Towards Mapping Activity Classes for Transfer Learning in Human Activity Recognition

Md Shafiqul Islam, Sayeda Shamma Alia and Sozo Inoue

Abstract In human activity recognition, collecting a large amount of data from sensors is a time-consuming and error-prone task. If there exists mislabeling that is action and labels are different then the performance of machine learning degrades. To handle this mislabeling issue, we propose two methods, sub-classing, and merging. In the sub-classing method, we make several sub-classes from an activity class. We then map new data records to newly created sub-class. In the merging method, we merge two activity classes and rename it with a new label. Then we map test data records of similar activity to newly merged activity. We integrate these approaches into the transfer learning model. The transfer learning model transfers knowledge from source to target dataset. If the target dataset has a small amount of data then we can train our transfer learning model on the source dataset and then transfer knowledge to the target dataset. Combining sub-classing or merging techniques with transfer learning will help to reduce the problems regarding mislabeling and a small amount of data.

Key words: Mislabeling, Activity Recognition, Transfer Learning

M.S. Islam
Dept. of Human Intelligence Systems, Kyushu Institute of Technology, Japan
e-mail: mdshafiqul.islam603@gmail.com

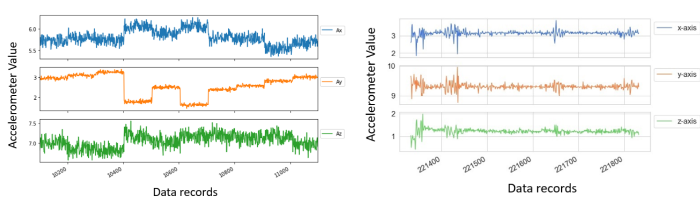
S.S. Alia
Dept. of Human Intelligence Systems, Kyushu Institute of Technology, Japan
e-mail: alia.sayeda-shamma944@mail.kyutech.jp

S. Inoue
Dept. of Human Intelligence Systems, Kyushu Institute of Technology, Japan
e-mail: sozo@brain.kyutech.ac.jp

1 Introduction

Human activity recognition is a popular research area [1]. Many researchers are exploring sensor-based activity recognition systems for over a decade. In this system, data is collected from various sensors (e.g., accelerometer, gyroscope, magnetometer) from wearable [3], earable [4, 9] devices, or smartphones [5, 7]. Then machine-learning algorithms are applied to the data to recognize different types of activities like walking, sitting, jogging, etc. [8]. Different types of knowledge based or hybrid approaches are also used for human activity recognition [19, 20]. In traditional machine-learning models, several features are extracted from raw sensor data, and then a machine learning algorithm is applied to the data. But for extracting features from raw data requires experts who have feature engineering knowledge. Besides it is tough to identify which features will yield good classification results. To solve this problem several deep learning-based algorithms [6] have been used by many researchers as it automatically extracts features from raw data. But deep learning requires a large amount of data to yield good accuracy. Therefore, many researchers have adopted the transfer learning concept to solve the problem.

In transfer learning, there are 2 domains of datasets called source and target datasets with the similar type of activities. These datasets are completely different. The model is trained on the source dataset and then tested on the target dataset. If the activities in both sources and targets are not labeled properly then there is a high probability of misclassification by the model. As a result, the performance of the model degrades. To illustrate this point, an example is given here. We have plotted the sitting activity of both University of Dhaka Mobility Dataset (DUMD) [17] and Wireless Sensor Data Mining (WISDM) [15] datasets.



(a) Sitting activity of DUMD dataset (b) Sitting activity of WISDM dataset

Fig. 1: Sitting activity in different datasets

Fig. 1 shows the graph of the sitting activity of DUMD [17] and WISDM [15] datasets. From the figures, it is seen that the data records of sitting activity in both datasets are quite different but they are labeled as sitting activity. That means maybe the data records are not labeled properly. If this type of mislabeling exists, in source and target datasets then the model will make mis-classification to lots of data records and the performance of the model will degrade.

The objective of this paper is to propose methods to solve this mislabeling issue while using transfer-learning. The paper is organized as follows: after introducing the works in Section 1, we present related works in Section 2, the proposed method in Section 3, experimental setup in Section 4. Finally, we conclude the paper with future works guidelines.

