An Efficient Method for Calibrating Piezoresistive Pressure Sensor

Zhongnan Pu
Graduate School of
Computer Science and Engineering
University of Aizu
Fukushima 965-0006, Japan
m5272018@u-aizu.ac.jp

Daisuke Miyata
Graduate School of
Computer Science and Engineering
University of Aizu
Fukushima 965-0006, Japan
daisukem@u-aizu.ac.jp

Lei Jing
Graduate School of
Computer Science and Engineering
University of Aizu
Fukushima 965-0006, Japan
leijing@u-aizu.ac.jp

***Abstract*—This paper presents an efficient calibration method for piezoresistive pressure sensors. We applied this method to calibrate 35 pressure sensors integrated into an e-textile insole, utilizing machine-measured pressure-resistance pairs within the pressure range of 1-10 N as reference values for error assessment. The efficient calibration process required only 15 minutes, resulting in an average relative error of 14.4%. In contrast, traditional calibration methods necessitated more than two hours, achieving a relative error of 12.1%. This method effectively addresses the calibration challenges of piezoresistive pressure sensors within practical device and time cost constraints, holding significant implications for the real-world application of pressure sensor products that require frequent calibration.**

***Index Terms*—e-textiles, piezoresistive sensor, pressure sensor, sensor calibration.**

I. INTRODUCTION

In recent years, with advancements in sensor technology, pressure sensors have been widely applied in health [1], [2] and wearable device [3] domains. E-textiles, with their simplicity and comfort, offer vast potential for the application of pressure sensors in these areas [4]–[6]. Among various types of pressure sensors, piezoresistive pressure sensors are widely utilized in e-textile devices and applications due to their low cost, flexibility, and ease of manufacturing and processing [7], [8]. However, the pressure-resistance characteristic curves of piezoresistive pressure sensors exhibit individual differences, and variations in the sewing positions within e-textiles can lead to different detected force component at the sensor point. Even for the same sensor, prolonged use can result in changes to the characteristic curve due to material aging, leading to reduced accuracy. Therefore, regular calibration is necessary when using piezoresistive pressure sensors [9].

In laboratory settings, the readings from pressure and resistance measuring instruments are commonly used as reference values to calibrate pressure sensors. Although this method can yield relatively accurate calibration reference values, it is often very time-consuming—especially for e-textile devices that are equipped with a large number of pressure sensors. The calibration issue poses a significant obstacle to the practical application of e-textile devices configured with such sensors. The equipment and time demands of traditional calibration methods make practical implementation challenging for commercialization.

In recent years, a series of novel calibration methods for piezoresistive sensors have been proposed. These methods, based on machine learning models [10], [11] and algorithms [12], [13] or on optimizations to the sensor structure itself [14], have achieved enhancements in calibration performance. Unfortunately, these efforts primarily focus on optimizing sensor accuracy in laboratory environments, rather than addressing practical needs: achieving a relatively acceptable calibration accuracy within feasible equipment and time costs, thereby facilitating the practical commercial application of e-textile devices equipped with these sensors.

In this paper, we tested the resistance-pressure characteristic curves of piezoresistive pressure sensors within their specified range. We found that these sensors exhibit a well-defined functional relationship $R = kF^{\alpha}$ within an appropriate pressure range. Consequently, the parameters of the equation $\log R = \alpha \log F + \log k$ can be determined using the two-point regression method, allowing the characteristic function of the sensor to be derived using only two pairs of resistance-pressure values. This article employs measurements from pressure gauges and resistance testing instruments as benchmarks to compare the relative errors of calibrating 35 pressure sensors using the two-point method versus the all-measurement-point method. The findings confirm that the two-point method with properly selected two resistance-pressure pairs can achieve calibration accuracy comparable to that of the latter.

Inspired by the success of the two-point calibration method, we propose an efficient calibration approach: simplifying the simulation of two specific pressure points using two different weights, while resistance can be measured by deriving the voltage values through a voltage divider circuit in the e-textiles microcontroller. Experimental validation demonstrates that this method achieves a relative error of 14.4%, only marginally higher than the 12.1% of the traditional precise method, while consuming only one-tenth of the time required by the latter. This method enables the efficient calibration of e-textile devices equipped with pressure sensors outside of laboratory settings, representing a significant advancement toward its practical application and commercialization.

