Compressing Multiple Sensor Signals for Distributed Sensing by Autoencoder Preprocessing

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***Abstract*—This paper proposes an autoencoder-based approach to effectively extract sensor features by leveraging an autoencoder as a data preprocessing method. The autoencoder constrains the hidden units in a bottleneck structure, resulting in a compressed knowledge representation of sensor readings. In the latent space representation, the encoded data learns and describes the most prominent latent attributes of sensor readings. The algorithm is experimentally validated in a real-world setting, demonstrating its effectiveness in accurately extracting relevant features from sensor data. Nine flexible bending sensors are utilized for posture sensing of a bellow-shaped fluidic elastomer actuator. Compared to previous studies, the results demonstrate that valuable features can be extracted without employing a large dropout rate for overfitting prevention, while maintaining prediction accuracy and reducing the entire sensor signals to half. Additionally, the training time is reduced by 7.2%. By providing a reduced and featured input to the regression neural network, the proposed approach not only prevents overfitting but also alleviates the computational redundancy and complexity brought by an increasing number of sensors.**

***Index Terms*—autoencoder, flexible sensor, distributed sensing, soft robotics, deep learning**

I. Introduction

The advancement of soft sensors has attracted great attention in the field of soft robotics. Due to their natural compliance and compactness, soft sensors exhibit unique potential in on-board sensing for soft body posture acquisition, as well as various applications in proprioception and exteroception [1]–[5]. While typical and traditional perception methodologies, including optical tracking [6], [7], magnetic tracking [8], and IMUs [9], have been proven reliable, however, they suffer from limited portability and rigidity. In terms of compactness, soft sensors, such as resistive and piezoresistive sensors [1], [4], [5], [10], [11], can be customized with respect to scale, position, and function.

The use of compliant materials in soft sensors can result in high non-linearity, hysteresis, and drift problems [12]. To address these issues, researchers have proposed calibration approaches, particularly data-driven techniques. To overcome the issue of high non-linearity and hysteresis, long short-term memory (LSTM) neural networks have been utilized as a solution to the regression problem [12]. Moreover, to enhance the calibration ability against sensor signal long-term drift, optimal transportation transfer learning through domain adaptation has been implemented for bias correction with superior efficacy [13].

The calibration of soft sensors has seen the successful adoption of numerous approaches to solve specific tasks or deal with characteristics in a single sensor. However, with the increasing number of sensors, such as in distributed sensing methods [1], [7], a new challenge arises. As is fundamental to learning approaches, it usually requires a large amount of data and time to train a single accurate and robust neural network. Given that each sensor contributes partial posture sensing information, the entire input dataset fed to a calibration neural network can become cumbersome, significantly impeding the prediction result for testing due to the overfitting problem. In a previous study [1], researchers employed a dropout layer with a large dropout rate of 0.5 to address this issue. However, such a large hyperparameter value could potentially cause the loss of crucial information for regression. Alternatively, a more intuitive way to solve this problem is to compress multiple sensor readings and extract valuable knowledge representation, which can be achieved through techniques such as autoencoders as depicted in Fig. 1.

The autoencoder is an unsupervised learning model that is trained to recreate its output to its input [14]. It is capable of condensing inputs into a smaller number of encoded data

