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Identifying Highly Responsive Locations For Spinal Motion Tracking Sensors

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Honors Thesis

IDENTIFYING HIGHLY RESPONSIVE LOCATIONS FOR SPINAL MOTION TRACKING SENSORS

by

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ABSTRACT

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Tracking spinal motion in the lower back serves as a useful tool for aiding diagnostics. This study seeks to determine if a fabric garment with integrated strain sensors may provide sufficient information to identify key spinal motion characteristics typically manifested in skin strain. Sensors adhered directly to an individual's skin would be the most effective means of capturing such characteristics. However, adhering sensors to skin of the lower back is difficult for frequent or everyday application. This research aims to integrate a sensor system into a more comfortable and readily user-applied device. Here we examine the implementation of such a device, along with the optimal placement for strain gauges on a fabric garment to capture key characteristics in a differentiable way.

Leveraging a professional motion capture lab, motion data was collected at both the skin and garment surface positions, and analyzed using machine learning techniques. The optimality of each sensor position and orientation was based on how much information it provided to the best performing models. Our analysis utilized the ability of ML models to discriminate between various motion types as an indicator of information gained. Models were given strain data from markers adhered to skin and a proposed

garment designed for measuring lower back motion. Findings from both models were like those in existing literature, in that more sensors typically resulted in better performing models (Baker et al., 2023; Gibbons, McMullin, et al., 2021). A set of reasonable strain gauge positions and orientations were obtained from modeling and can be applied to future versions of the tested garment.

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Introduction

Tracking the biomechanical response of the human lower back during physical activity can produce valuable data. Doing so can provide vital information which significantly aids medical diagnostic techniques or enables clinicians to make treatment plans with more precision. Biomechanical data can be used to guide rehabilitation in a variety of physical disorders. This is especially true in the context of lower back pain (Clark, 2022), where individuals and patients may be able to self-locate pain but are unlikely to be able to express their biomechanical behaviors which may cause or be resultant from this pain.

Several methods for sensing and tracking these biomechanical behaviors and their kinematic expressions have been developed (Mauck et al., 2023; Stickley et al., 2024). These methods include visual motion tracking, inertial measurement devices, and strain gauges among others. Each method or system will offer differing advantages and disadvantages in varying contexts as they capture highly distinct types of biomechanical information.

Recent materials science advances have led some researchers to develop nanocomposite strain gauges, or sensors, with significant improvements in width of operating range (Baker et al., 2023; Gibbons, Peterson, et al., 2021). These sensors have been shown to successfully provide critical information about individual biomechanics when used in a system which adheres them to an individual's skin. One such system, shown in figure 1, utilizes an array-type device with several sensors adhered to the lower back of individuals (Gibbons, McMullin, et al., 2021; Quirk et al., 2022).

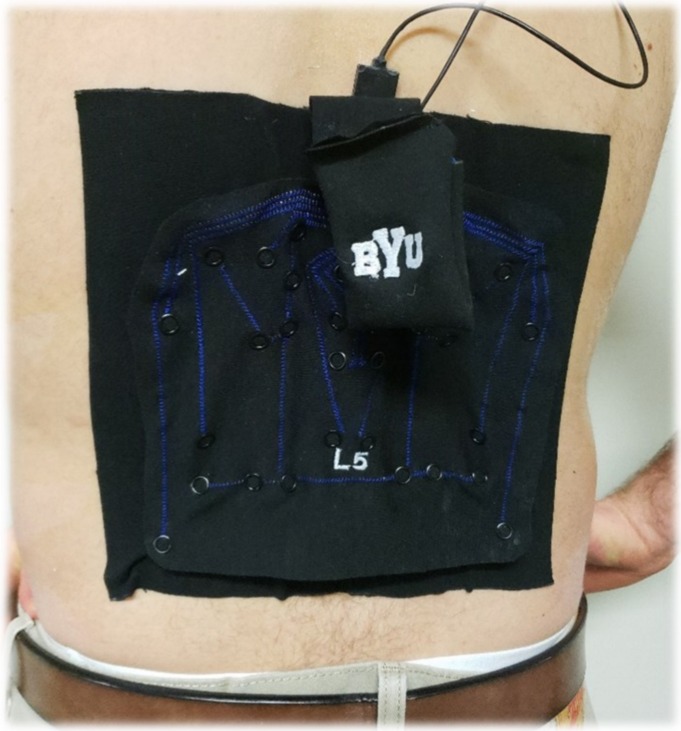


Figure 1: Brigham Young University's SPINE Sense System, applied to the lower back of a researcher

