A Comparative Study on Missing Data Handling Using Machine Learning for Human Activity Recognition

Tahera Hossain and Sozo Inoue

Kyushu Institute of Technology, Sensui-cho, Tobata-ku, Kitakyushu-shi, Fukuoka, 804-8550, JAPAN
{tahera|sozo}@sozolab.jp

Abstract— **In mobile computing era, human activity recognition is an important research area for eldercare and healthcare center. Activity recognition performance decrease while partial data are lost due to various reasons, such as limited power, transmission capabilities of sensors, hardware failures, and network issues (e.g., packet collision, unreliable link, and unexpected damage). Therefore, data loss or missing is a realistic challenge. In this research, we eavaluate the performance of algorithms to perform their ability to handling missing data. It is required to investigate the optimal missing percentage in the dataset and its effect on accuracy. In this case, missing data are implemented randomly in the dataset with incremental scaling. We evaluate the performance using two benchmark datasets named HASC dataset and Single Chest-Mounted accelerometer dataset with data missing at random pattern. Here, we classified using support vector machine and random forest classifiers with eleven statistical features. The dataset has no missing data. However, to evaluate the performance, we added various levels of missing data randomly and studied the performances. Our study demonstrated that over 8% missing data in the dataset greatly reduce recognition results. Moreover, this recognition result has impact on sampling rate during data collection time.**

Keywords- Activity recognition, Sensor network, Assisted Living, Random Forest, Support Vector Machine.

I. INTRODUCTION

Assisted living aims to support elderly people by monitoring their daily activities using intelligent environments. This kind of support need to know about a person's current activity, and therefore a robust recognition of her/his actions. Sensor-based human activity recognition has promising impact in various important applications related to healthcare monitoring, activities of daily living, assisted-living, surveillance, entertainment, etc. [14,15,16]. For assisted-living facilities, "smart homes" [29] are equipped with different kinds of sensors to extract required information from the sensors data. It will help to detect elderly's activity in elder care center or health care center. These sensors continuously monitoring and collecting large amounts of data containing important information. By this continuous data collecting process it becomes a big collected data which we need to analyze for extract required information. It's considered that these big datasets contain highly useful and valuable information. Learning from these large amounts of sensor data is expected to carry significant information for improvements of quality of life. Therefore, sensor-based activity recognition systems are explored for over a decade by many researchers [2-3]. In this system, data are collected from various wearable sensors (e.g., accelerometer, gyroscope) from each individual, then these are transferred to near-by access points then to servers. Data loss or the presence of incomplete data can also happen for low-battery power in sensors, longer distance between sensors and access points, failures of sensors to send data properly, hardware failures, synchronization problem, signal strength fading, packet collisions, weakness in Wi-Fi or network, environmental interference, etc. [22-24].

Furthermore, missing data become larger as sensor networks grow in scale [30]. These missing values cause great difficulties for data analysis methods such as classification, prediction, and other machine learning methods. It's often failed to deal with missing values, especially when the amount of missing data is large. Therefore, missing sensors data contains important information for elderly support care center. Another important issue is data missing patterns which can be one of the following: data missing at random, not missing at random, or missing completely at random. If data is completely lost for a period, we can assume that there are network problems or failure. It can be considered as data missing completely but at random pattern. It can be relatively easily understood as data are missed completely for a period of time. However, data missing at random is more frequently happened and it is difficult to identify this pattern.

Based on our study, there are no works on sensor-based activity recognition considering random data missing pattern. Random data missing pattern is similar to realistic problem in wireless sensor network data collection time. It is important to know the optimal amount of missing percentage in the datasets. As well as to know the missing percentage which not leads to recognition performance in extremely low level. We have attended this challenge in this paper. Therefore, the contributions of this research are to study about optimum amount of missing percentage of data in the dataset; to find out any dependency of machine learning classifiers to handle missing data; and finally, to know the reason of recognition accuracy variation when missing percentage is same in different datasets. As the datasets are usually built with the availability of continuous time-series data, the existing research works on sensor-based activity recognition deal with these data, having no missing information. Earlier, we explored the missing data scenarios by using several features [1]. We developed a method to study and evaluate the missing data issue in the domain of activity recognition [28]. We studied different combination of feature sets to analyze the performance of missing data.

In this paper, we extract different statistical features from the time-series data by some overlapping windowing technique. Using our classification strategy, we explore the missing data performance in two benchmark datasets on sensor-based activity recognition. Note that these datasets have no missing data pattern. We call it 'clean data'. To create missing data in different percentages or levels, we introduce missing data randomly. In this paper, we explore two benchmark datasets, namely the HASC dataset [6,7] and the Single Chest-Mounted Accelerometer dataset from UCI machine learning repository [31]. Therefore, this research and our findings are extremely instrumental for network design having missing data rate. The missing data tolerance rate will vary from network to network and the purpose of recognition levels. Some actions are very crucial to recognize in real-time, and some actions are less important. For a network and sensor-based system, we need to analyze the missing data pattern and missing data rate according to the findings in this paper.

We organize the paper as follows: Section 1 covers the introduction of the paper. In Section 2, we present some related works on activity recognition and background. In Section 3, we present our methodology and workflow of the system. In Section 4, we present the evaluation of experimental results and analysis. In Section 5, we present the discussion and motivation. Finally, we conclude the paper with some future work points in Section 6.