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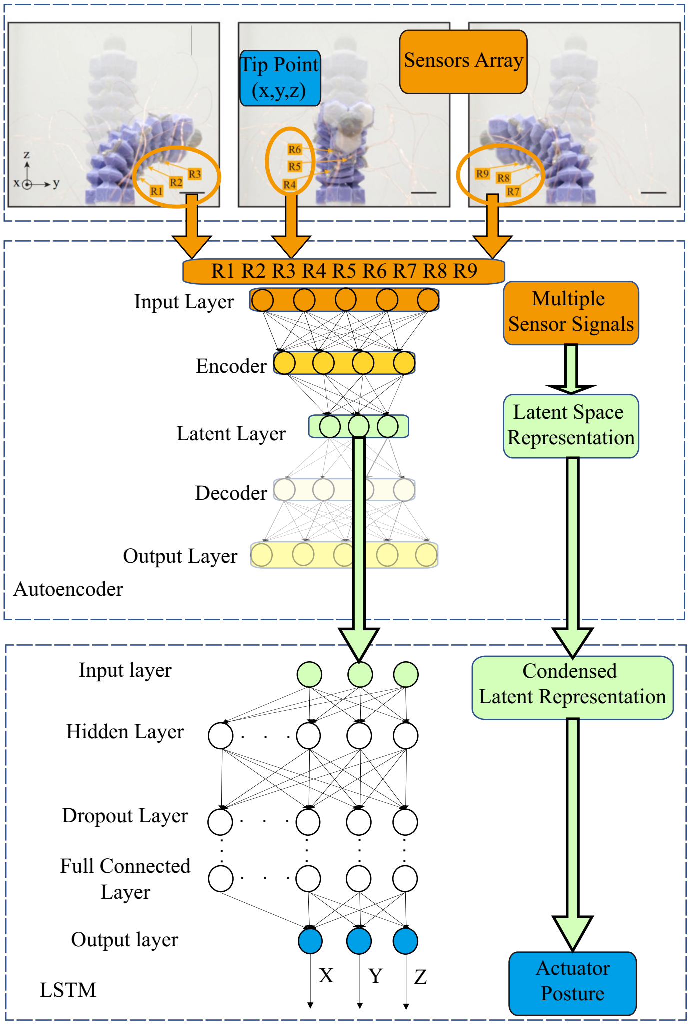

Fig. 1. Neural Network Architecture. The key component is a data compressing autoencoder. The sensor pictures are adopted from [1].

through latent space representation, thereby extracting hidden and useful information [15]. Inspired by its success in digital image processing and pattern recognition, this characteristic can be adopted to extract and compress readings collected from multiple sensors without losing features. In combination with conventional recurrent neural networks, such as the LSTM neural network, the proposed data preprocessing method can be used to extract valuable and condensed expressions from increasing numbers of sensors, thereby reducing learning complexity and eliminating the need for additional hyperparameters to prevent overfitting.

This paper presents a novel method to condense multiple sensor readings by leveraging an autoencoder to extract valuable and representative expressions through latent space representation. The learned information is then fed to a conventional LSTM neural network for regression. The algorithm is experimentally validated in a real-world distributed sensing application, where nine flexible bending sensors are utilized to sense the posture of a bellow-shaped fluidic elastomer actuator. The proposed approach provides a data preprocessing technique for compressing multiple sensor signals, alleviating computational redundancy and complexity brought by an increasing number of sensors.

II. Algorithm

A. Compressing Multiple Sensor Readings Using Autoencoder

With the increasing number of soft sensors, training and predicting the calibration neural network can be cumbersome and tends to overfit the training datasets. To deal with numerous sensor signals properly, a compression technique that does not lose valuable information can be adopted to condense and extract multiple sensor readings into fewer latent representations for further applications, such as regression and classification tasks. The autoencoder is an unsupervised learning model with replication capability that can learn and extract the input to the latent space representation in the encoder. Following the philosophy of this algorithm, we leverage the autoencoder to compress multiple sensor measurements in the form of latent space representation through the encoder. After data preprocessing, the encoded data is then fed into the regression or classification neural network.

B. Neural Network Structure

As demonstrated in Fig. 1, the neural network structure consists of a data compressing autoencoder and an LSTM regression neural network. The autoencoder has two main components: the encoder and decoder. The encoder constrains the input through limited hidden units in the hidden layer, and the decoder does the reverse to recreate the input, establishing a mirrored bottleneck configuration. The LSTM neural network has a full structure consisting of an input layer, a hidden layer, a dropout layer, a fully connected layer, and an output layer.

To validate the autoencoder's feature extraction ability, we condensed original 9 sensor reading to various hidden representations [1, 3, 5, 7] as compressed input of the following LSTM neural network, and compared with an optimal neural network that used the full original sensor signals as a reference [1]. The LSTM neural network's training and testing settings were similar to the structure in [1]: one hidden layer with 100 hidden units. Notably, the reference neural network utilized a dropout layer following the hidden layer with a large dropout rate of 0.5 to prevent overfitting. The training was early stopped with a patience of 100 steps, and the overall root mean square error (RMSE) was utilized as the cost function for performance evaluation. The whole neural network was established based on the MATLAB Deep Learning Toolbox.