However, this adherence approach for nanocomposite strain sensors has significant limitations in terms of usability and reusability. Due to cross-contamination and sanitary concerns, each array device can be adhered only once with a limited number of reusable components. The adherence process is also difficult, requiring a trained technician to both apply and remove the device from a wearer's back (Stickley et al., 2024). Additionally, wearers of this device have expressed discomfort when using it for extended periods of time.

A straightforward approach to address these concerns is to devise a sensor array which attaches to an easily removable garment instead of an adhesive array, provided the garment and sensors can be shown to adequately track lumbar biomechanics. Initial efforts (not reported here) tested several fabrics for garment design to determine which most closely followed skin strain in the lower back across a range of exercises. The most effective was a fabric belt-style garment, shown in figure 2. When fitted with strain sensors, this garment is significantly more comfortable than the adhesive array discussed above for extended use, is much easier for individual users to apply to themselves, and is reusable for several applications. However, questions remain concerning the optimal position of sensors on this garment and the ability of the sensors to capture biomechanical information effectively without direct adherence to skin.

Figure 2 : Selected fabric, with hook latching mechanisms and loops (not seen) on the left and right

This study will investigate whether sensors applied to a fabric waist-belt style of garment, rather than an adhered device, may capture sufficient biomechanical information to detect key motion characteristics in the lower back. It will also determine optimal positions and orientations, referred to generally as locations, for nanocomposite strain sensors attached to this fabric belt. The analysis relies upon quantification of the increase or decrease of information gained, by adjusting sensor locations toward effectively predicting a variety of motion categories when used across a range of exercises. The optimization will seek the maximum quantity of information gain.

In this quantification, skin strains are the key indicators of biomechanical response which will be used. As a result, any testing done will need to measure both the effectiveness of varying sensor placements, as well as the degree of similarity between stretch shown on the fabric belt and the skin of subjects who wear it. This must also be done across some sample of exercises which effectively represent the human range of motion in the lower back. Collecting results from tests on bare skin alongside the fabric belt will allow for a more complete comparative evaluation of sensors placements and performance. These considerations were used in developing a testing procedure.

Methods

A professional motion capture laboratory was used to capture data for this study. To obtain motion data, a set of 8 motion capture markers were placed on the lower backs of subjects in an orientation shown in figure 3. A total of 6 subjects provided motion capture data. This cohort was composed of BYU students, split equally into male and female groups. Each subject was instructed to perform 6 exercises, or motions, chosen to cover the range of possible spinal motions. Subjects were also instructed to repeat each motion 5 times. The selected motions included lumbar flexion, extension, rotation to the right, rotation to the left, side bending to the right, and side bending to the left. Motion capture markers were then applied to the fabric belt, at locations equivalent to those used for skin motion capture, as shown in figure 4. Markers were applied on the reverse side of the silicone alignment patches. Subjects put the fabric belt on, and the motion capture process was repeated. This data is also visualized in figure 5.