2 Related Works

In sensor-based human activity recognition many traditional and deep learning algorithms have been used. In recent years, there have been numerous research works in activity recognition using deep learning algorithms as these algorithms provide a better result and require no feature extraction manually. Many deep learning algorithms like Convolutional Neural Network (CNN), [11] Recurrent Neural Network (RNN), Transfer Learning, etc. Islam et al. [10] used Maximum Mean Discrepancy (MMD) based transfer learning among different datasets for human activity recognition. In [13], the transfer learning model was used to transfer knowledge from one user to another user. Wang et al. [12] proposed Unsupervised Source Selection for Activity Recognition (USSAR) algorithm to select the right source domain and then transfer knowledge across different body parts of humans. Toda et al. [2] worked on human activity recognition for labels with inaccurate time stamps.

According to the literature survey, transfer learning can be categorized into different categories. For example, instance-based, parameter-based, feature-based, mapping-based methods, etc. In Parameter-based methods, first a model is trained using the labeled source domain, then clustering on target domain is performed. [12] Feature-based methods learn a feature transformation between source and target domains when the distance can be minimized. Instances-based [14] deep transfer learning refers to the re-weighting technique. In this technique, partial instances from the source domain are selected as supplements to the training set in the target domain by assigning appropriate weight values to these selected instances. Mapping-based [14] transfer learning refers to mapping instances from the source and target domain into a new data space.

In this paper, we want to address the mislabeling issue in the different datasets and propose possible approaches to handle this problem. The goal is to reduce the mislabeling of different activities and improve the classifier's performance.

3 Proposed Methods

In sensor-based activity recognition after collecting sensor data when it is labeled then there is a probability of mislabeling. Some of the data records might be mislabeled which means labels and actions are different. It might lead to poor performance for the classifier. To solve this problem we propose 2 methods, the sub-classing method, and the merging method.

3.1 Sub-Classing Method

In this method, one or more activity classes in a dataset are clustered into subclasses. For example, the Sitting activity might be sub-classed to S1, S2, S3, etc. using K-means clustering. In the original activity class if there is mislabeling then-new test data records with proper labels might be dissimilar to the original class. On the other hand, if we make one big activity class into several sub-classes then-new test data records might be similar to any one of these sub-classes. As a result, the model will provide a good result.

For example, we will choose a random number for ‘K’ to apply k-means clustering. We will randomly try with different number and choose optimal number through several experiments. Suppose, we choose 3 for ‘k’. In this case we first make several sub-classes of an activity class using k-means clustering. For example, we make 3 sub-classes of Sitting activity of source and relabel to S1, S2 and S3. We will then pass the each of sub-class data and corresponding target sitting activity data to the transfer learning model. We are considering all possible combinations. If the data records of sub-class and target activity are similar (both actually sitting records) then the distance between the feature spaces of source and target will be small. On the other hand, if the data records are different then the distance will be large. Comparing the distances among different combinations we will choose the minimum distance. The combination that will yield highest accuracy, will be our desired combination. In this way we will get the proper label for mislabeled data records of that particular sub-class. We will relabel it properly. For the other sub-classes we will follow same procedure but in this case we will map with different activity class (Jogging, Walking, Running etc.) of target dataset. We will apply this whole process for all the activity classes of source dataset. In this process the data records will be labelled properly. As a result, the performance of the model will be improved.

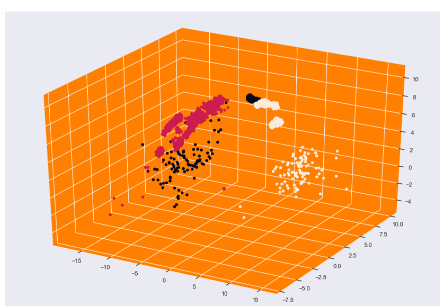


Fig. 2: The sitting activity of DUMD dataset

Fig. 2 shows the 3D plot of the sitting activity of the DUMD dataset. It is seen that data records are grouped into several groups. So we can make 3 sub-classes. It is challenging to find out the optimal number of sub-classes for different activities. We can try with a different number of sub-classes and compare performances to get optimal sub-classes.

