Hand Gesture Prediction in Continuous Time with a Limited Number of Strain Gauge Sensors

Wentai Zhang
Carnegie Mellon University
Pittsburgh, PA
wentaiz@andrew.cmu.edu

Jonelle Z. Yu
Carnegie Mellon University
Pittsburgh, PA
zyu1@andrew.cmu.edu

Fangcheng Zhu
Carnegie Mellon University
Pittsburgh, PA
fangchez@andrew.cmu.edu

Yifang Zhu
Carnegie Mellon University
Pittsburgh, PA
yifangz@andrew.cmu.edu

***Abstract*—Tracking hand gestures of human operators when working in production plants and factories is beneficial for manufacturing process control and ergonomic improvement. Consistently applying standard and correct hand gesture in work would prevent operators from accumulative hand injury, and also decrease defective products due to operational error. We propose an instrumented glove with only a few strain gauge sensors and a micro-controller that records continuous streams of the sensor data, and an algorithm that can re-construct the hand gestures in high dimension from the low dimensional sensor data. The operator working hand gestures can be analyzed afterward and improved accordingly. 10 strain gauges are first placed at knuckle locations to perform layout optimization. Data from 10 gauges are collected when English letters in American Sign Language (ASL) are demonstrated. The optimal sensor configurations for 3 through 10 strain gauges are obtained by using support vector machine (SVM) and 10-fold cross validation (CV). We further collect the strain gauge data concurrently with the data of the real knuckle angles measured by Leap Motion. Linear regression, quadratic regression and neural network are then applied to train the mapping models between data of 3 to 10 strain gauges and the real knuckle angles. After comparing the models trained from various number of strain gauges using different algorithms, we use**

I. Introduction

One of the longstanding challenges for plants and factories is to standardize production and to improve efficiency, especially when human operators are involved. Following the standards and correct procedures in work will not only minimize the occupational injury for operators but also reduce the defective products caused by operational errors. Taking a leading position in increasingly competitive markets necessitates effective supervision and management of all the possible operations to achieve high production yield and low product failure. Human hand gesture recognition can be applied to monitor and track human operators' hand gestures and movement when processing expensive and/or challenging products. However, most commercialized products for hand gesture recognition are vision-based for virtual reality gaming, which require external devices like cameras to be placed facing the objects from a certain distance. Such non-wearable and non-portable settings are not feasible in an industrial environment, as it is not practical to carry the devices around during work.

The goal of this study is to develop a wearable device that is able to track and record hand gestures over a period of time. Meanwhile, the device should not interfere with normal hand movement of the wearers. Here we propose an instrumented glove with strain gauge sensors attached on the knuckle locations and a micro-controller to collect and record the sensor data. We first build a glove starting with 10 strain gauges on 10 knuckles to optimize the strain gauge layout. Labeled data of demonstrating English letters in American Sign Language (ASL) are collected. The optimal combinations of 3 to 10 gauges are obtained by using support vector machine (SVM) and 10-fold cross validation (CV). Afterwards, we use knuckle angles measured from Leap Motion Controller in real time as the ground truth. When a random hand gesture is performed, strain gauges data are collected concurrently with joint angle values measured from the Leap Motion device. Linear regression, quadratic regression, and neural network are used to develop multiple mapping models between the data from 3 to 10 strain gauges and the real knuckle angle values from Leap Motion. The models trained from various number of strain gauges using different algorithms are compared and summarized.

Our main contributions are:

1) A wearable glove with a limited number of strain gauge sensors to recognize hand gestures with high accuracy.
2) A novel experiment setup to predict knuckle angles by mapping from lower dimensional space (strain gauge data) to higher dimensional space (knuckle angle values).

Section 2 presents related work. Section 3 presents an overview with technical details in Section 4. Results of the proposed approach are presented in Section 5, conclusions are summarized in Section 6, and future work are mentioned in Section 7.