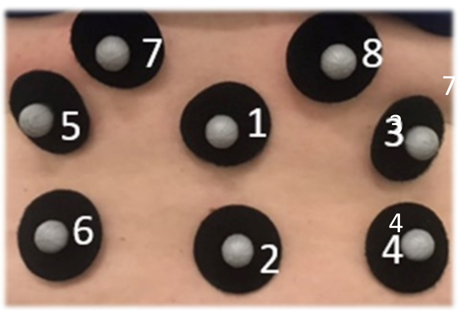


Figure 3 (left): Spinal markers with labels on one subject's lower back

Figure 4 (right): Selected fabric with silicone alignment patches

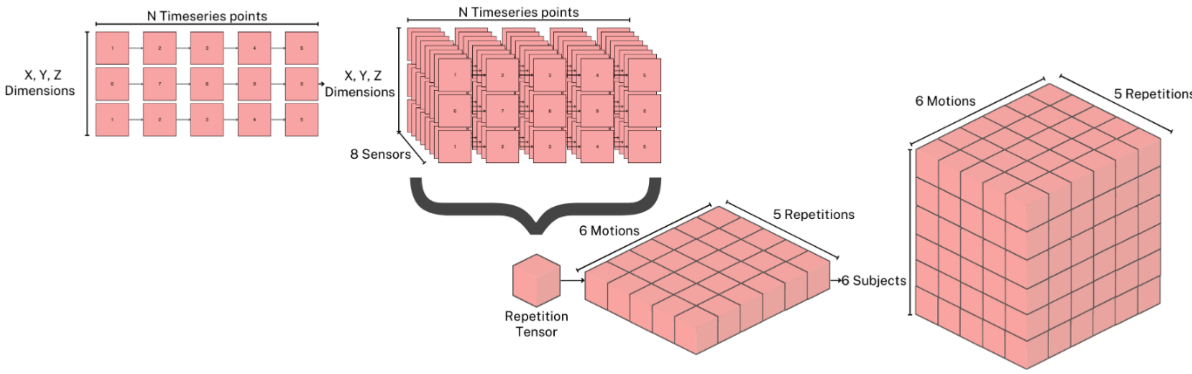


Figure 5: Visualization of collected motion capture data

While motion capture data is spatial, we obtained deflection information which was transformed to use as an analogue to strain collected by strain sensors. Each marker on the lower back and waist belt was assigned 3 spatial coordinates by the motion capture system and was recorded in time. Strains were computed between each marker point when extension was at a minimum and maximum using equations 1 and 2, the change in 3-dimensional location and definition of strain equations. This process for obtaining strain from deflection was done for each repetition of each motion for each subject.

$$d(x, y, z) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \quad \text{Eq. 1}$$

$$\epsilon = \frac{\Delta L}{L} \quad \text{Eq. 2}$$

To make use of the strain information captured, statistical methods were employed. This research questions how well sensors can capture information generated in motion. To approximate this, motion data can be used to predict the 6 distinct motion categories used while collecting data. Classification-type machine learning models are especially well suited to predicting classes based on input information, particularly in the form created here. Thus, this set of strains obtained were then used to train several classification machine learning models. These models were trained with strain data as inputs and specific motions as outputs. They were then tested on the same kind of information. To ensure models were demonstrating the most realistic possible performance, they were cross-validated. Cross validation was done by removing data from 1 of our 6 subjects from the training pool and using it as testing data. This was done 6 times with model performance being averaged across all 6 training sessions.

Two important features were extracted from each model after training and testing was complete. This study was primarily interested in the accuracy and training weights assigned to each model. Features were extracted using built-in functions and methods from the python scikit-learn (sklearn) implementations of machine learning models. The accuracy, or score, of models were generated using the sklearn score method, which returns the subset accuracy or number of correctly predicted labels as a percent of total in our dataset. The training weight vectors were obtained by requesting the coefficients of models, along with their labels. Accuracies and coefficients formed the primary set of quantitative results to be examined.

Results

The accuracies and coefficients from 5 machine learning models are depicted in figures 6 and 7. The figures capture the performance of the machine learning models when applied to data from markers on human skin and markers on the selected fabric. Performance scores are listed at the top of each subplot of each figure. The coefficients used to train all models are also sorted by significance along the y-axis of plots, showing that different models weight the importance of different data collected for predicting exercise category labels. These extracted features also show some features are consistently more important than others, though exact rankings may differ.