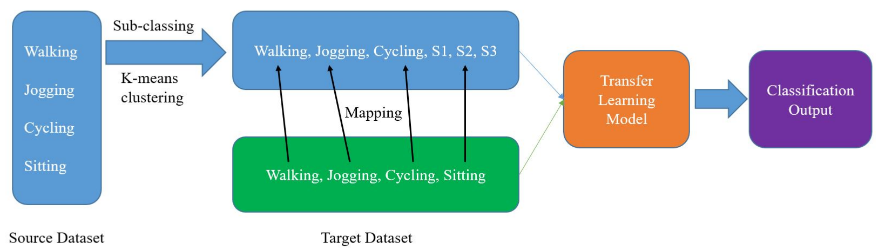


Fig. 3: Sub-classing method

Fig. 3 shows the architecture of the sub-classing method. In this method, first we split one or more original classes of source dataset into several sub-classes. Then we map the activities of the target dataset to the source dataset. It is one to one mapping. We can map target activity to any of the sub-classes of similar source activity. Gradually we can change the mapping to other sub-classes to target activity and find out the proper mapping. Next, we pass both the source and target datasets to transfer the learning model and evaluate the performance.

3.2 Merging Method

In this method, we merge two activities and rename them with a different label. For example, activity C and activity D might be merged and rename to activity E. If the number of activities of source and target datasets are different and contain mislabeling data then this method might be used. If there is mislabeling in the source dataset then most of the records of target activity might not be similar to source activity. Suppose, in source dataset we have 4 activities (A, B, C, D). On the other hand, in target dataset we have 3 activities (A, B, C). If we normally map source and target we will map A-A, B-B and C-C. But if there are some records of activity C which are mislabeled as D when we will miss this data records in mapping. These data records of activity D in source dataset should be mapped activity C of target dataset. If we merge activity C, D together, relabel as E and then map them to activity C of target dataset then there is good change of mapping a large number of data records properly between source and target activities. In that case, the performance of the model might be improved.

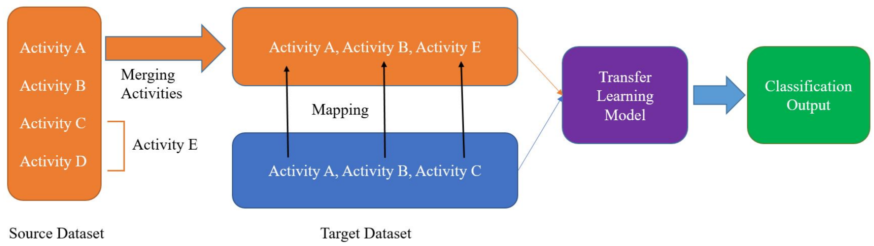


Fig. 4: Merging method

Fig. 4 shows an overview of the merging method. After merging two activities into one activity in the source dataset, we will map them to the activities of the target dataset. It is one to one mapping. Then we pass both source and target dataset to transfer-learning model and evaluate the model's performance.

4 Experiment

For our experiment, initially we have chosen 4 datasets: Wireless Sensor Data Mining (WISDM) [15], University of Dhaka Mobility Dataset (DUMD) [17], Human Activity Sensing Consortium (HASC) [18], and Single Chest Mounted [16]. These datasets contain a different number of activities. These data are collected from a different number of users at different sampling rates. While collecting data different types of devices were used and these devices were placed at different body parts of the volunteers. For example, for WISDM dataset, a smart phone was used and it was placed in the pocket of volunteer. The Volunteers of DUMD dataset collected data using wrist mounted sensors that contain accelerometer. The HASC data was collected from iPhone which was placed in waist pocket. The volunteers collected data for Single Chest Mounted dataset from a wearable accelerometer mounted on the chest. In the future, we will apply our proposed method on other datasets.

Table 1: Dataset description

Dataset	Sensors	Users	Activities	Sampling Rate
WISDM	Accelerometer	35	6	20 Hz
Single Chest	Accelerometer	15	7	52 Hz
HASC	Accelerometer	10	6	100 Hz
DUMD	Accelerometer	14	4	30 Hz

Table 1 represents the overview of different datasets including sampling rate, sensors, activities, etc. For training and evaluation, we will make one dataset as a source and another as a target. For example, WISDM as source and DUMD as a target dataset. We will follow this procedure for other datasets too. Then we will compare the results of the transfer learning approach and the traditional approach.

5 Conclusions and Future Work

In this paper, we proposed two methods, sub-classing and merging to handle the mislabeling issue. There are some challenges. For example, how many activity classes should be sub-classed, what is the optimal number of sub-class for a different type of activity classes? As for the model, we want to use a deep transfer learning model. Therefore, in the future we will design a deep transfer-learning model, as it will automatically extract features from input data. We will integrate sub-classing or merging methods to the model as per the architecture. Initially we will use the datasets, which are described in the experiment section. In the future, we will use some other datasets like PAMAP2, UCI HAR dataset, etc.

