Exploration of Lossy Posture Classification Model using in-Bed Flexible Pressure Sensors

Aekyeung Moon
ETRI
akmoon@etri.re.kr

Seung Woo Son
UMass Lowell
seungwoo_son@uml.edu

Minjun Kim
ETRI
minjunkim@etri.re.kr

Seyun Chang
MiDAS H&T, inc.
seyun@midashnt.com

Hyeji Park
MiDAS H&T, inc.
hyeji@midashnt.com

***Abstract*—Advances in flexible and printable sensor technologies have made it possible to use posture classification for providing timely services in digital healthcare, especially for bedsores or decubitus ulcers. However, managing a large amount of sensor data and ensuring accurate predictions can be challenging. While lossy compressors can reduce data volume, it is still unclear whether this would lead to losing important information and affect downstream application performance. In this paper, we propose LCDNN (Lossy Compression using Deep Neural Network) to reduce the size of sensor data and evaluate the performance of posture classification models. Our sensors, placed under hospital beds, have a thickness of just 0.4mm and collect pressure data from 28 sensors (7 by 4) at an 8 Hz cycle, categorizing postures into 4 types from 5 patients. Our evaluation, which includes reduced datasets by LCDNN, demonstrates that the results are promising.**

***Index Terms*—Flexible and Printable Sensor, Posture Monitoring, IoT Monitoring, Pressure Sensor, Classification**

I. Introduction

In digital healthcare, effectively exploiting actionable knowledge extracted from a steady stream of sensor data can offer helpful information for timely services. For example, in the case of patients with dementia or critically ill patients who have difficulty moving on their own, there is a high possibility of severe health disease, bedsores, or decubitus ulcers, caused by remaining in a long time in the same posture. Pressure ulcers or bedsores due to a lack or less changing posture could result in a partial or complete blood flow obstruction in soft tissue, leading to damage in the skin or underlying tissue [5]. Preventing these health diseases requires a change periodically in the patient's posture by the nursing staff or others. The predictive alarm using adequately captured patient posture data can enable more efficient proactive steps. However, the growing demand for recording pressure signals to improve the effectiveness of preventing serious health diseases such as bedsores is contributing large amounts of sensor datasets, which is cost prohibitive.

This study demonstrates the feasibility of using a few pressure sensors or even small extracted features for patient posture monitoring, suggesting research directions for designing a cost-effective application. Pressure sensors would be ideal candidates for measuring postural information, which indicates identifying a patient's lying posture. However, the volume of sensor signals increased at an unprecedented rate to be practically feasible. Several data-aware lossy compression algorithms have been proposed to overcome such a burden by aiming to meet higher compression ratios with lesser information loss [7], [9].

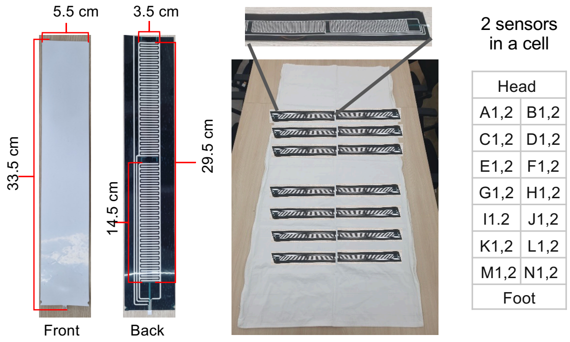
We apply lossy compression to explore the possibility of using a small number of pressure sensors for patient posture classification. The insight of this paper is to develop a lossy model to extract features, namely, the LCDNN (Lossy Compression using Deep Neural Network), which can significantly reduce the amount of data. Since LCDNN would suffer from irreversible information loss, evaluating the tradeoff between volume reduction and information loss is crucial.

In our experiment, we reduce from 28 sensor data to 3 features to obtain an 89.3% reduction ratio. We then apply four different supervised machine-learning techniques to recognize the postures of each patient and evaluate their prediction performance. Our results show that the optimized RF (random forest) classifier outperforms the other classifiers with an average classification accuracy of 96.29% and 95% in the case of data reduction by LCDNN and the heuristic-selected sensors, respectively.

II. Related Works

Matar et al. [5] estimated the posture using body pressure distribution images of 4 postures (supine, left, right, and prone). In [11], they used two pressure mats made by XSENSOR technology corporation with a resolution of 42 by 44. They showed that the random forest (RF) outperformed others like support vector machine (SVM) and multilayer perceptron (MLP) [12]. The automatic classification of position and the duration of the position for the lying patient on the bed is essential. Several studies proposed a monitoring system for recognizing and correcting the importance of sitting posture using these pressure sensors [2], [3]. Lee et al. [4] presented a method for identifying sleep postures using an intelligent fabric pad with 14 pressure sensors placed on top of a mattress that can detect the pressure distribution of a person's body during sleep. However, the accuracy of the proposed fabric pad depends on the pressure distribution patterns and the person's body shape and height.

