ECAI 2016
G.A. Kaminka et al. (Eds.)

doi:10.3233/978-1-61499-672-9-1624

Long-Time Sensor Data Analysis for Estimation of Physical Capacity

Yoshikuni Sato and **Yoshihide Sawada** and **Toru Nakada**[1] and **Tadayoshi Nonoyama** and **Masafumi Kubota** and **Yusuke Koie** and **Masaki Yasutake**[2] and **Osamu Yamamura**[3]

Abstract. In this paper, we present a feature learning method for long-time sensor data. Although feature learning methods have been successfully used in many applications, they cannot extract features efficiently when the dimension of training data is quite large. To address this problem, we propose a method to search effective features from long-time sensor data. The important characteristic of our method is that it searches the features based on the gradient of input vectors to minimize the objective function of the learning algorithm. We apply our method to the estimation of physical capacity from wearable sensor data. The experimental results show that our method can estimate leg muscle strength more accurately than conventional methods using a feature learning method and current clinical index.

1 INTRODUCTION

Recently, machine learning has been successfully applied in a wide range of artificial intelligence fields, such as computer vision [5], speech recognition [4], and games [7]. State-of-the-art machine learning methods incorporate feature learning [2]. Such methods can learn classifier features from training data without any heuristics of the target application. These methods are quite effective when the dimension of training data is small. However, they cannot accept large-dimensional raw data such as sensor data measured over a long time. In such case, they need heuristic pre-processing to determine the viewpoint of the long data. This negates the advantage of the methods that they do not need heuristics of the target applications.

To address this problem, we propose a feature learning method for long-time sensor data analysis. Our method searches the effective features from sensor data efficiently by using the gradient of input vector. In this research, we will apply our method to the estimation of physical capacity from wearable sensor data. Evaluating physical capacity has become increasingly important as the demographic trends towards an older population. Our approach will enable easy and highly accurate estimation of the physical capacity of the elderly.

2 RELATED WORK

2.1 Sensor data recognition

There are many studies on activity recognition from wearable sensor data [1]. The conventional methods estimate daily activities, such as walking, standing, and running, from the acceleration and angular velocity measured by wearable sensors. Traditional methods extract statistical features from the sensor data, and predict the activity with more than approximately 80% accuracy. Recently, feature learning methods such as RBM and PCA have been applied to activity recognition [6]. These methods achieved higher accuracy compared to the methods using statistical features. However, the conventional methods are effective for "short time" activity recognition, and a method for the analysis of long-time input data has not yet been proposed.

2.2 Evaluation of Physical Capacity

Evaluation of physical capacity, particularly leg muscle strength, is important for the elderly to prevent them from falls and a bedridden state. Conventionally, leg muscle strength is measured using an isokinetic dynamometer under the supervision of a physical therapist. However, this method requires expensive devices and heavy physical load, and it is therefore not suitable for the elderly. In clinical practice, a 6-minute walk distance (6MWD) [3] is generally used for the evaluation of physical capacity. This method is quite simple but has a drawback in terms of its accuracy. In this paper, we estimate leg muscle strength from wearable sensor data obtained during a 6-minute walk test. Our approach aims at realizing easy and highly accurate estimation of the leg muscle strength, especially for the elderly.

3 METHOD

Figure 1 shows an overview of the proposed method. Our method repeats weight updating in the common training process and feature updating based on the gradient of input vectors.

In the common training phase, where such a method as logistic regression or SVM is used, we minimize the objective function based on the gradient of the weights, $w_j = w_j - \partial f(\boldsymbol{w}, \boldsymbol{x})/\partial w_j$. where $\boldsymbol{x}$ and $\boldsymbol{w}$ are input variables and weights, respectively, and $f(\boldsymbol{w}, \boldsymbol{x})$ denotes an objective function of the learning algorithm.

The characteristic of our method is that it adds the phase of calculating the gradient of input vectors, $\partial f(\boldsymbol{w}, \boldsymbol{x})/\partial x_{ij}$. Certainly, we cannot change the input vector $\boldsymbol{x}$ arbitrarily; thus, we search features to extract $\boldsymbol{x}$ that minimize the objective function of learning algorithm. In this study, we introduce two parameters t_j and p_j to extract j-th feature ($1 \leq j \leq M$). t_j and p_j denotes the time range where the feature is extracted and component number of PCA, respectively. Our method tunes these feature parameters by following equation.

$$(t_j, p_j) = \underset{(t_j, p_j)}{\operatorname{argmax}} \sum_{i}^{N} \left((x_{ij} - X(t_j, p_j)) \cdot \operatorname{sgn}\left[\frac{\partial f(\boldsymbol{w}, \boldsymbol{x})}{\partial x_{ij}} \right] \right) \tag{1}$$

[1] Advanced Research Division, Panasonic Corporation
[2] Division of Physical Therapy and Rehabilitation, University of Fukui Hospital
[3] Department of Community Medicine, Faculty of Medical Sciences, University of Fukui