II. Related Work

Human hand gesture recognition has been extensively studied using different hardware setups and computational approaches. Wearable devices integrated with various sensors [1-3] were developed for the potential applications such as sign language translation and rehabilitation therapies. Kramer et al. [1] patented a method of hand gesture recognition using an instrumented glove with approximately 20 sensors. Each sensor comprises two linear strain gauges with a backing in between to predict the bending angle when one gauge is in tension and the other in compression. Bayesian and artificial neural network classifiers were applied to recognize gestures using the sensor inputs, i.e. the angles of the bent sensors. However, a main disadvantage is the lack of convenience and comfort of wearing a glove with too many sensors. Federico et al. [2] developed a glove attached with patterned sensor made of conductive mixture to predict hand gesture. Due to the non-linearity of the conductive mixture, electromechanical characteristics of the sensor were modeled first. The mapping matrices among nonlinear sensor readings, posture space, and goniometer calibration were established by using interpolation and pseudo-inverses. The study obtained 100% accuracy on classifying 32 well-known basic grips and ASL at the first wearing by a tester, and 98% accuracy at the second wearing by the same person. However, this study only covered the recognition of discrete hand gestures instead of continuous hand moving, and the accuracies of repetitive wearing more than two times and wearing by different testers were not studied. Lei et al. [3] developed an accelerometer-based method to detect 12 predefined index finger movements of stroke patients during rehabilitation therapies. The study applied C4.5 decision tree, 1-neuron network and naive Bayes classifiers on different combinations of extracted features from the XYZ accelerometer to predict the 12 movements. The recognition accuracies varied from 59% to 87%. Though this method could track different types of continuous movements of one finger, it would be cumbersome to wear accelerometers on all the fingers and palm to monitor the hand movements, as accelerometers are inherently much larger and heavier than strain gauges.

Vision-based approaches were widely applied to recognize hand gestures and motion using optical and infrared cameras [4], [5] or RGB cameras and depth sensors [6], [7]. Gioliu et al. [8] computed an ad-hoc feature set based on the positions and orientations of the fingertips and fed it into a multi-class SVM to recognize the 10 predefined gestures using both Leap Motion (based on infrared cameras) and Kinect (based on RGB cameras and depth sensors). The accuracy of the studies varied from 65% to 92% by using different combinations of feature sets. However, there are three main disadvantages of vision-based approaches when hand gesture recognition is applied in industrial operations. First, it is inconvenient or even impossible for an individual to carry the above-mentioned devices around to record information when the person need to move among different places. Second, the vision-based devices have inherent drawbacks when the hand is grabbing objects. The devices are not able to distinguish the hand from the objects. Third, the intensity and noise of the light source could negatively affect the data recording of the vision-based devices. Even if a model is established to overcome and compensate these factors, it may need to be re-built when the environment changes, e.g. an individual moves from indoor to outdoor.

Indeed, technologies of recognizing hand gestures and motion have been applied in varied commercial products, such as Proglove for industrial logistics [9], Gest and Myo for human computer interaction [10], [11], and Leap Motion and Kinect as virtual reality technologies [12], [13]. It is worth noting that Leap Motion observes a roughly hemispherical area within a radius of about 1 meter using two monochromatic IR cameras and three infrared LEDs with the overall average accuracy of 0.7 millimeters [14]. Although as above-mentioned, vision-based approaches are not applicable to our study, the knuckle angles will be obtained using Leap Motion as the ground truth. Posture recognition systems for other body parts such as arm [15], leg [16], and body [17], [18] have also been reported, which can be referred to when designing hand gesture recognition systems, but the hardware design should be scaled down and resolution should be improved. To our knowledge, our study is the first to focus on hand gesture recognition with or without objects in hands by using limited strain gauge data to predict hand gestures and motion in continuous time.

III. Overview

The objective of our proposed methodology is to develop an instrumented device using only a limited number of strain gauge sensors and an algorithm to recognize hand gestures by mapping the low dimensional sensor data to the high dimensional knuckle angles. To achieve this goal, discrete hand gestures are selected to optimize the sensor layout first, and continuous hand gestures are performed to develop a mapping model between the sensor data and hand gestures subsequently. Our strategy of using low dimensional data to predict high dimensional hand gestures is composed of 4 main steps. First, 10 strain gauges are initially attached to an exam grade latex glove on the knuckles. The user performs gestures for the first 13 letters in ASL while wearing the instrumented glove and recording the sensor readings. Second, a multi-class SVM is applied to find the optimum combinations of the strain gauges to recognize the selected gestures in ASL. Third, the hand with the optimized instrumented glove continuously moves above Leap Motion. Readings from strain gauges and knuckle angles from Leap Motion are recorded simultaneously. Last, regression models and feed-forward neural networks are utilized to develop a model that maps the low dimensional strain gauge data to high dimensional knuckle angles.