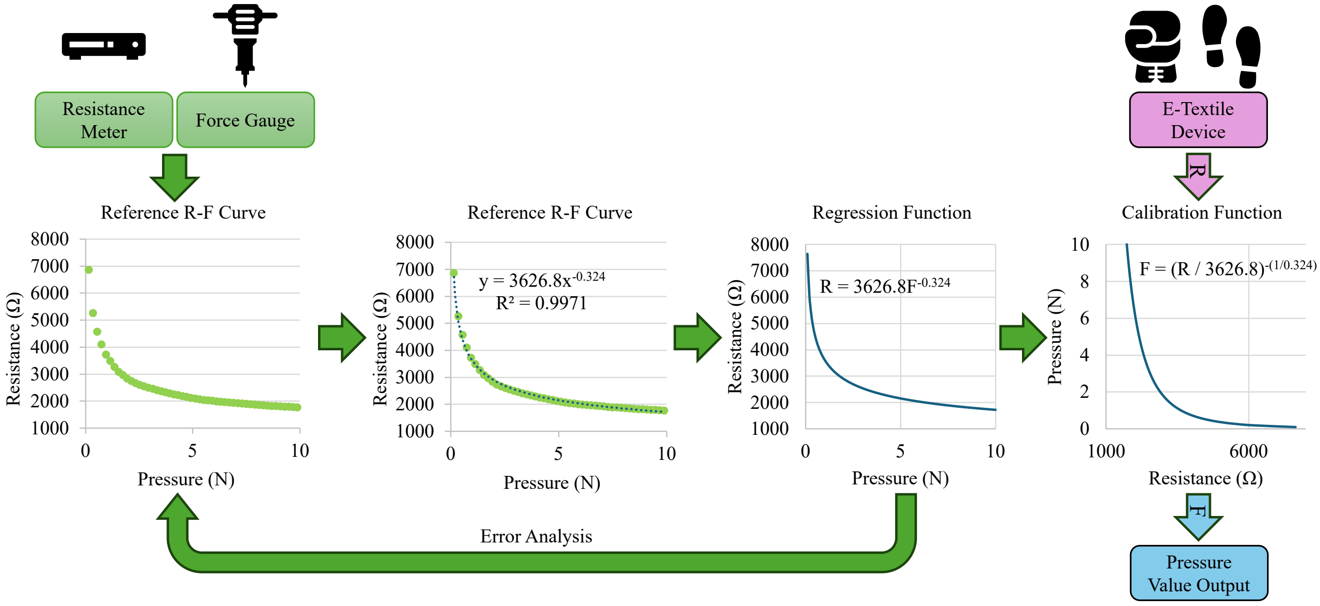


Fig. 1. Workflow Diagram of the Calibration System

II. METHODS

A. Traditional Precise Calibration Method

Traditional calibration methods use resistance-pressure pairs obtained simultaneously from force gauges and resistance meters as reference values. Then, based on the functional relationship exhibited by the resistance-pressure response of the pressure sensors, a calibration function can be derived through regression modeling.

Fig.1 illustrates the workflow of the calibration system. Based on the reference resistance-pressure relationship, an appropriate functional model is selected for regression analysis. The inverse of the regression function is then derived to obtain the calibration function. The calibration function reads resistance values from the e-textile device and outputs the corresponding pressure values.

The accuracy of this calibration method relies on the measurement precision of the pressure and resistance instruments themselves. It also depends on the degree to which the characteristic curve of the pressure sensor conforms to the functional model. The precision of the instruments is generally much higher than that of the pressure sensors, so the calibration accuracy primarily depends on the correct selection of the functional model. Typically, pressure sensors only conform to the functional model within a specific range (known as the linear range), which is determined by factors such as material and manufacturing processes. However, achieving high sensitivity often requires operating outside of this linear range, which represents one of the challenges of pressure sensors. In other words, as long as the specified linear range of the pressure sensor is observed, the functional model can be considered relatively accurate.