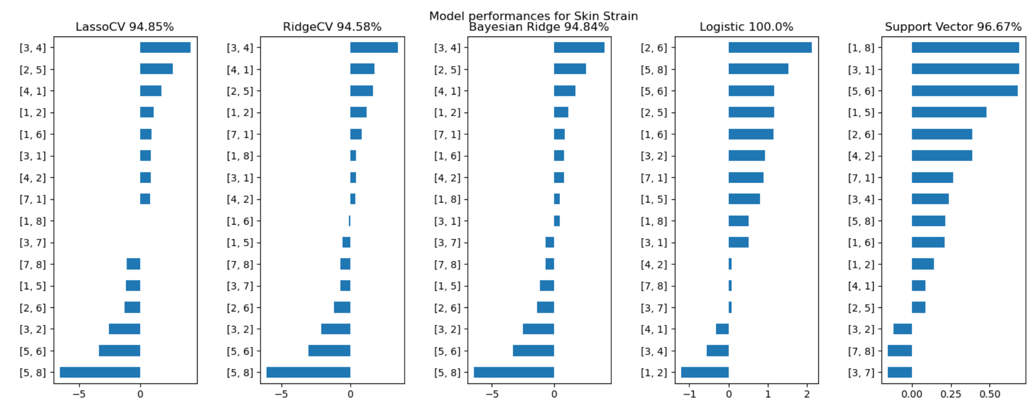


Figure 6: Performance of ML models predicting categories from skin-attached marker motion data

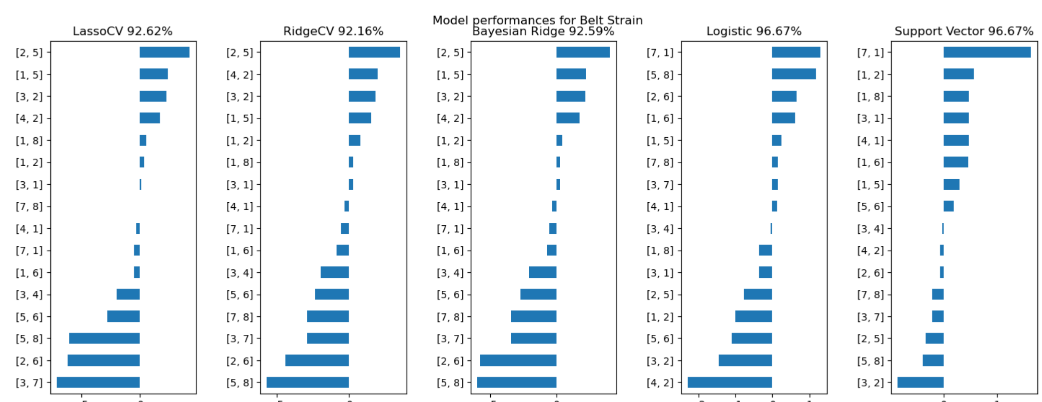


Figure 7: Performance of ML models predicting categories from fabric-attached marker motion data

Following sorting, extracted features of least significance were then iteratively removed. This process included steps to train and cross-validate a new model, determine the least significant feature for the model, remove the feature from the training dataset, and was repeated until only a fraction of the initial data were left for training and testing. This process slowly removed interfering locations for strain sensors, allowing models to approach a physically realistic array design. As features were removed, changes in model scores were tracked to ensure the best combination of model and array were preserved. Score changes relative to strain sensor removals are shown in figure 8.

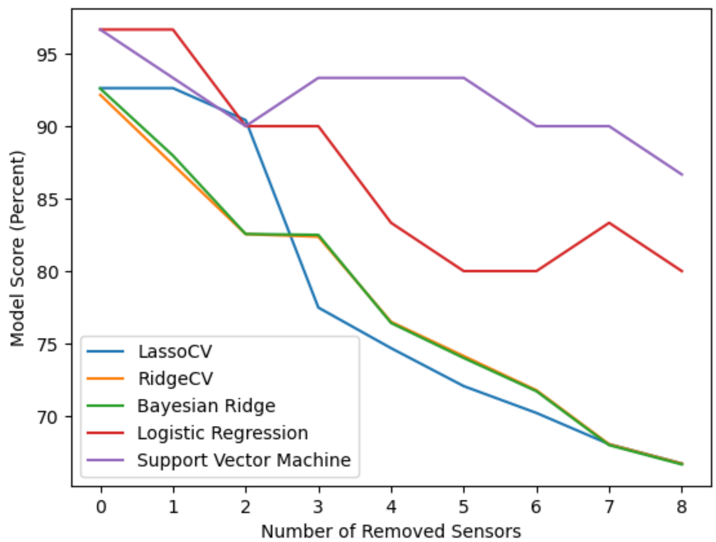


Figure 8: Fabric model performance reductions when dropping sensors of lowest information gain, starting from an initial 16 sensors