IV. Technical Approach

A. Sensor Layout Optimization

1) Hardware Setup: 10 strain gauges (KFH-20-120-C1-11L1M2R, Omega) were attached on a medium-sized Latex glove (Microflex Diamond GripTM, ULINE) using double-sided tapes. First, a male tester wore the glove on his right hand. The glove tightly wrapped around the testers fingers and palm as the glove was stretched. Marks were drawn on the knuckles of each finger when the tester bent his fingers, and the optimum bending locations were identified. Afterwards, 10 strain gauges were attached using double-sided tape on top of the marks when the hand is placed flat on a table, as Figure 1 illustrated. By doing so, all the strain gauges stay neutral without tension or compression when the hand is relaxing and flat. The strain gauge would be stretched or compressed only when the fingers move.

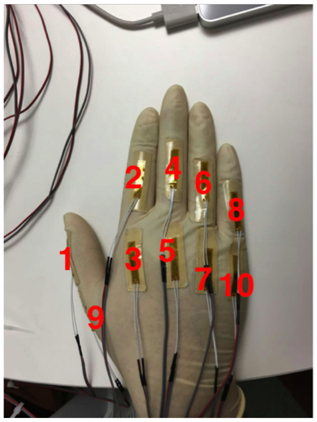

Fig. 1. The layout of 10 strain gauges on the latex glove on the male tester

The change in electrical resistance of strain gauges due to applied force is minimal. Therefore, a Wheatstone bridge [19] with an amplifier (INA125P-ND, Texas Instruments) was used to reflect the change with precision, as shown in Figure 2. The potentiometer R2 was initially set equal to the strain gauge resistance. When there was no stress in the gauge, the bridge was balanced and the voltmeter would indicate zero voltage; however, when the gauge was either compressed or stretched, the change in strain gauge resistance would unbalance the bridge and resulting in an indication in the voltmeter. The amplified signal was then input to an analog port of an Arduino Mega Board (Figure 2), which has 16 analog input ports to meet the requirement of collecting the data from 10 strain gauges. Figure 3 shows the final setup of the hardware.

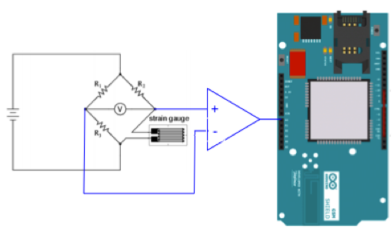

Fig. 2. The schematic design of hardware setup (1 channel)

2) Data Collection and Layout Optimization Algorithm: The goal is to model hand gestures with as few as three strain gauges. In order to find the optimal locations for placing the strain gauges, data were collected for all 10 strain gauges for classifying selected gestures, but only a limited number of selected strain gauge data were extracted each time to train a model. The accuracy of each possible combination was used to evaluate its performance. A total of 13 hand poses were selected. Pose 0 served as the calibration point to zero all sensor readings before each trial.The first 13 letters in American Sign Language were selected and performed during data collection, as shown in Figure 4. Pose 1 to pose 13 correspond to the gesture for letter A to M. In each iteration, the male tester

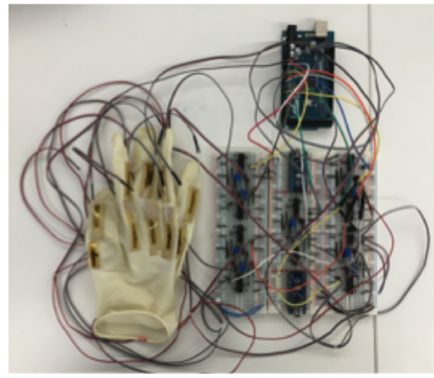
Fig. 3. The final setup of the hardware (10 channels)

made the poses following the order from 1 to 13 and held each pose for about 10 seconds. Meanwhile, the Arduino microcontroller collected the readings every 100 milliseconds from the 10 strain gauges. After performing all the poses, the male tester repeated the experiment with a second wear. Finally, all collected data were pre-processed to remove the transition periods between poses and labeled from 1 to 13. Multi-class SVM classifier with 10-fold cross validation was applied to train the classification model. Different combinations of 3 to 10 sensor data were selected to train the new models. The training strategy was to use first wear data to train, and test the model with second wear data. By comparing the accuracy of different models, the most informative sensor configurations were determined by choosing the combination with the highest accuracy.