We tested three sensors each from the glove and insole, with their R-F curves displayed in Fig.2 and Fig.3. It can be observed that within their operational range (1-10 N), they generally conform well to a power function relationship $R = kF^{\alpha}$, appearing approximately linear in the logarithmic plot.

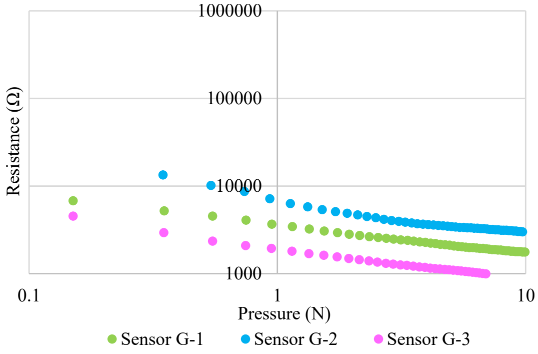


Fig. 2. R-F Curve of 3 Sensors in Data Glove

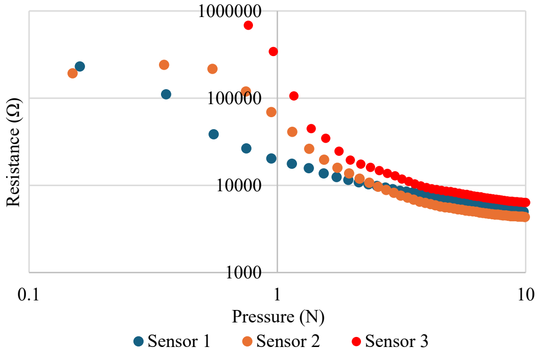


Fig. 3. R-F Curve of 3 Sensors in Insole

For data gloves made of soft, thin fabrics, the pressure sensors experienced minimal interference, resulting in a characteristic curve that exhibited a strong power function relationship over the entire pressure range. In contrast, sensors embedded in the insoles often exhibited deviations at lower pressure levels. By taking the logarithm and applying linear regression, we can achieve good regression results by selecting two suitable resistance-pressure pairs and avoiding significantly deviating low-pressure regions.

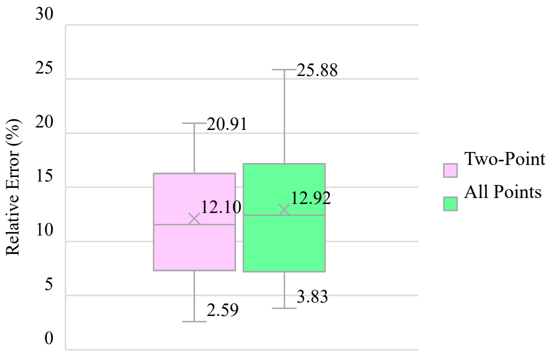


Fig. 4. Error Analysis of Two-Point and All Points Methods

We used an insole integrated with 35 pressure sensors and employed measurements from a pressure gauge and resistance meter as reference standards. From these measurements, we selected two resistance-pressure pairs at pressure values of 5 N and 10 N for linear regression. We then compared this approach with the method using regression across all measurement points. The results in Fig.4 show that using two appropriately selected resistance-pressure pairs for regression can achieve performance comparable to that of using all points for regression, while avoiding deviations in low-pressure regions that could introduce additional errors.

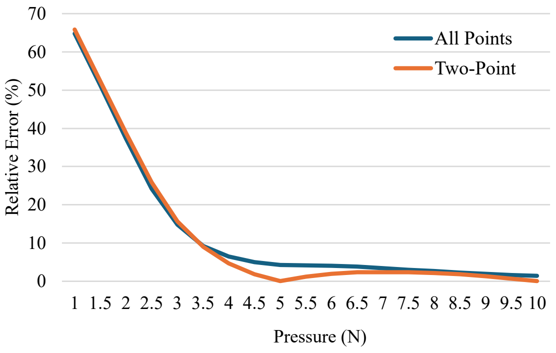


Fig. 5. Variation of Mean Relative Error with Pressure

Further analysis of the variation in relative error with pressure in Fig.5 reveals that errors are concentrated in the low-pressure region—where the calibration function does not hold—while performance in the linear region is excellent.

