by Pytorch, γ=0.9
Scaler	Standard

that an advantage of using a time window input is that real-time abnormal (or incorrect) movements can be achieved, although it was not a focus of this study. As mentioned earlier, a total of 25 correct and 25 incorrect movement sequences were recorded for each Test. Of these, 60% of the data was used for CAE training, 20% for validation, and 20% for testing.

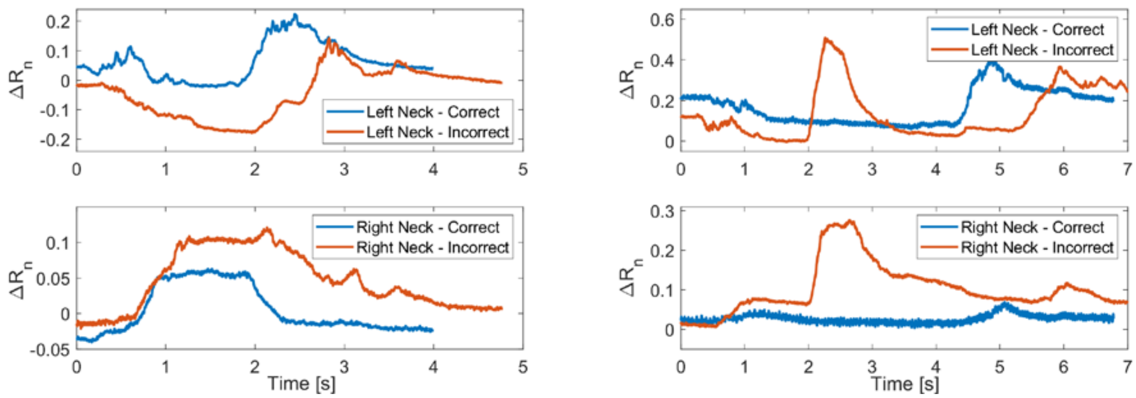
Model Architecture and Hyperparameters

The CAE model architecture is shown in Figure 5. For all the one-dimensional convolution layers in the CAE model, zero-paddings were used to ensure that the operation of the convolutional layer did not change the length of time windows (*i.e.*, the number of time frames). To reduce the dimension of input data in the encoder, bilinear interpolation was used to downsize the feature by half. Conversely, the dimension of feature in the decoder was doubled after the bilinear interpolation. Because a deep CAE model was implemented to extract features from the input signal, it was imperative to use the skip-connection, which is a widely used technique to prevent gradient vanishing when the deep learning model is too deep. This was achieved by simply adding the feature map of the current layer with that of previous layer before passing the feature map to the next layer, which not only prevented the updates of the gradient from gradually becoming negligible but also made the search of the optimal set of parameters easier (Mao, Shen, & Yang, 2016).

Apart from the model architecture design, some techniques were also used to facilitate training and improve model performance. First, Motion Tape measurements were normalized by Equation (4) to ensure the scales of input features were comparable with each other.

$$\boldsymbol{z_i = \frac{x_i - \mu}{\sigma}} \tag{4}$$

where x_i is the i^{th} sample in the ΔR_n training data, while μ and σ are the mean and the standard deviation of N training data selected, respectively. Second, L2 regularization and dropout were also adopted to mitigate the occurrence of overfitting, which is essential for a CAE model, because failure to generalize the data could lead to excessive false detections of abnormal signals (Adelina, Kusumastuti, & Ying, 2019). Eventually, Parametric Rectifies Linear Unit (PReLU) was selected to be the activation function of the CAE model, because it has been shown that PReLU could improve performance at no extra computational cost (He, Zhang, Ren, & Sun, 2015). A full list of the hyperparameters and techniques used for training the proposed CAE model is shown in Table 1.



(a) **(b)**

Figure 6. Motion Tape measurements during (a) Test #1 forward shooting posture and (b) Test #2 90° shooting posture

RESULTS AND DISCUSSION

Motion Tape Time History Analysis

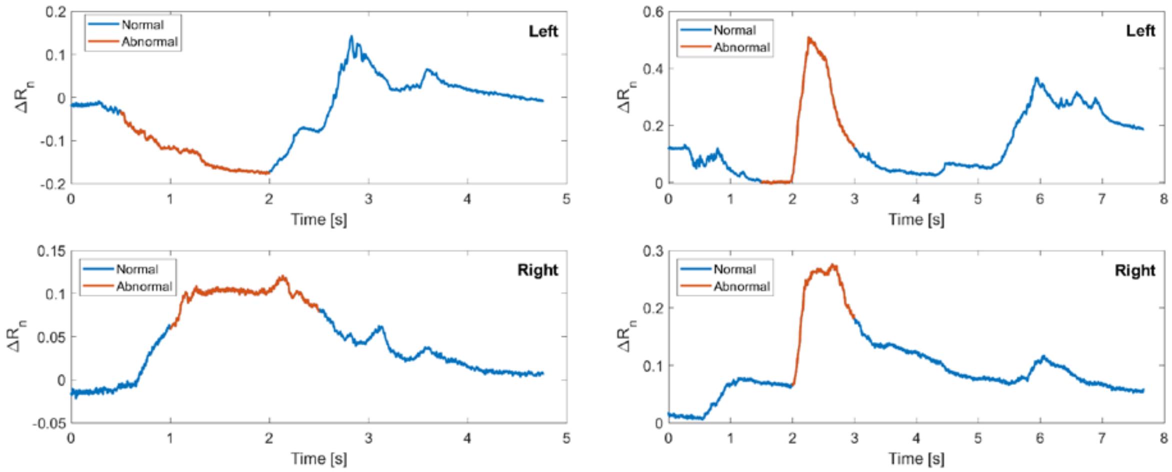
As was mentioned earlier, two sets of human participant test protocols that emulated marksmanship training were designed and conducted. First, the forward shooting posture test was performed with participants aiming the rifle in a way that their heads were either leveled (*i.e.*, correct) or tilted (*i.e.*, incorrect) with respect to the ground (Figure 3). Second, the 90° shooting test involved the participants rotating their body to aim and shoot at the target. The correct movement sequence consisted of head, rifle, and body rotation in unison so that the subject continuously looked where the rifle was pointed. In contrast, the incorrect movement sequence involved participants turning their head to look at the target prior to rotating the body and rifle to aim and shoot the target (Figure 4).