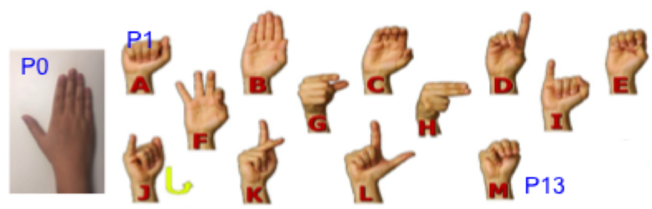

Fig. 4. The hand gestures of the calibration (P0) and the first 13 letters (A-M) in American Sign Language (P1-P13)

B. Hand Gesture Tracking System

1) Hand Skeleton Reconstruction: Leap Motion was used in the experiment to measure the knuckle angles associated with any hand gestures. Leap Motion is able to directly record the 3D coordinates of all the knuckles on a hand in real time. All 14 knuckle angles of interest, shown in Figure 5, were calculated using vector geometry. Angles collected from Leap Motion served as ground truth for the strain gauge readings.

By only using 14 knuckle angles to represent a hand gesture, essential statistics such as finger's bending can be reconstructed while other information such as finger orientation and bone length are lost. Figure 6 shows the real-time hand motion visualization in JavaFX. The model on the left is reconstruction using coordinate data from Leap Motion; the

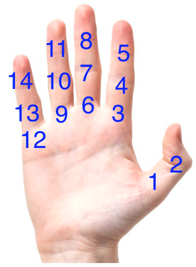

Fig. 5. Knuckle Angles to be Predicted for a Hand Gesture

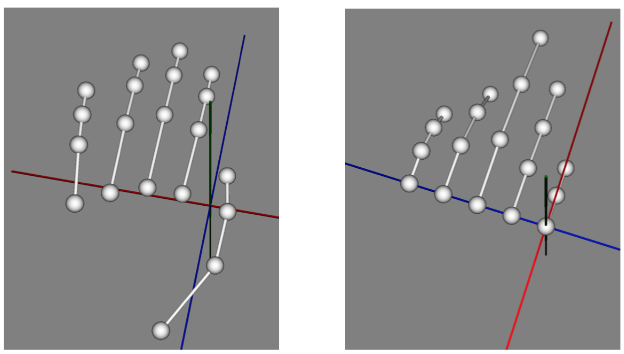

Fig. 6. Hand Model Visualization in JavaFX. Left figure is reconstructed using knuckle coordinate data; right figure is reconstructed using knuckle angle data

model on the right uses only 14 knuckle angles computed from knuckle coordinates, but bone lengths, palm orientation and finger base knuckle location have to be constrained.

2) Data Collection: During testing, data for a series of hand gestures were collected for a male tester. The tester was instructed to move his finger while wearing the instrumented glove. The motion should be slow enough for sensor readings to stabilize. Arduino micro-controller collected the readings every 100 milliseconds from the 10 strain gauges attached to the glove and Leap Motion concurrently records the knuckle coordinates.

Note that because Leap Motion tracks hand motion in an event-driven fashion, the recorded time interval ranges from 10 to 100 milliseconds. Therefore, the Leap Motion data were linearly interpolated and down-sampled to match the time stamps from strain gauge data before they were used to train the models. Data interpolation is performed in MATLAB with its built-in linear interpolation function.

3) Algorithm and Model: Three models were used to map strain gauge readings to knuckle angles: linear regression, quadratic regression, and feed-forward neural networks. The models performed mapping between selected k strain gauge readings to the 14 knuckle angles obtained from Leap Motion. The optimum strain gauge configurations containing 3 to 10 strain gauges were determined by choosing the combinations with the least root mean square error (RMSE).

For regression models, the transformation matrix $\mathbf{T}$ needs to be determined to achieve the mapping from lower dimension to higher dimension.

$$S\mathbf{T} = J \tag{1}$$

S is of dimension $N \times k$, where k is the number of selected strain gauges and N is the number of data points recorded; J is of dimension $k \times 14$, corresponding to 14 knuckle angles. By applying matrix pseudo-inverse, transformation matrix $\mathbf{T}$ can be calculated as:

$$\mathbf{T} = (S'S)^{-1}S'J \tag{2}$$

Furthermore, two regression models with different levels of complexity are selected to explore the relationship between strain gauge readings and knuckle angles. Linear regression model and quadratic regression model are used to compute the transformation matrix $\mathbf{T}$.