This work is supported by the Korea Innovation Foundation (INNOPOLIS) grant funded by the Korean government (MSIT) (2020-DD-UP-0278). This material is also in part based upon work supported by the National Science Foundation under Grant No. 1751143. The Titan X Pascal used for this research was donated by the NVIDIA Corporation.



(a) (b)

Fig. 1: (a) Specification of an individual cell comprising two pressure sensors. (b) The layout of pressure sensors deployed on the test bed.

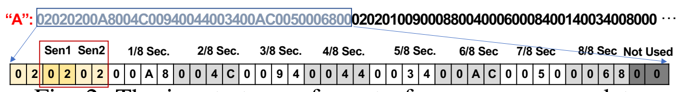


Fig. 2: The input stream format of pressure sensor data.

III. Materials and Methods

A. Data Acquisition

Fig. 1a shows the specification of sensory cells (from A to N) containing two pressure sensors: 33.5 cm in length, 5.5 cm in width, 0.4 mm in thickness, and 10 μs of response time. Due to this thin thickness, it causes minimal or no inconvenience and discomfort to patients or users. We attach 14 cells (7 rows and 4 columns) to a mat and collect data in 00-FF hexadecimal (or 0-255 in decimal) format at 8 Hz (or 8 cycles/second). Fig. 2 shows the data format for the collected data for a 1-second duration from Cell A, which contains 40 data points. Columns labeled Sen 1 and Sen 2 in Fig. 2 are the average values collected at 8 Hz, and we use them as representative values of Cell A. We follow the same method to extract data from Cells B to N.

B. Data Preprocessing

We gather the patient's posture data, corresponding to one of the four predefined postures (supine, left lateral, right lateral, and head elevation), at 2-hour intervals. For instance, the caregivers record their patient's posture every 2 hours, and then the final posture information labeled uses this information. We also impute sensor data since measurement error is inevitable due to potential malfunctioning in communication/network, hardware/sensor, or power/battery [1]. Imputation is, in general, filling missing values with estimated values. Our imputation method performs every three seconds and uses sensor data values around the missing value. We use the average value if the middle cell is missing; otherwise, we use the closest sensor value.

Even though we collect pressure sensor data 8 times per second from our in-Bed sensors, the observed patient's posture information is rare and not synchronized due to the 2-hour intervals of posture. Therefore, to construct data for learning prediction models using the observed data collected at two-hour intervals, we assume that there is no change in posture within 10 minutes from the time of posture recording. Through this process, we construct 17,600 posture learning data and use them as input sensor streams to our posture classification system, as shown in Fig. 3. Fig. 4 shows the characteristics of pressure sensor data, such as max, mean, standard deviation, and 75% values. These characteristics show that values collected at each pressure sensor vary greatly.

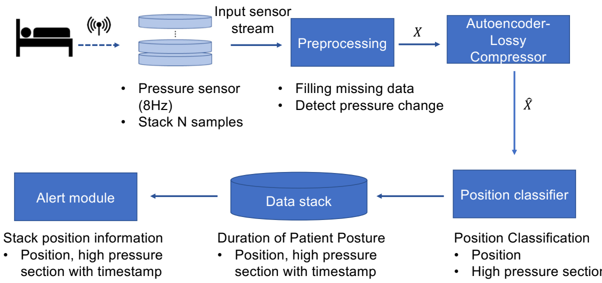


Fig. 3: Overview of the proposed posture classification system.

C. LCDNN Data Compression

In developing IoT applications with posture classification models, ordinary methods using entire pressure sensor data can be wasteful and resource-consuming. Several recent studies demonstrated that errors introduced by lossy compressors could be controlled to meet user-defined bounds [6], [8]. In this paper, we design LCDNN, an approach based on lossy compression adopted by deep learning networks (DNN), especially autoencoders. The autoencoder is a type of DNN that consists of an encoder and a decoder where the encoder modulates input data into a lower-dimensional space. In contrast, the decoder reconstructs the original input from the compressed representation. We first model the encoder and decoder suitable for our pressure sensor and extract the developed encoder module to apply lossy compression. Fig. 5 shows the sequences of LCDNN, which extracts 3 features from 28 sensors (i.e., the original 7 by 4) to reduce the amount of collected data and to classify the posture of lying patients using them. When reconstructing with 3 features, the error (in RMSE) between the original and the reconstructed datasets is 3.53, which is very small and means that the original and the reconstructed ones are almost similar.