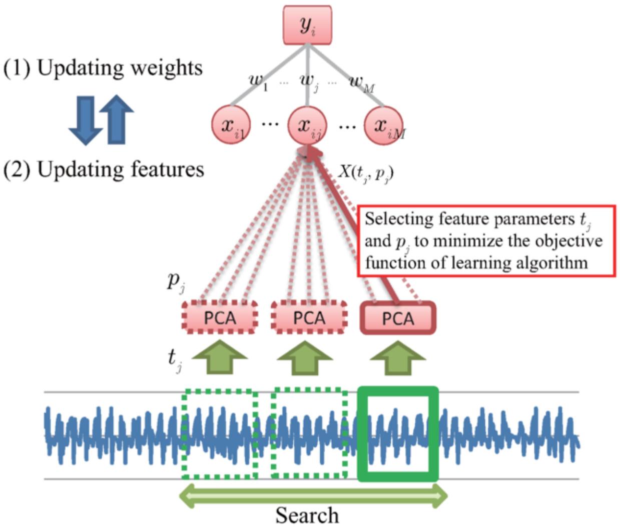

Figure 1. Procedure of proposed method.

where N, x_{ij} and $X(t_j, p_j)$ represent the number of training data, the current input variable, and the feature variable using feature parameters t_j and p_j. This procedure means that our method updates the features to change the input variables for the direction of the gradient to minimize the objective function of the learning algorithm.

The size of time window to extract a feature is set to 30sec. We slide the window by 15sec and search the best parameter of t_j and p_j. By the above procedure, our method enables the search of effective viewpoint for prediction from long time sensor data without any heuristics.

4 RESULTS

We tested our method by estimating the knee extensor strength of 102 subjects. In this experiment, we measured 3-axis accelerator, 3-axis angular velocity, heart rate, and temperature. Accelerometers and gyroscopes are attached to the waist and right ankle.

We compared the results obtained with our method and conventional methods. In this experiment, we use 6MWD [3] and PCA as baselines. 6MWD is a common index in clinical practice, and PCA is a basic feature learning method that has been successfully used in activity recognition [6]. PCA cannot accept the 6-minute sensor data directly because of the quite large dimension, and hence, we introduce the pre-processing phase that extracts averaged step wave form from the sensor data.

The number of features extracted by PCA and our method is set to 64. We use the neural network regression as a predictor in PCA and our method. In this study, we use shallow network architecture because of the number of training data. The number of hidden layers and hidden nodes is set to 1 and 32, respectively. All experiments were performed by 6-fold cross validation.

Table 1 and Figure 2 show the errors and correlations between the estimated values and the accurate values measured by an isokinetic dynamometer. The results show that the estimates using our method are much closer to the accurate values measured by an isokinetic dynamometer. The accuracy of our method is improved by more than 6 percentage points compared to the current clinical index, 6MWD, although the load to the subjects is the same.

Table 1. Errors between estimated and measured values.

Method	Error (%)
6MWD	19.9
PCA(average) + 6MWD	16.7
Proposed Method + 6MWD	**13.7**

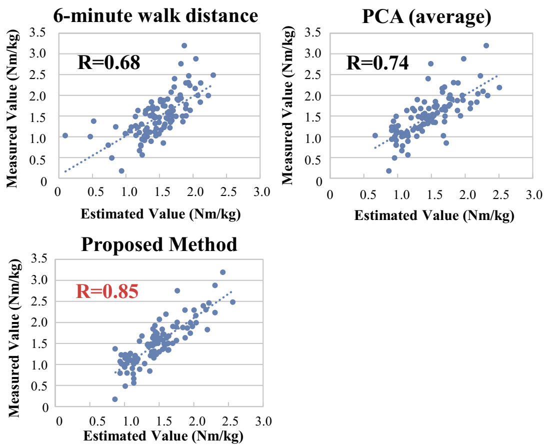

Figure 2. Correlations between estimated and measured values.

5 CONCLUSION

In this paper, we presented a feature learning method for long-time sensor data analysis. Our method searches effective features by using the gradient of input vector to minimize the objective function of the learning algorithm. We applied our method to the estimation of physical capacity from wearable sensor data. Experimental results show that our method can estimate the knee extensor strength, one of the most important indicators of physical capacity, more accurately than conventional methods. In future work, we will apply our method to the analysis of longer time of sensor data, which includes various daily activities. Our method is considered to be effective for situations that include large and complex data.

REFERENCES

[1] L. Bao and S. S. Intille, ‘Activity recognition from user-annotated acceleration data.’, in *Proceeedings of the 2nd International Conference on Pervasive Computing*, pp. 1–17, (2004).

[2] Y. Bengio, A. Courville, and P. Vincent, ‘Representation learning: A review and new perspectives’, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **35**(8), 1798–1828, (2013).

[3] G. H. Guyatt, M. J. Sullivan, P. J. Thompson, et al., ‘The 6-minute walk: a new measure of exercise capacity in patients with chronic heart failure’, *Canadian Medical Association Journal*, **132**(8), 919, (1985).

[4] G. E. Hinton, L. Deng, D. Yu, et al., ‘Deep neural networks for acoustic modeling in speech recognition’, *IEEE Signal Processing Magazine*, **29**(6), 82–97, (2012).

[5] A. Krizhevsky, I. Sutskever, and G. Hinton, ‘Imagenet classification with deep convolutional neural networks’, in *Advances in Neural Information Processing Systems 25*, 1106–1114, (2012).

[6] T. Plötz, N. Y. Hammerla, and P. Olivier, ‘Feature learning for activity recognition in ubiquitous computing’, in *Proceedings of the 22nd International Joint Conference on Artificial Intelligence*, pp. 1729–1734, (2011).

[7] D. Silver, A. Huang, C. J. Maddison, et al., ‘Mastering the game of go with deep neural networks and tree search’, *Nature*, **529**, 484–503, (2016).