For a linear regression model, the dimension of S is $N \times (k+1)$ and S includes strain gauge readings $s_1, \cdots, s_k$ plus a bias term. For a quadratic regression model, the dimension of S is raised with quadratic terms $s_1^2, \cdots, s_k^2$ and products of all combinations of size 2 from k strain gauges such as $s_1 \cdot s_2, s_1 \cdot s_3, \cdots, s_{k-1} \cdot s_k$. Therefore, the dimension k_s for S can be calculated by

$$k_s = k + k + C(k, 2) + 1 \tag{3}$$

To reduce over-fitting, L-2 regularization was applied to the model

$$\mathbf{T} = (S'S + \lambda I)^{-1}S'J \qquad (2)$$

λ is the regularization parameter. The value was selected and tested in the range between 0 to 1 with spacing of 0.005.

The last model applied was feed-forward neural network. Neural network with different complexity were trained. Both single and double layer (Figure 7) networks were tested, with number of hidden nodes in each layer from $10, 20, \cdots, 50$. In order to avoid variance from random initialization, each network was trained three times and evaluated based on the average RMSE.

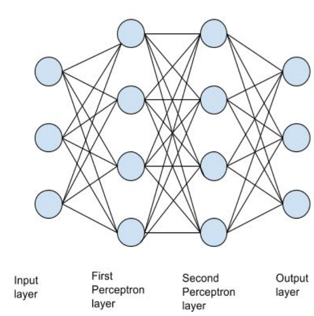

Fig. 7. Double-layer feed-forward neural network

V. Results

A. Layout Optimization Results

The final data sets were generated from a single tester with multiple-time wearing. The data are made up of two parts: calibration data and sign language data. Calibration data was used to define an initial value for all the strain gauges. The number of selected features(strain gauges) varies from 3 to 9. In the case of k selected features, all the possible combinations are extracted from the whole data set and form in total 10 choose k data subsets. Then linear SVM model was implemented to classify each of the data subset. The strategy is using all the first wear data to train the SVMs and test the overall performance on the second wear data. The training sets were shuffled before training. 10-fold cross validation was conducted.

TABLE I
BEST FIVE CONFIGURATIONS USING THREE STRAIN GAUGES

Configuration	Training Accuracy(%)	Test Accuracy(%)
5,8,9	98.29	63.44
5,6,8	95.96	59.56
5,6,9	93.11	58.72
6,8,9	90.90	57.04
7,8,9	94.02	50.80

If the number of selected strain gauges k = 3, the results for the best 5 strain gauge configurations are shown in Table I. The fall-off between test accuracy and training accuracy mainly results from the misalignment among different wearings. Judging from the test accuracy, the best configuration containing 3 strain gauges is 5, 8 and 9. Similarly, the best configuration for any number of selected strain gauges from 3 to 9 can be acquired by choosing the configuration with the best performance among all the combinations. The overall optimization results are listed in Table II.

TABLE II
BEST CONFIGURATION FOR CERTAIN NUMBER OF SELECTED STRAIN GAUGES

No. of SGs	Best Configuration
3	5,8,9
4	6,7,8,9
5	5,6,7,8,9
6	2,4,5,7,8,9
7	1,2,4,5,7,8,9
8	1,2,3,5,6,7,8,9
9	1,2,4,5,6,7,8,9,10

B. Hand Gesture Tracking Results

1) Linear and Quadratic Regression: With linear regression, if all the ten strain gauges are used, the root mean square error is 7.59. Based on this mapping, L-2 regularization was implemented to avoid overfitting. According to figure 8, as the regularization parameter λ increases, the RMSE also linearly increases. The least RMSE is achieved when λ = 0. Thus, L-2 regularization is not necessary in this case.