D. Design of the Classification Model

After the preprocessing and data reduction through LCDNN, which involves balancing the class distribution of given data, normalization, and missing value analysis, selecting an appropriate classification model is essential since determining a general yet superior algorithm is not feasible. Therefore, we evaluate four representative classification methods: DT (decision tree), RF (random forest), AB (adaptive boosting), and MLP (multi-layer perceptron). These methods prove their superior performances in various real-world applications [10].

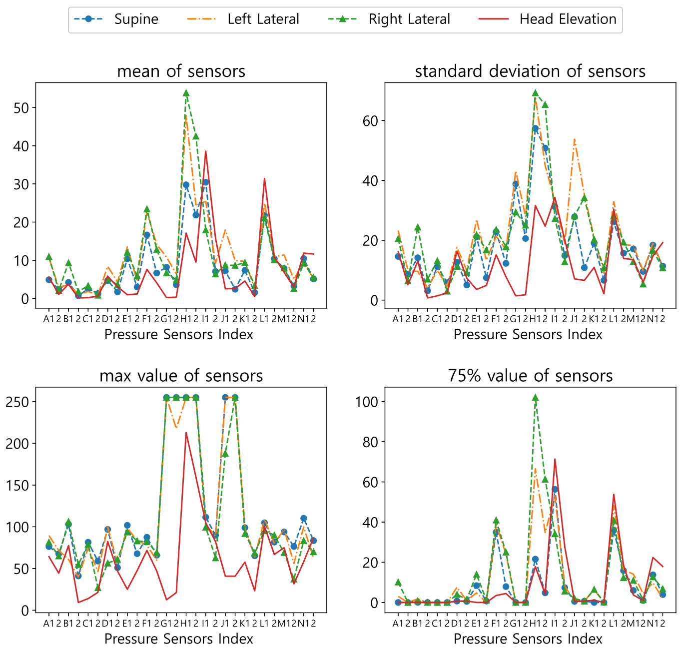


Fig. 4: Characteristics of collected pressure sensor data.

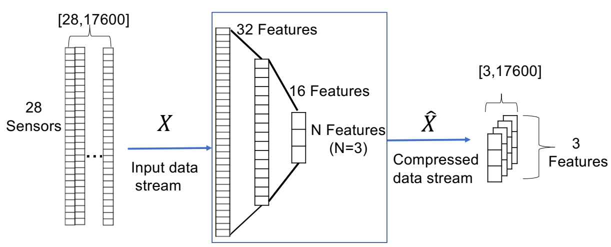


Fig. 5: Our proposed LCDNN architecture.

IV. Evaluations

A. Datasets

In our evaluation, we define three data groups derived from the obtained pressure sensor datasets from patients.

- **Group 1**: The datasets using all 28 sensors (Fig. 1).
- **Group 2**: The heuristically selected five sensors (F2, H2, H3, I2, L2) datasets from Fig. 3 and Fig. 4.
- **Group 3**: The 3 feature datasets extracted by our lossy compression algorithm described in Section III-C.

B. Performance Metrics

The following metrics are measured, primary indicators of how well the proposed scheme performs in prediction performance and data reduction/quality.

- We measure the prediction performance using Accuracy, Precision, Recall, and F1 score.
- We measure the compression performance using Compression Ratio (CR) and Error Rate (ER), which are given by $CR = (1 - \frac{|\hat{X}|}{|X|}) \times 100\%$, $ER = \frac{mean(\sum\sqrt{(X-\hat{X})^2})}{max(X)-min(X)}$, where $|X|$ is the size of X, $|\hat{X}|$ is the reduced size by LCDNN compressor. X and $\hat{X}$ represent the original and reconstructed data, respectively.

TABLE I: Comparison of classification performance.

Data	Group 1				Group 2				Group 3			
	DT	RF	MLP	AB	DT	RF	MLP	AB	DT	RF	MLP	AB
accuracy	0.98	**0.99**	0.97	0.64	**0.95**	**0.95**	0.86	0.79	0.95	**0.96**	0.88	0.74
precision	0.98	**0.99**	0.97	0.65	0.95	**0.96**	0.86	0.81	0.95	**0.96**	0.88	0.75
recall	0.98	**0.99**	0.97	0.63	**0.95**	**0.95**	0.86	0.79	0.95	**0.96**	0.88	0.74
F1-score	0.98	**0.99**	0.97	0.64	**0.95**	**0.95**	0.86	0.79	0.95	**0.96**	0.88	0.73