B. *Feasibility of the Two-Point Calibration Method*

In this study, the two-point calibration method was adopted primarily for its practicality and ease of implementation in real-world applications, rather than to achieve the highest possible calibration accuracy. This approach significantly reduces the time and effort required for calibration, which is crucial in practical settings. As long as the additional error introduced by the two-point calibration remains within acceptable limits relative to the time saved, and does not substantially impair the usability or reliability of the data, this method is considered acceptable.

We acknowledge that the drift in the sensor's response curve involves various nonlinear effects, particularly after applying a logarithmic transformation to the resistance-force (R-F) relationship. This complexity explains why a simple linear model with only two parameters may not fully capture the sensor's behavior. However, experimental results have demonstrated that, within the pressure range commonly used in E-textile devices, the responses of many different sensors can be effectively approximated by linear regression. Moreover, the linear operating range of these sensors has not exhibited significant degradation with continued use. Ongoing long-term tracking experiments are being conducted to further substantiate these findings.

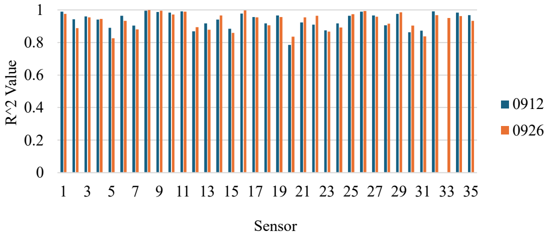


Fig. 6. R^2 Values of Sensors

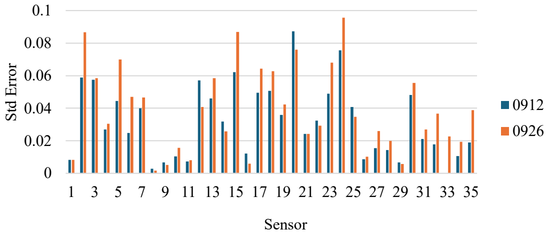


Fig. 7. Std Error Values of Sensors

We conducted experiments over two separate days to evaluate the linear regression coefficients of determination (R^2) and standard errors of 35 sensors within the 1–10 N range (excluding the data for sensor P33 on September 12 due to anomalies) in Fig. 6 and Fig. 7.

C. *Efficient Weight-Based Calibration Method*

Observing Fig.3 and Fig.8, we observe that even for the same sensor, the characteristic curve can shift over time due to aging. Consequently, piezoresistive sensors require frequent calibration. In our laboratory, calibrating each pressure sensor using the method described in the previous section typically takes 3-5 minutes. This means that an insole equipped with 35 sensors would require approximately two hours; a pair of insoles would take four to five hours. If insoles of various sizes are needed for the experiment, this time requirement would further double—leading to an unacceptable time cost, which is impractical even within a laboratory setting.

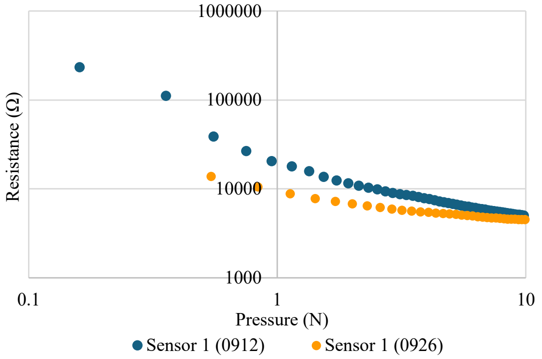


Fig. 8. R-F Curve of Sensor 1 in Different Calibration Date

The success of the two-point regression method has inspired us. We can use weights to replace specific pressure points, and the resistance is measured via the onboard voltage divider circuit of the microcontroller. This method significantly simplifies the calibration process.