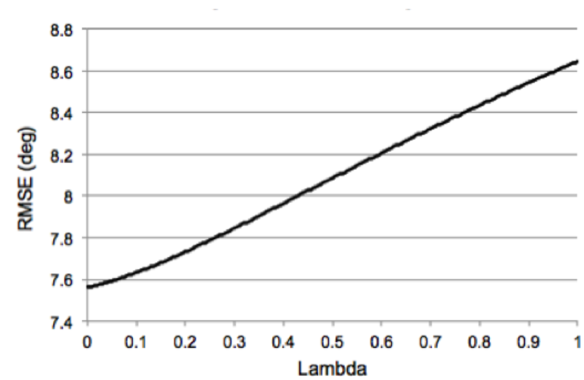

Fig. 8. L-2 regularization results for linear regression

In similar approach, with quadratic regression, the least root mean square error is 4.02 if 10 strain gauges are involved. Although the RMSE shown in figure 9 has two stationary points, the minimum point is still at λ = 0, which means L-2 regularization is also unnecessary in this case.

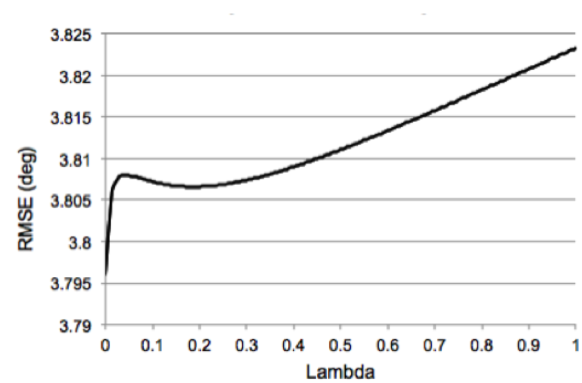

Fig. 9. L-2 regularization results for quadratic regression

2) Neural Networks: Parametric studies were conducted to determine the best structure of the neural networks. All the networks were trained with 90% of shuffled data and tested with the remaining 10%. Training was stopped when the validation error was increasing. When there is only one hidden layer, the number of hidden nodes varies from 5 to 50 with an increment of 5. The results are shown in figure 10. The RMSE remains at about 3 degrees when there are more than 15 hidden nodes. In terms of expense of computational time, the best structure for single layer neural network is k-15-14(k is the number of selected features).

which means relative good performance is achieved only if 10 strain gauges are involved. But the performance of quadratic regression stays at 4 degrees when there are 8 or more strain gauges. The RMSE of neural network model stays at a pretty low value (about 3 degrees) even after 4 strain gauges. This means the whole sensing system can provide a pretty precise prediction of the hand pose only with four strain gauges.

Considering the high complexity of the data set, double hidden layer structure was also implemented. In similar approach, the number of hidden nodes in the first and second hidden layer are both varied from 10 to 50 with an increment of 10. Based on the results shown in figure 11, the best structure is k-10-30-14(k is the number of selected features).The least RMSE is 2.73 degrees. Since the results are better than the single layer results, the final optimum structure of neural network should be consistent with the best double layer structure.

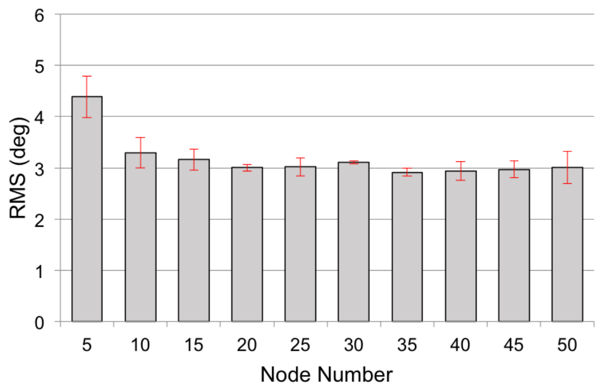

Fig. 10. RMSE for single layer neural networks

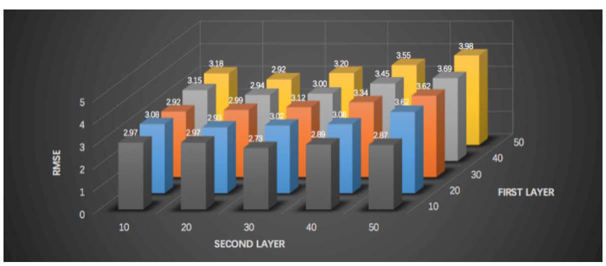

Fig. 11. RMSE for double layer neural networks

VI. Conclusions

For the optimization on the sensor configuration, the gestures of first 13 letters in ASL were performed when the readings from 10 strain gauges attached on knuckle locations were collected. By using multi-SVM classifier with 10-folder cross validation, the best configurations corresponding to 3 to 9 strain gauges were selected.