Applying this approach to marker strains on the selected fabric type, the typical gain of information was quantified by model scores. This also provides insight into the most optimal set of physical strain sensor locations in a geometrically reasonable pattern. However, removing sensors is a double-edged sword. As seen in figure 8, several models rapidly lose fidelity when sensors are removed. This analysis was run for the best performing model types and the results are shown in figure 9. A visual representation of these same results is presented in figure 10.

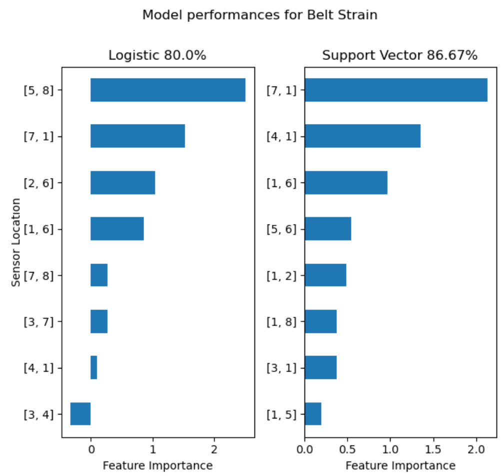


Figure 9: Selected best-performing ML models after score reduction

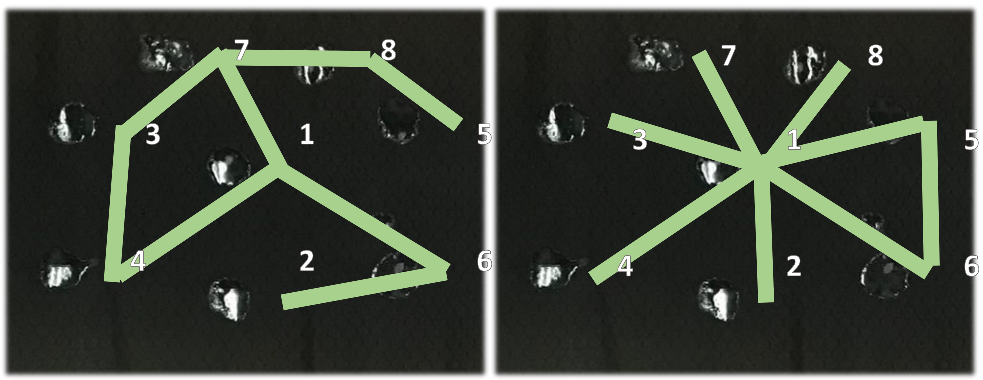


Figure 10: Proposed 8-sensor arrays given fig. 9

Analysis

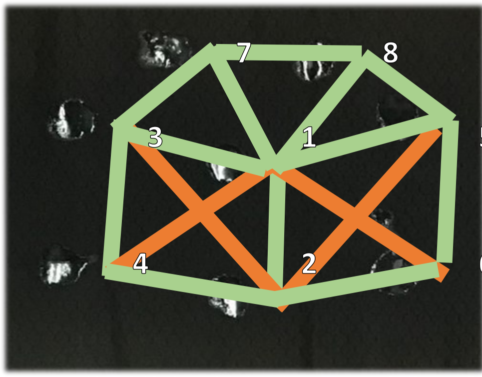
An evaluation of results provides a few key insights to answer vital questions. First, whether fabric-mounted strain sensors can provide similar quantities of information to skin-adhered sensors, second, the connection between biomechanical motion and discrete exercise types discussed throughout this paper, and third, what an optimal arrangement of sensors on some fabric garment will be to obtain a maximum quantity of information. A comparison of the information presented in figures 6 and 7 shows a high degree of similarity between the predictability of exercise categories from data collected from skin and fabric-mounted strain values. In every model type there is a drop in prediction accuracy ranging from 0-2% when using fabric mounted sensors rather than skin mounted sensors. The minimal loss observed between sensor applications carries highly positive implications, highlighting the advantageous tradeoffs of utilizing fabric-applied sensors over those adhered directly to the skin. This is particularly significant given the substantial simplifications it offers for clinicians, patients, research subjects, and users when applying an array of sensors.