We used common 500g and 1kg weights along with a plastic base (bottom diameter 16mm, the same size as the force gauge probe) to simulate the 5 N and 10 N pressures generated by the force gauge. During calibration, the weights only need to be placed on each sensor for a few seconds, allowing the calibration of all 35 sensors to be completed in a matter of minutes.

Fig. 9. 500g weight and plastic base

III. SYSTEM DESIGN

A. E-Textile Insole Design

We use Adafruit VELOSTAT piezoresistive material as the raw material for our pressure sensors. This material is a film made from a polymer (polyolefin) containing carbon black. It exhibits a decrease in resistance when subjected to pressure and conforms well to a functional relationship within a certain pressure range. Its characteristics include being cost-effective and providing sufficient accuracy for e-textile devices, though its accuracy depends on proper calibration. Its properties are listed in Table I.

TABLE I
SPECIFICATIONS OF ADAFRUIT VELOSTAT PRESSURE SENSOR

Specifications	Value
Price	\$4.95
Size	280 mm × 280 mm × 0.2 mm
Temperature Limits	$-45°$C to $65°$C
Volume Resistivity	$< 500\ \Omega \cdot \mathrm{cm}$
Surface Resistivity	$< 31000\ \Omega/\mathrm{cm}^2$
Linear Pressure Range	$1 - 10$ N
Resistance Range (1-10 N)	$1 - 10$ kΩ

We utilize a Brother PR1X sewing machine to stitch together the circuit and VELOSTAT material onto the insole, which is designed using sewing software with predefined outlines, circuit paths, and sensor locations. The GPIO pins of the microcontroller (ESP32) are connected to all row and column wires on the e-textile via designated pins reserved on the insole. Each pair of row and column wires uniquely identifies a pressure sensor, and the resistance between them represents the resistance of that sensor. The schematic of the fabrication process is shown in Fig.10.

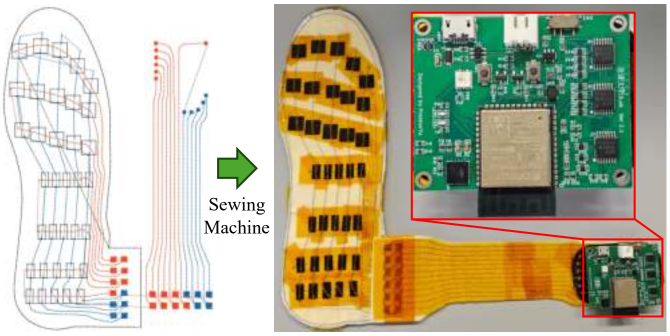


Fig. 10. Fabrication Process of an Insole (Equipped an ESP32 Microcontroller)

B. Hardware Design

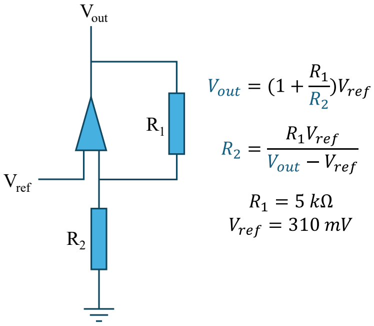


Fig. 11. Voltage Divider Circuit

We designed a voltage divider circuit on the PCB where the ESP32 microcontroller is located, as shown in Fig.11.

In this circuit, R_1 is the voltage divider resistor, R_2 is the resistance of the sensor under test, and a reference voltage V_{ref} is provided. According to the Resistance Range in Table.I, the range for R_2 is 1-10 $k\Omega$. Therefore, selecting a 5 $k\Omega$ voltage divider resistor R_1 is appropriate. The microcontroller reads the output voltage V_{out} from the circuit. By using the microcontroller, it is possible to measure the resistance of all sensors simultaneously at a high frequency (up to 100 Hz), obtaining pressure data with high temporal resolution.