III. Experiment Validation

A. Sensor Design and Fabrication

As shown in Fig. 2, a vacuum-powered bellow-shaped fluidic elastomer actuator (FEA) with flexible bending sensors was utilized as a real-world distributed sensing method validation, following previous work [1]. The flexible bending sensors were made of PU conductive sponge material (Beilong Inc.,

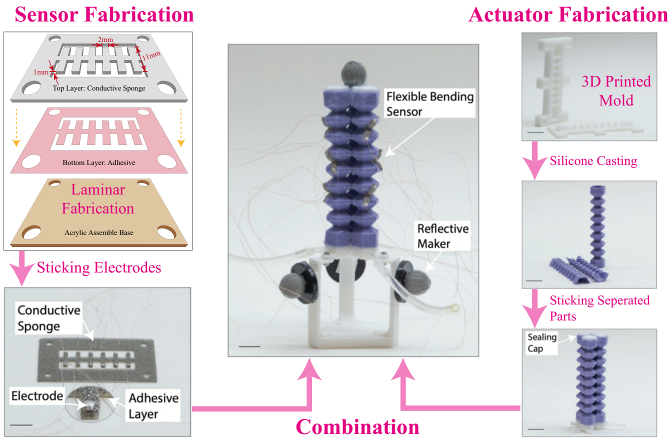

Fig. 2. The fabrication of vacuum-powered bellow-shaped fluidic elastomer actuators with flexible bending sensors. The figures are adopted from [1].

Wujiang, China) and were mass-produced using planar fabrication. The first and second layers were laser-cut with a designed pattern, and the bottom layer was adhesive (300LSE, 3M, Saint Paul, MI, USA). Using silver conductive adhesives (3703, Sinwei, Shanghai, China), the sensors were implemented by attaching two copper electrodes with leading wires to their two ends. To ensure adequate attachment between electrodes and sensors, they were left at room temperature for 12 hours, then trimmed to the desired shape before bonding to the FEA. The FEA body was casting-made using silicone material (Smooth-Sil 945, Smooth-On Inc., East Texas, PA, USA), consisting of three hexagonal bellow-shaped chambers connected in parallel using silicone adhesive (Sil-Poxy, Smooth-On Inc., USA). Each chamber was assembled by bonding two half-chambers with sealing caps. To fit the current FEA design and guarantee accuracy, a total of nine sensors were adopted, with three sensors in an array in each chamber

B. Experimental Setup

To validate the performance of the sensor data compressing technique, posture acquisition was conducted with respect to the random movement of the bellow-shaped FEA. Instead of directly controlling the FEA's posture, the FEA was vacuum-powered with varying pressure within a range of 0 to -70 kPa for each actuation chamber at a 25 Hz rate. The whole process was powered by a vacuum pump, regulated by three proportional valves (ITV2090-212L, SMC Corporation, Tokyo, Japan), and controlled by a micro-controller (Portenta H7, Arduino, Ivrea, Italy). For resistance measurement, each sensor was connected in series with a 20Ω resistor and 0.5V supplying voltage to form a voltage divider circuit and recorded using a daq device at 1000 Hz (USB-6212, National Instrument, Austin, USA). For posture measurement, a Vicon motion capture system (Bonita 10, Vicon Inc., Yarnton, UK) with nine distributed cameras was utilized. It captures the coordinates of reflective markers at a frequency of 100 Hz, with one marker at the top and three markers at the fixed pedestal. To match the frequency of the motion capture system and sensor measurement, a downsampled frequency of 100 Hz was applied, followed by a low-pass filter of 20 Hz.

As LSTM neural network requires large amount of data to train a reliable model [12], the whole process was running for 20 mins and to generate and collect sufficient training (10 mins) and testing datasets (400 s).

TABLE I
SENSOR SIGNALS COMPRESSING PERFORMANCE

No. Condensed Signals	xRMSE (mm)	yRMSE (mm)	zRMSE (mm)
1	13.01	18.61	12.74
3	10.55	11.31	7.37
5	10.27	7.67	4.64
7	7.56	6.96	5.06
9 (Original Signals)	7.37	6.35	3.70