C. Results

We first evaluate the performance of LCDNN in terms of CR and ER. The experiments showed LCDNN could generate CR of 89.38% and ER of 0.049, indicating that the reconstructed data using a small portion of original data (less than 10%) almost coincides with the original data. We next use machine learning libraries from scikit-learn [10] to validate the performance of our posture classification using the collected pressure datasets. Specifically, we train and evaluate four machine learning algorithms: DT, RF, AB, and MLP. The main hyper-parameters for these classification methods are as follows. DT uses the Gini index to tree split, and AB uses n_estimators=50. MLP uses RELU and Adam for activation and weight optimization, respectively. RF employs parameters of max_features=3 and n_estimators=70. We set 70% of the data for training and the remaining 30% for testing. Also, we select less number of sensors to evaluate the sensor's sensitivity in the case of low resolution. Table I shows the experimental results for the four classification algorithms we tested for three groups: entire sensor datasets (Group 1), the heuristic-selected datasets (Group 2), and 3-features datasets extracted by LCDNN (Group 3). As we can see, RF offers the best performance among all four models in all metrics. Lastly, RF, DT, and MLP outperform AdaBoost in all groups of data sets. That is, the accuracy of RF is improved by 1.5 times that of AdaBoost in the case of Group 1.

V. Conclusion

This paper proposed a posture monitoring system for bedridden patients to prevent bedsores in critically ill patients using a flexible printing pressure sensor. We used a pressure sensor manufactured by a flexible printing process technique to measure the pressure loaded on the body. We collected pressure data at an 8 Hz cycle from a pressure mat composed of 28 (7 rows and 4 columns) pressure sensors and classified postures into four types: supine, left/right lateral postures, and upper body raised posture (head elevation). To understand the influence of posture classification when the sensor resolution deployed in the test bed gets reduced, we designed three data groups, entire sensors, the selected sensor group, and the three featured sensors by our lossy compression. We validated their effectiveness with four classification algorithms. Our results demonstrated that LCDNN could achieve about 89.3% of compression ratios and 96.29 of the prediction performances with Random Forest. Consequently, successful predictions can be made with a small amount of compressed information. In our future work, we plan to further reduce the number of sensors to enable a model to operate in edge nodes with less computation and storage capabilities.

REFERENCES

[1] R. N. Faizin, M. Riasetiawan, and A. Ashari. A Review of Missing Sensor Data Imputation Methods. In *2019 5th International Conference on Science and Technology (ICST)*, volume 1, pages 1–6, 2019.

[2] A. A. Ishaku, A. Tranganidas, S. Matúška, R. Hudec, G. McCutcheon, L. Stankovic, and H. Gleskova. Flexible Force Sensors Embedded in Office Chair for Monitoring of Sitting Postures. In *2019 IEEE International Conference on Flexible and Printable Sensors and Systems (FLEPS)*, pages 1–3, 2019.

[3] H. Kim, H. Park, and J. Oh. Implementation of Real-time Sedentary Posture Correction Cushion Using Capacitive Pressure Sensor Based on Conductive Textile. *Journal of The Korea Society of Computer and Information*, 27(2):153–161, 2022.

[4] S. H. Lee, J.-u. Ahn, and B. M. Lee. Recognition Algorithm for Sleep Postures Using a Smart Fabric Pad with Multiple Pressure Sensors. In *Proceedings of the 2019 11th International Conference on Computer and Automation Engineering*, page 21–26, 2019.

[5] G. Matar, J.-M. Lina, and G. Kaddoum. Artificial Neural Network for in-Bed Posture Classification Using Bed-Sheet Pressure Sensors. *IEEE Journal of Biomedical and Health Informatics*, 24(1):101–110, 2020.

[6] A. Moon, J. Kim, J. Zhang, H. Liu, and S. W. Son. Understanding the impact of lossy compressions on IoT smart farm analytics. In *IEEE International Conference on Big Data (Big Data)*, 2017.

[7] A. Moon, S. W. Son, H. Kim, and M. Kim. Lossy Predictive Models for Accurate Classification Algorithms. In *2022 IEEE International Conference on Big Data (Big Data)*, pages 4576–4582, 2022.

[8] A. Moon, S. W. Son, H. Kim, and M. Kim. Lossy Predictive Models for Accurate Classification Algorithms. In *2022 IEEE International Conference on Big Data (Big Data)*, pages 4576–4582, 2022.

[9] A. Moon, S. Woo Son, J. Jung, and Y. Jeong Song. Understanding Bit-Error Trade-off of Transform-based Lossy Compression on Electrocardiogram Signals. In *2020 IEEE International Conference on Big Data (Big Data)*, pages 3494–3499, 2020.

[10] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, et al. Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, 12(Oct):2825–2830, 2011.

[11] M. Zhao, G. Beurier, H. Wang, and X. Wang. Driver posture monitoring in highly automated vehicles using pressure measurement. *Traffic Injury Prevention*, 22:278 – 283, 2021.

[12] M. Zhao, G. Beurier, H. Wang, and X. Wang. Exploration of Driver Posture Monitoring Using Pressure Sensors with Lower Resolution. *Sensors*, 21(10), 2021.