C. Algorithm Design

1) Weight Activation Value Detection: We employ a simple peak-detection and window-smoothing method to identify readings when weights are placed on different sensors. This procedure preprocesses pressure data using a simple moving average filter to smooth the raw signal and eliminate noise. It then detects sensor activation upon weight placement by setting a threshold and identifying pressure activation regions based on duration. The threshold constraint is designed to prevent interference between closely spaced sensors, while the duration constraint helps avoid accidental activation of non-target sensors during the experiment.

Due to the potential for random errors from manual placement of weights, repeating the experiments can enhance accuracy. We conducted one to five repetitions of the weight calibration method on a sensor located in a corner of the insole (where it is difficult to stabilize the weight) and analyzed the relationship between the relative error and the number of repetitions of the experiment. We found that three repetitions effectively improved precision, achieving a balance between time required and accuracy, as shown in Table II.

TABLE II
TESTING FOR RELATIVE ERROR WITH REPEAT TIMES

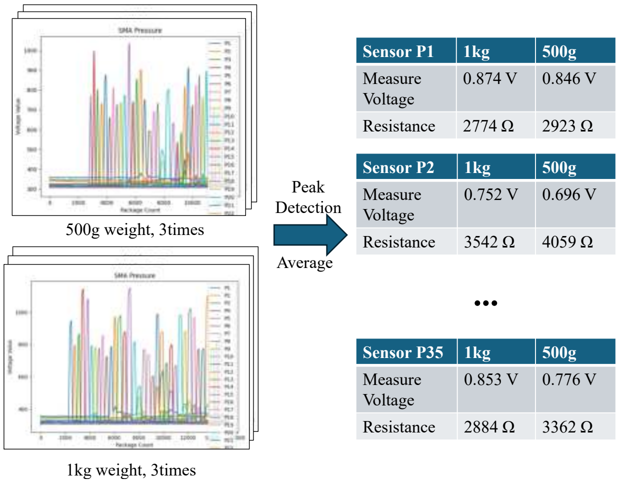
Method	Weight (Repeat Times)					Two-Point
	1	2	3	4	5	
Relative Error (%)	14.63	10.15	8.49	8.05	7.41	4.82

The workflow of the entire algorithm is depicted in Fig.12.

2) Regression Algorithm: The principle of the regression algorithm is quite straightforward, based on the sensor following the function $R = kF^{\alpha}$. Taking logarithms, we obtain a linear function $\log R = \alpha \log F + \log k$. For the two-point method, these two points are used directly to determine the line, and the parameters k and α are then solved for. For the all points method, due to significant offsets in the low-pressure area, it is necessary to filter out these outlier values. Fortunately, our LCR meter provides output fluctuations for each measurement point, which we directly use as a basis to filter permissible resistance-pressure points for regression analysis. Experiments have shown that point i satisfying the condition that:

$$\text{Fluc}_i < \min(5 \times \text{Fluc}_{\min}, 100)$$

generally falls within the linear range.



Sensor P1	1kg	500g
Measure Voltage	0.874 V	0.846 V
Resistance	2774 Ω	2923 Ω

Sensor P2	1kg	500g
Measure Voltage	0.752 V	0.696 V
Resistance	3542 Ω	4059 Ω

Sensor P35	1kg	500g
Measure Voltage	0.853 V	0.776 V
Resistance	2884 Ω	3362 Ω

Fig. 12. Weight Activation Value Detection

3) Error Assessment Algorithm: The workflow of the error assessment algorithm is depicted in Fig.13. After deriving the regression function through the regression algorithm, the pressure values from the reference measurements are input as the independent variable into the regression function. The difference between the output of the regression function and the actual resistance values in the reference data is used to calculate the relative error.