IV. RESULTS AND DISCUSSION

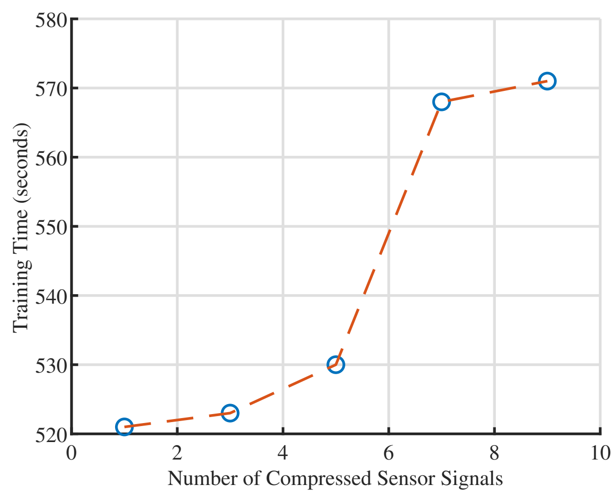

Fig. 3. The training computation time. The scatter plot shows the training computation time for the neural network corresponding to different numbers of compressed sensor signals, represented by blue data points

The training results in terms of training time against the number of compressed sensor signals are depicted in Fig. 3. The training time drops dramatically with a number of condensed signals less than 7 and reaches a plateau when the number is below half of the total number of sensor signals, exhibiting an approximately 7.2% reduction in computation time. As demonstrated in Fig. 4 and listed in Table I, the mean, standard deviation, and RMSE error in each axis increase with a decrease in the number of condensed signals. It is obvious in the error of the y and z axis that the error tends to be significant if the number of compressed signals after autoencoder preprocessing is less than half of the total number. A more detailed illustration of the testing result is shown in Fig. 5. The output displacement in the extreme compressing condition (condensed to 1 sensor signal) in all axes is flattened due to the overabstraction of the original sensor readings. With

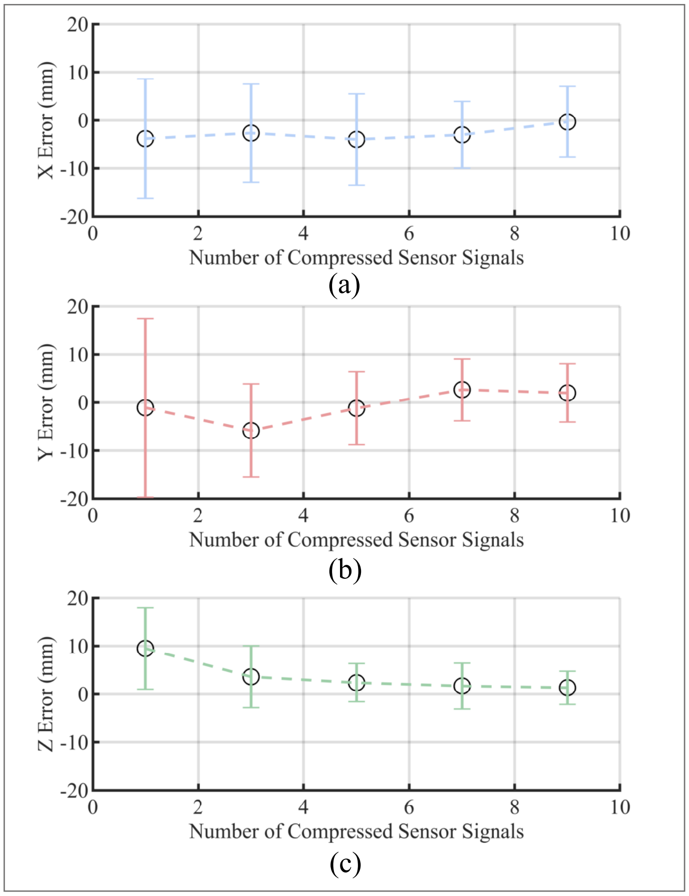

Fig. 4. The Error plot of coordinate axes. Panel (a), (b), and (c) show the error plot of each axis (x, y, z). The black scatter points represent the mean error, while the error bars in pastel colors (blue for x-axis, red for y-axis, and green for z-axis) represent the standard deviation.