References

1. A. D. Antar, M. Ahmed, and M. A. R. Ahad, “Challenges in Sensor-based Human Activity Recognition and a Comparative Analysis of Benchmark Datasets: A Review,” Intl. Conf. on Activity and Behavior Computing (ABC), 2019.
2. T. Toda, S. Inoue, S. Tanaka, and N. Ueda. Training human activity recognition for labels with inaccurate time stamps. UbiComp 2014 - Adjunct Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing. 863-872. 10.1145/2638728.2641297.
3. T. Hossain, T. Tazin, Md Atiqur Rahman Ahad, and S. Inoue, "Activity Recognition by Using LoRaWAN Sensor", ACM Int’l Conf. Pervasive and Ubiquitous Computing (Ubicomp), 2018.
4. F. Kawsar, C. Min, A. Mathur, and A. Montanari, “Earables for Personal-Scale Behavior Analytics”, IEEE Pervasive Computing, 17, 2018.
5. G. Ogbuabor and R. La, “Human Activity Recognition for Health- care Using Smartphones”. Intl. Conf. on Machine Learning and Computing, 2018.
6. J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A Survey”, Pattern Recognition Letters, 2018.
7. N. Mairittha, T. Mairittha, S. Inoue, “FonLog - A Mobile App for Nursing Activity Recognition,” ACM Int’l Conf. Pervasive and Ubiquitous Computing (Ubicomp) Demo, 2018.
8. S. Inoue, T. Mairittha, N. Fah, T. Hossain, “Integrating Activity Recognition and Nursing Care Records: the System, Experiment, and the Dataset,” International Conference on Activity and Behavior Computing, 2019.
9. T. Hossain, M. S. Islam, M. A. R. Ahad and S. Inoue, “Poster: Human Activity Recognition Using Earable Device,” ACM International Joint Conference on Pervasive and Ubiquitous Computing and the International Symposium on Wearable Computers (UbiComp/ISWC ’19 Adjunct), 2019.
10. M.S. Islam , T. Okita , S. Inoue, “Evaluation of Transfer Learning for Human Activity Recognition Among Different Datasets”, 2019 IEEE International Conference on Pervasive Intelligence and Computing (PiCom), pp. 6 pages, Fukuoka, Japan, August 5, 2019.
11. M. Inoue, S. Inoue, T. Nishida, Deep recurrent neural network for mobile human activity recognition with high throughput. arXiv:1611.03607, 2016

12. J. Wang, V.W. Zheng, Y. Chen, M. Huang, Deep Transfer Learning for Cross-domain Activity Recognition. In Proceedings of the 3rd International Conference on Crowd Science and Engineering, Singapore, 28–31 July 2018.
13. R. Ding, X. Li, L. Nie, J. Li, X. Si, D. Chu, G. Liu, D. Zhan, "Empirical Study and Improvement on Deep Transfer Learning for Human Activity Recognition", Sensors (Basel) 2019 Jan; 19(1): 57. Published online 2018 Dec 24.
14. C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, and C. Liu. A survey on deep transfer learning. In International Conference on Artificial Neural Networks, pages 270–279. Springer, 2018.
15. G. M. Weiss, K. Yoneda and T. Hayajneh, "Smartphone and Smartwatch-Based Biometrics Using Activities of Daily Living," in IEEE Access, vol. 7, pp. 133190-133202, 2019, doi: 10.1109/ACCESS.2019.2940729
16. Casale, P. Pujol, O. and Radeva, P., 'Personalization and user verification in wearable systems using biometric walking patterns', Personal and Ubiquitous Computing, 16(5), 563-580, 2012.
17. S. S. Saha, S. Rahman, M. J. Rasna, A. K. M. M. Islam, and M. A. R. Ahad, "DU-MD: An open-source human action dataset for ubiquitous wearable sensors," in Proc. Joint 7th Int. Conf. Inform., Electron. Vis. (ICIEV) and 2nd Int. Conf. Imag., Vis. Pattern Recognit. (IVPR), 2018.
18. N. Kawaguchi et al., "HASC challenge: Gathering large scale human activity corpus for the real-world activity understandings,"' in Proc. 2nd Augmented Hum. Int. Conf., 2011, Art. no. 27.
19. K. Yordanova et al. Analysing Cooking Behaviour in Home Settings: Towards Health Monitoring. In Sensors, 2019
20. J. Ye et al. KCAR: A knowledge-driven approach for concurrent activity recognition. In Pervasive and Mobile Computing, 2015.