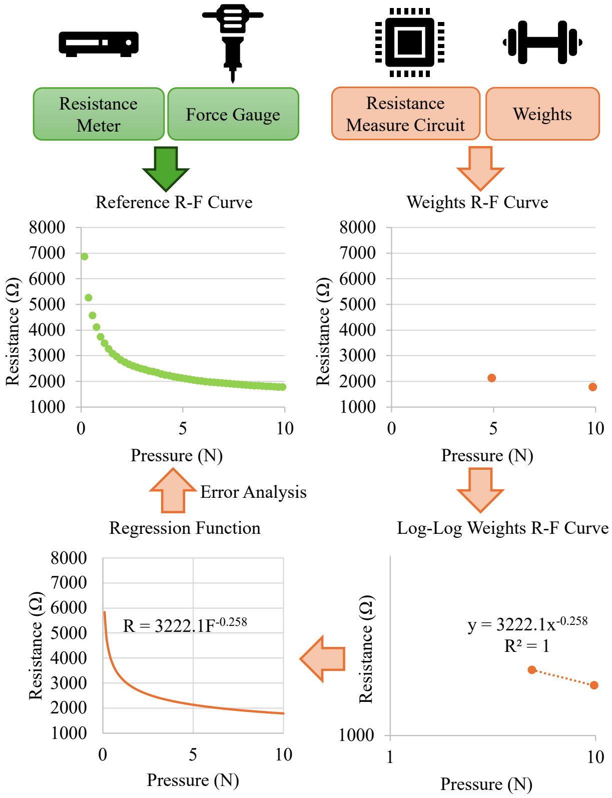


Fig. 13. Error Evaluation Workflow for the Weight Method

IV. EXPERIMENT

A. *Experiment Settings*

In our laboratory, we use an IMADA ZTA-50N pressure gauge to measure pressure and an NF ZM2372 LCR meter to measure resistance, using the resistance-pressure values measured by these instruments as reference values. The test insole is a laboratory-manufactured e-textile insole, incorporating 35 pressure sensors fabricated using Adafruit VELOSTAT piezoresistive material.

This method requires approximately three minutes to calibrate each sensor, and the prolonged repetitive tasks can lead to decreased attention and concentration, thereby increasing the likelihood of errors and further extending the time required. Calibrating all 35 sensors takes about 150 minutes.

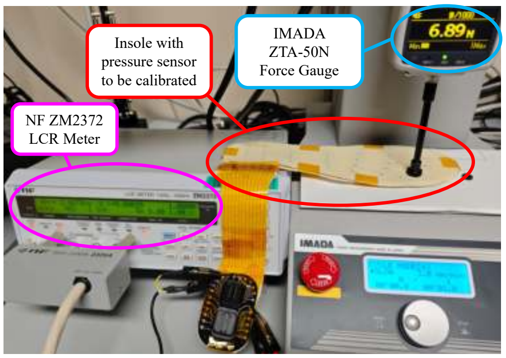


Fig. 14. Measurement Instruments

Subsequently, we use two pairs of resistance-pressure values, measured with two different weights and a microcontroller, as regression parameters for the efficient calibration method. Repeating this procedure for all sensors three times completes the entire calibration process.

B. *Experiment Result*

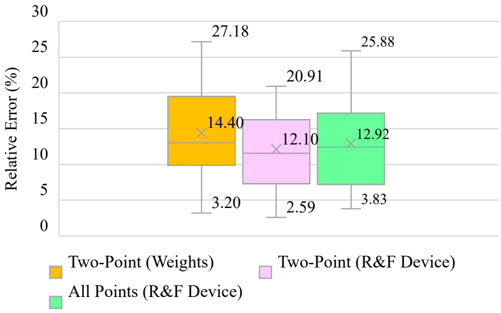


Fig. 15. Relative Error of Different Methods

Using this method, calibrating each sensor takes only about 5 seconds. Even with three repetitions of the experiment, calibrating all 35 sensors takes only about 15 minutes, which is one-tenth the time required by the precise method. The results shown in Fig.15 illustrate that using the efficient method with weights increases the average relative error by only 2.3%, while saving 90% of the time.

V. CONCLUSION

In this study, we developed and validated an efficient calibration method for piezoresistive pressure sensors integrated into e-textiles. The new method dramatically reduces calibration time to just 15 minutes for 35 sensors, compared to over two hours required by traditional precise methods, while maintaining a reliable average relative error of 14.4%, only marginally higher than the 12.1% of the traditional precise method. Such efficiency, coupled with satisfactory accuracy, represents a significant improvement in the field of pressure sensor calibration, particularly for practical applications requiring frequent calibrations. The practical implications of this research are profound, enabling the deployment of pressure sensor equipped e-textile technologies in real-world applications beyond the confines of laboratory environments.