The prediction accuracy, however, refers specifically to discrete exercise or motion categories. Briefly mentioned in methods, these exercise categories were selected to cover the range of common motions exhibited in the human lower back. Since exercise categories encompass this wide range of motion, experimenting with data collected using these exercises is an effective means of testing whether a device might adequately monitor the human range of biomechanical motion in the lower back. Where this research exists in a context of chronic low back pain, there is extra care taken to ensure motions were performed accurately so applications of this research can extend to more eccentric forms of the same motions exhibited by those with low back pain, or those who may soon develop low back pain. The high degree of similarity between skin and fabric-attached sensors, along with the high accuracy of models in predicting motion classes provides confidence the tracking capabilities of a sensor system designed with following arrangement recommendations will be adequate for distinguishing biomechanical motion characteristics of chronic low back pain.

Further, with regards to the prediction accuracy of modeling, findings of the study indicate that every additional sensor added to this array tends to produce significant quantities of meaningful information. Referring to figure 9, it is clear removing just one or two results in non-trivial degradation of information gained for every model. Removing additional sensors provided mixed results, with varying magnitudes of downward slopes for all. Thus, retaining up to 14 of the original 16 sensor placements is recommended. Using 14 sensors in the array provides accuracy up to 90% in classification modeling. Adding more sensors will have diminishing returns and requires examination of alternative placement locations.

This result comes after observing the impacts of reduced quantities of information and their influences on model performance. No model type started from a poor position. With all sensor positions available for testing and training, every model type was able to predict the correct motion category from fabric data more than 92% of the time with some models reaching 96-97% accuracy. However, as sensors were removed the reduction in predictive capacity varied dramatically for different models. While Support Vector Machine and Logistic Regression models had significant score reductions as strain sensor locations were removed, the remaining models fared far worse, leading us to use only Support Vector Machines for final determinations. The specific outcomes from Support Vector Machine models point us to eliminate only the physically impossible sensors from our design.

The overlapping strain sensors, shown in figure 11, include sensor 1-4 and 2-3, and 1-6 and 2-5. Since sensors 2-3 and 2-5 do not appear on either of the best performing models, seen in figure 9, it is recommended these and only these are removed from the final fabric design as presented in figure 12. However, these recommendations should be tempered with additional considerations. This study does have limitations which could have improved model performance had they been tested further.



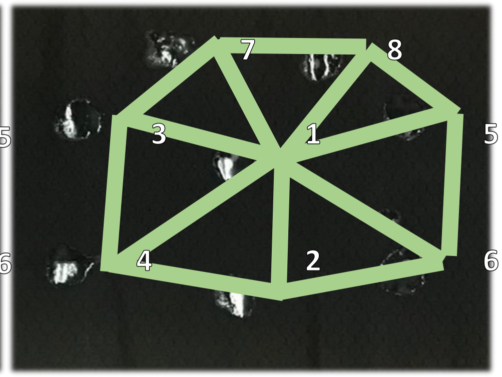


Figure 11 (left): Overlapping strain regions resulting in impossible geometry, marked in orange

Figure 12 (right): Proposed strain sensor locations on a fabric belt

One of the notable limitations was our relatively low sample size, which likely impacted model performance and may influence generalizability. Motion repetitions were used to offset model performance limitations but could not have solved the problem entirely, especially given our cross-validation approach, which limited the models to seeing, effectively, 5 very refined versions of a motion rather than 25 highly distinct versions. This low sample size could also skew to over-represent the small demographic, or to not represent some demographics at all. Despite this limitation, the study's findings highlight the surprising accuracy of some machine learning models in predicting motion patterns based on strain.