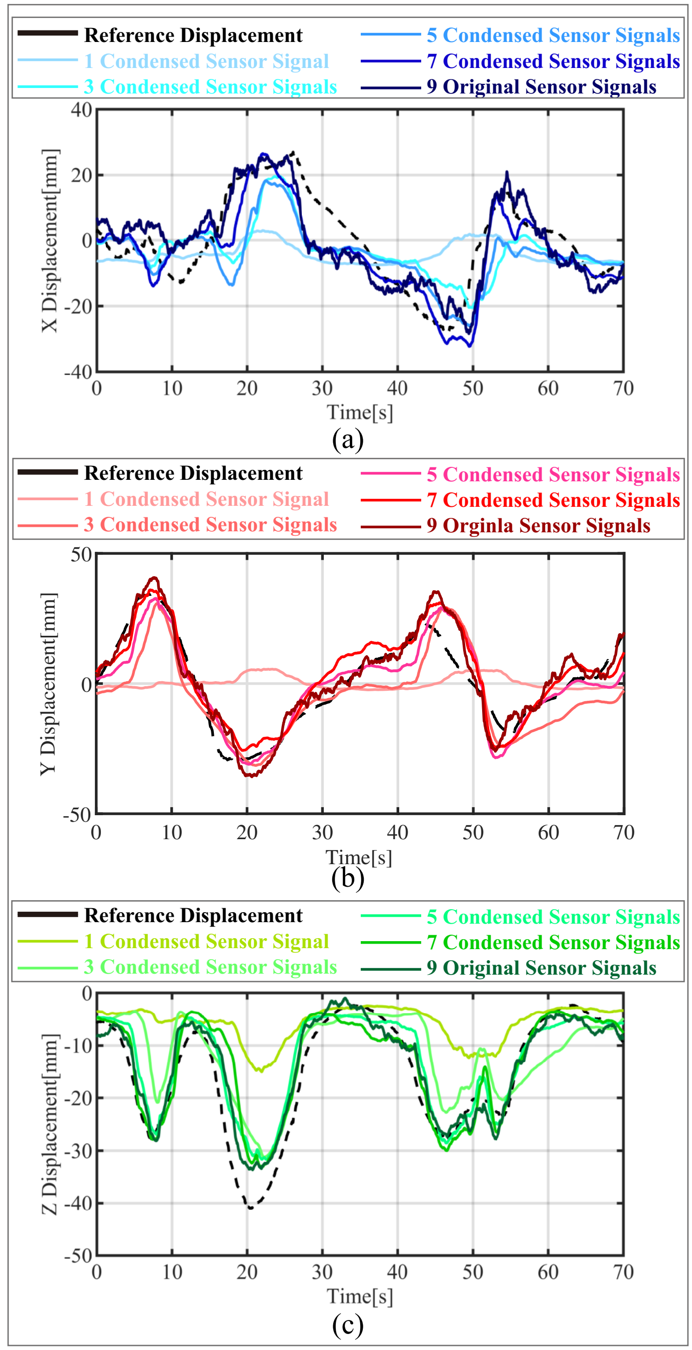

Fig. 5. Testing results on random actuator motions. The testing results on random actuator motions are shown in Panel (a), (b), and (c), displaying the displacement over time of each axis (x, y, z). The black line represents the ground truth as reference displacement, while the lines in graduated colors (blue for x-axis, red for y-axis, and green for z-axis) represent the compressed sensor signals

more than half of the complete sensor arrays compressed, it shows similar performance compared to the entire original sensor signals. According to the overall performance, data compressing with condensation of half the quantity in the autoencoder latent representation to the original input signals captures valuable information for the following regression task without the need for overfitting prevention tricks and reaches an optimal point between training time and error evaluation.

V. Conclusion

In this paper, a novel approach for compressing sensor data is presented, which utilizes an autoencoder to condense and extract multiple sensor readings into latent representation. To evaluate the performance and effectiveness of this approach, a vacuum-powered bellow-shaped FEA with nine distributed flexible bending sensors was utilized to collect sensing data in random movement. The results show that valuable features can be extracted without the need for a large dropout rate for overfitting prevention while maintaining prediction accuracy and reducing the entire sensor signals to half, which is an improvement over previous studies. Moreover, the training time is reduced by 7.2%. By providing a reduced and featured input to the regression neural network, the proposed approach not only prevents overfitting but also reduces computational redundancy and complexity caused by an increasing number of sensors.

Constrained by the dimensions and configuration of the current FEA body, the number of sensors within a chamber is currently limited to three. However, there is potential to expand this number in order to validate the effectiveness of the proposed pre-processing algorithm on a larger scale. Additionally, future research could explore the inclusion of diverse sensor types, such as force sensors, to cater to the broader sensing demands associated with real-world robot operations.

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