REFERENCES

[1] T. Xu, H. Wang, Y. Xia, Z. Zhao, M. Huang, J. Wang, L. Zhao, Y. Zhao, and Z. Jiang, "Piezoresistive pressure sensor with high sensitivity for medical application using peninsula-island structure," *Frontiers of Mechanical Engineering*, vol. 12, pp. 546–553, 2017.

[2] K. Kang, J. Park, K. Kim, and K. J. Yu, "Recent developments of emerging inorganic, metal and carbon-based nanomaterials for pressure sensors and their healthcare monitoring applications," *Nano Research*, vol. 14, no. 9, pp. 3096–3111, 2021.

[3] W. Li, W. Lu, X. Sha, H. Xing, J. Lou, H. Sun, and Y. Zhao, "Wearable gait recognition systems based on mems pressure and inertial sensors: A review," *IEEE sensors journal*, vol. 22, no. 2, pp. 1092–1104, 2021.

[4] L. M. Castano and A. B. Flatau, "Smart fabric sensors and e-textile technologies: a review," *Smart Materials and structures*, vol. 23, no. 5, p. 053001, 2014.

[5] M. Stoppa and A. Chiolerio, "Wearable electronics and smart textiles: A critical review," *sensors*, vol. 14, no. 7, pp. 11 957–11 992, 2014.

[6] M. J. Saikia, "Smart fabric and e-textile sensor technology for wearables to measure high pressure," *IEEE Transactions on Instrumentation and Measurement*, 2023.

[7] S. Suprapto, A. Setiawan, H. Zakaria, W. Adiprawita, and B. Supartono, "Low-cost pressure sensor matrix using velostat," in *2017 5th International Conference on Instrumentation, Communications, Information Technology, and Biomedical Engineering (ICICI-BME)*. IEEE, 2017, pp. 137–140.

[8] A. Dzedzickis, E. Sutinys, V. Bucinskas, U. Samukaite-Bubniene, B. Jakstys, A. Ramanavicius, and I. Morkvenaite-Vilkonciene, "Polyethylene-carbon composite (velostat®) based tactile sensor," *Polymers*, vol. 12, no. 12, p. 2905, 2020.

[9] M. Hopkins, R. Vaidyanathan, and A. H. Mcgregor, "Examination of the performance characteristics of velostat as an in-socket pressure sensor," *IEEE Sensors Journal*, vol. 20, no. 13, pp. 6992–7000, 2020.

[10] A. M. Almassri, W. Z. Wan Hasan, S. A. Ahmad, S. Shafie, C. Wada, and K. Horio, "Self-calibration algorithm for a pressure sensor with a real-time approach based on an artificial neural network," *Sensors*, vol. 18, no. 8, p. 2561, 2018.

[11] A. Antonini, S. Melani, A. Mazza, L. Baldini, E. Adirosi, and A. Ortolani, "Development and calibration of a low-cost, piezoelectric rainfall sensor through machine learning," *Sensors*, vol. 22, no. 17, p. 6638, 2022.

[12] Z. Wang, Q. Li, Z. Wang, and H. Yan, "Novel method for processing the dynamic calibration signal of pressure sensor," *Sensors*, vol. 15, no. 7, pp. 17 748–17 766, 2015.

[13] J. Yu, F. Li, Y. Gao, and Y. Jiang, "Optimization of linearity of piezoresistive pressure sensor based on pade approximation," *Sensors and Actuators A: Physical*, vol. 364, p. 114845, 2023.

[14] Z. Yao, Y. Li, Y. Ding, C. Wang, L. Yao, and J. Song, "Improved shock tube method for dynamic calibration of the sensitivity characteristic of piezoresistive pressure sensors," *Measurement*, vol. 196, p. 111271, 2022.