In this paper, three different regression methods were introduced to realize a mapping between a limited number of strain gauge data to 14 joint angles. From linear regression, quadratic regression to neural network, the complexity of the model is increasing. According to figure 12, the overall performance is: Neural network > Quadratic regression > Linear regression. This means the complexity of the data space is pretty high that common regression methods can't have a fair performance on it.

From 3 to 9 selected features (strain gauges), the RMSE of linear regression keeps decreasing from 10.80 to 7.69,

The test error of each joint angle using the optimum prediction model is shown as a histogram in figure 13. The red line is a normal distribution fitting to the error data. Overall, the mean of the data μ = -0.0746 degree (table III). The standard deviation σ = 3.3356 degrees which is pretty small compared to the total range of the joint angle change (90°).

This optimum hand gesture recognition system can contribute to the industry in many fields. Apart from the applications of monitoring and operation analysis in manufacturing, a more attractive outlook is to function as an aided device for robots(such as hand-like robots or mechanical arms) to learn some complex operation process which can only be done by human hand for now. Then they can operate like real human hands to conduct some frequently repeated tasks or work under some very extreme working conditions.

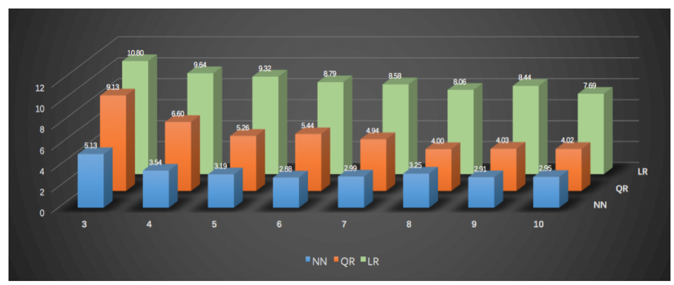

Fig. 12. Comparison among different regression methods with different numbers of selected strain gauges

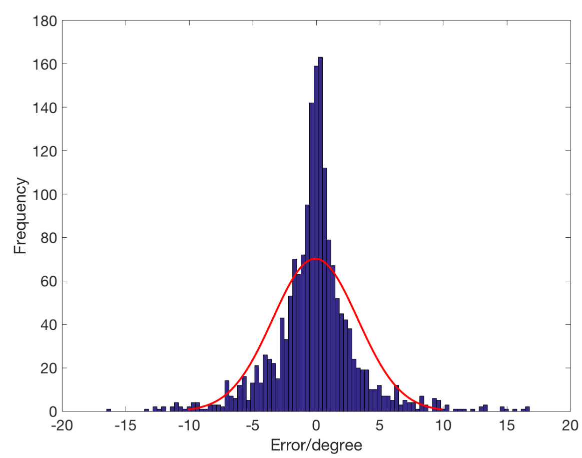

Fig. 13. Test error histogram using best prediction model

TABLE III
NORMAL DISTRIBUTION FITTING RESULTS

Parameter	μ	σ	Absolute max	Absolute min
Value(degree)	-0.0746	3.3356	16.7301	0.0004

VII. FUTURE WORK

The limitations with the current hand gesture tracking device are two-fold: 1) In terms of the algorithm, the best configurations for prediction models are determined from a relatively small training set which consists of tracking data for only limited hand gestures. As a result, the trained model might not be able to perform as accurately if it were used to track some more tricky hand gestures. 2) In terms of the hardware, the strain gauge-based glove setup faces limitations in repeatability and portability. Because strain gauges rely on being mounted on tight gloves (e.g. Latex surgical gloves) in order to be accurately aligned with the knuckles angles, strain gauge-based glove setup is sensitive to hand sizes and repetitive wears. To achieve good tracking results, the glove needs to be re-trained for every new wear. In addition, our current glove is not yet portable due to exposed wires and circuit boards.

For future work, further improvement could be achieved on both algorithm and hardware aspects. First of all, the tracking accuracy could be improved by increasing the training set sizes and encompassing a wider range of hand gestures. By making sure that individual motion of each knuckle are covered during training, the tracking accuracy could be guaranteed even for predicting more complicated hand gestures. Secondly, strain gauge sensors could be replaced with flexible electronics to make the glove more flexible and thus less sensitive to repetitive wears. Lastly, the glove setup could be made portable by integrating the exposed circuits into a single printed circuit board.

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