Additionally, optical motion capture and strain gauge sensors do not have a 1:1 ratio for resolution. Each sensor system will have variations in resolution which will require adjustment and tuning of both collection and analysis systems. The motion capture system used in this study had sub-millimeter spatial resolution and was able to track the several marker points at 100hz. Other systems may sample far less frequently or have less absolute certainty in spatial dimensions. Computing strains from motion capture spatial coordinates serves as an effective analogue to strain sensors, though, perhaps with higher resolution than novel nanocomposite strain gauges can offer just yet.

These findings are in alignment with similar validation research done for BYU's SPINE Sense system, seen in figure 13. While the models lose effectiveness far faster than the SPINE sense system, it is clear removing sensors from either would result in a loss of meaningful motion data. It is also clear the combined power of nanocomposite strain gauges and machine learning models unlocks a potential future of unreasonably effective biomechanical monitoring and testing tools for home and clinical use.

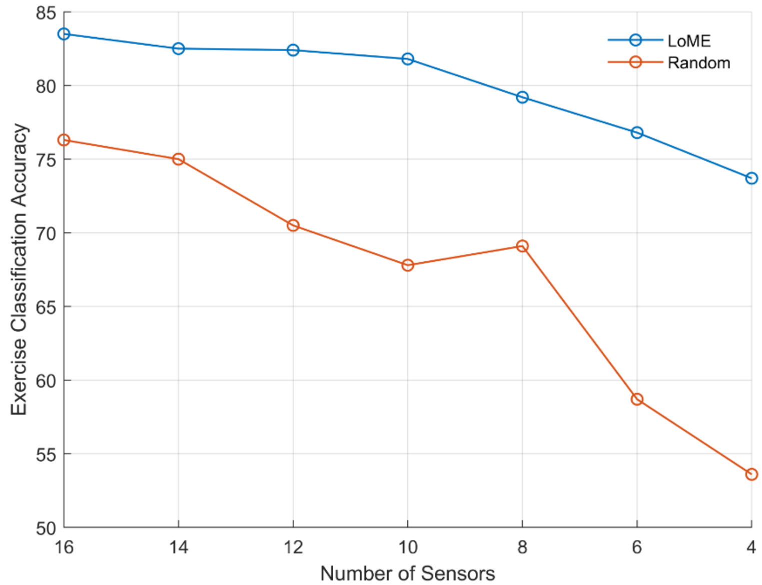


Figure 13: Data from SPINE Sense classification accuracy analysis, using arrays with varying numbers of sensors, starting at 16 and being reduced by both worst predictors (LoME) and at random

Conclusions

This study draws a few primary conclusions regarding the biomechanical tracking ability of a fabric garment, placement and number of strain sensors in a suggested final design, and comparisons with other systems. The first is that a removable fabric garment in the presented waist-belt form factor appears to be capable of tracking the biomechanics of the human lower back. Support Vector Machine models had equivalent performance between skin and fabric data, with both correctly classifying 96% of the cross-validation tests when run with 16 sensors. It is expected the resolution of these strain gauges will be less than the resolution of the motion capture lab and that applying strain gauges to the fabric belt may slightly alter the belt's deformation properties during human motion, however these impacts are not anticipated to significantly impact the findings of this study.

To do this, the findings presented here suggest as many sensors as reasonable should be used in validation. Given the information tested here, 14 sensors as arranged in figure 12 are considered optimal. This retains the maximum amount of information found with higher numbers of sensors while allowing for a real device to be constructed. Further reduction in the number of sensors used tends to severely hamper any ability of machine learning models to predict exercise or motion categories, indicating there is not enough information to build an effective connection between strain and motion type. This finding is comparable to observations of the SPINE Sense system, which also uses 16 strain sensors. When removing sensors, first by least significant, then at random, the SPINE Sense system saw noteworthy reductions in performance on tested machine learning classification models. Differences in the quantity of training and testing data, along with other previously discussed factors are expected to explain differences beyond shared trends. Overall, proceeding to design a fabric-based strain sensor system is an effective way to solve some existing problems with adhesive array systems, allowing for longer tracking use as well as significantly improved user-friendliness

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