Motion Tape measurements near the trapezius muscles on both sides of each participant were obtained, and representative normalized change in resistance time histories for Tests #1 and #2 are shown in Figure 6(a) and 6(b), respectively. First, it should be noted that the data in Figure 6 all correspond to the same individual, so that the results can be directly compared. Second, the results also show that Motion Tape was able to measure skin-strain changes associated with these different movement sequences. The ΔR_n time histories in Figure 6 exhibited high signal-to-noise ratios and did not seem to have baseline drift issues. Third, even though the movements emphasized the neck for Test #1 and torso and neck for Test #2, it is known that the execution of functional movements involve many different muscle groups all over the body. The trapezius muscles sufficiently engaged during these movements, and how these muscles engaged over time were successfully captured by the use of two Motion Tapes.

Furthermore, a qualitative assessment of the results shown in Figure 6 suggest that the Motion Tape ΔR_n time histories do not exhibit major differences. This is especially true for Test #1, where the measurement waveforms between correct and incorrect postures look similar. One can possibly say that the magnitude of change of ΔR_n may be larger for incorrect movements. In addition, it can be observed from Figure 6(a) that the left Motion Tape experienced compression, while the right was in tension, since ΔR_n decreased and increased, respectively. On the other hand, for Test #2, there is a more distinct difference in the Motion Tape sensing streams, where the incorrect case shows a peak-like waveform due to the head turn prior to body movement. Overall, while differences are present in the time history measurements, identifying movement deficiencies from these results, especially in an autonomous way, may not be accurate nor straightforward or may require certain assumptions be made (*e.g.*, pre-defining a ΔR_n threshold).

Machine Learning Results

A deep learning model was implemented and trained with the objective of automatically characterizing Motion Tape measurements and identifying abnormalities in the sensing streams that suggest movement deficiencies. Figure 7



(a) **(b)**

Figure 7. Trained deep learning algorithm identified abnormal muscle engagement during (a) Test #1 forward shooting posture and (b) Test #2 90° shooting posture

presents a set of representative results for Tests #1 and #2; these results correspond to the same datasets presented in Figure 6 to facilitate direct comparisons. In addition to plotting the ΔR_n time histories of the incorrect cases, the deep convolutional autoencoder successfully labeled which data points corresponded to normal (*i.e.*, in blue) versus abnormal (*i.e.*, in orange) movements.

The results in Figure 7 can be directly compared with the ΔR_n time history overlays of correct versus incorrect movements in Figure 6. First, for the forward shooting posture, the CAE-labeled abnormal sensing streams of Figure 7(a) corresponded to when the ΔR_n time history of the incorrect case exhibited a greater magnitude of change relative to the correct posture in Figure 6(a). Second, the deep learning model successfully labeled the peak-like waveform in Figure 7(b) as abnormal during the 90° shooting test. As was mentioned earlier, this peak-like response during the incorrect case was due to the head turning prior to the body, which caused engagement of the trapezius muscles to execute the head turn, which was successfully measured by the two Motion Tapes. Overall, the ability of the deep learning model to automatically process Motion Tape sensing streams and identify abnormalities was successfully demonstrated through these two human participant test protocols.

CONCLUSIONS

The goal of this study was two-fold. The first objective was to test whether self-adhesive elastic fabric sensors called Motion Tape could measure and differentiate skin-strains corresponding to differences in body posture and movements. The second objective was to validate a deep learning model in identifying abnormalities in Motion Tape sensing streams that corresponded to incorrect movements in military relevant settings. These objectives were tested by conducting two sets of human participant tests that emulated basic marksmanship training. Test #1 involved a forward shooting posture, while Test #2 was to aim and shoot at a target 90° relative to the individual. The test results showed that Motion Tape was sufficiently sensitive to changes in skin-strains near the trapezius muscles (*i.e.*, between the neck and shoulder) when different postures and movement sequences were performed. The sensing streams were also stable and exhibited high signal-to-noise ratios. Even more significant was the deep learning results, where the trained model was able to automatically process Motion Tape sensing streams and label instances in the measurements that corresponded to abnormalities or incorrect movements. Future work will include more test scenarios associated with typical military marksmanship training. Reference sensor measurements (*e.g.*, mocap) will also be used as a reference so that a more detailed quantitative assessment of the results can be performed to verify Motion Tape results. The long-term vision is that Warfighter Digital Twins powered by Motion Tape sensing streams and machine learning models can be used for assessing the performance, training, and health of military service members.

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