II. Related Work

The study of assisted living by automatic human activity recognition is highly expected in hospital, elderly care center for improving health and lifestyle. A recent work [4] has described several promising healthcare applications and highlighted the key technical challenges that faces in healthcare. Sensor data loss environment is common issue in wireless sensor network while various sensor data traverse from one source to another. Human activity recognition will not possible properly if we will not able to evaluate all sensors data properly. In the real-world scenario, assisted living facility centers have big challenges to collect all sensor data properly. This missing data is sometimes serious in some situation which brings a big challenge to the applications of sensor data. However, the traditional data estimation methods cannot be directly used in wireless sensor network and existing estimation algorithms fail to provide a satisfactory accuracy or have high complexity. The author in [19], address this problem. Author proposed, Temporal and Spatial Correlation Algorithm (TSCA) to estimate missing data as accurately as possible in their work. Firstly, they save all the data sensed at the same time as a time series, and the most relevant series they selected as the analysis sample, which improves efficiency and accuracy of the algorithm significantly. Secondly, they estimate missing values from temporal and spatial dimensions.

The missing value problem is common in datasets [17]. If the missing data are directly deleted, a large amount of raw data will be lost which will reduce the accuracy and reliability of analysis results and cause a great waste of energy. In statistics, the estimation algorithms of missing data have been extensively researched. Mean Substitution, Imputation by Regression, Expectation Maximization, Maximum Likelihood, Multiple Imputations, Bayesian Estimation, and Hot/Cold Deck Imputation [18] are many of them. However, none of these algorithms can be used in wireless sensor network (WSN), because in WSN they require the data miss at random and their efficiency is low.

To utilize sensor data properly, in recent years, with the development of sensing technology, wireless communication, and computing technology, wireless sensor network (WSN) [20] has been a focus of research and attracts strong attention from academia. In many applications of WSN, data loss [21, 22] is common due to limited resources of sensor nodes [23], interference of noise, and influence of environment. Without optimizing network performance, it will not possible to improve activity recognition accuracy in real time environment. These approaches aim to provide higher reliability, lower end-to-end delay, and higher packet delivery ratio. Authors in [5], reviewed a comprehensive survey of QoS-Aware Routing Protocols in Wireless Body Area Networks. In wireless data transmissions processes, data loss is an important factor that reduces the robustness of wireless sensor networks [8]. However, data loss in wireless sensor networks is a common problem. Data loss has its special patterns due to noise, collision, unreliable link, and unexpected damage, which greatly reduces the accuracy of reconstruction [9]. Earlier, we proposed a method while exploring the recognition performances with missing data in the features [1].

To the best of our knowledge, no earlier works in activity recognition domain explicitly addresses missing sensors problem except [24]. Nevertheless, several works in different areas have used to interpolate missing data [25,26]. Author in [27] propose a method based on an adversarial autoencoder for handling missing sensory features and synthesizing realistic samples.

III. Methodology For Performance analysis

Sensor-based activity recognition needs sensor-based time-series data. We can get data from sensors for different activities. Data can be extracted from sensors like accelerometer, gyroscope, etc. Usual datasets have no missing data and have clean or continuous data. In this paper, we explore activity recognition from sensor-based continuous data, as well as, data having missing data at random pattern.

The basic recognition process is shown in Fig. 1. In this block diagram, data are collected from different sensors for various activities. Then from these data (either continuous or missing data at random pattern), we compute various statistical features. Later, we exploit different classifiers to classify activities in the dataset.

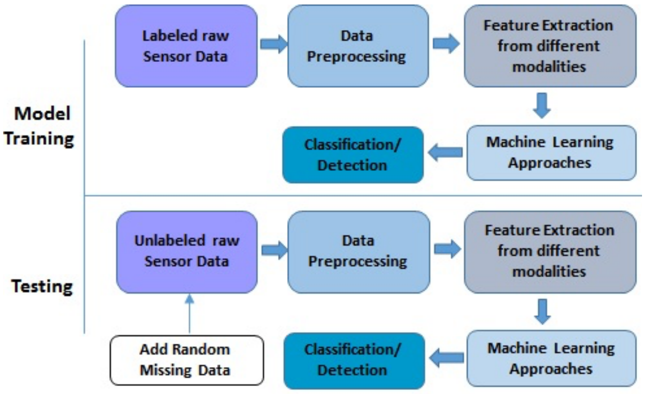

Fig 1. Flow diagram for sensor-based activity recognition considering missing data patterns.

However, in our system, we amended the dataset with missing data at random at different levels. We have added missing data randomly in testing data module, while the training with good quality data.

A. Datasets

We have explored two benchmark datasets for performance evaluation. Human Activity Sensing Consortium (HASC) dataset and Single Chest-Mounted Accelerometer dataset (Single Chest).

The HASC dataset [6] is a benchmark dataset that has 6700+ accelerometer data from 540 subjects. It is a structured dataset with lots of sensor data. The dataset consists of six activities: stay, walking, jogging, skipping, stair-up action, and stair-down action. It has two modules: (a) segmented data where each activity by different persons, and (b) sequence data covering continuous different activities. The segmented dataset is taken as the training dataset, whereas, the sequence data is considered as the test dataset. The measurement time of the segmented data is 20 seconds, whereas the number of measurement times is 5 sets. Accelerometer data is stored as a simple comma-separated values (CSV) format with time stamp and x, y, z axis-acceleration data. The sequence module has different activities in different orders. Each action was done for 10 seconds or more. Total measurement time for this sequence data was 5 minutes, which are taken from ten persons (nine men and one women) using Apple iPod touch 3G. The sampling rate was varied from 10 ~ 100 Hz. Subjects' age range was 21 ~ 32 years. In this dataset, the training set is by accomplished by 10 persons as separate modules, while the testing module has different persons' data. We considered 1-person-left-out cross-validation approach while computing the feature vectors.

The Single Chest dataset collects data from a wearable accelerometer mounted on the chest. The accelerometer data are collected from 15 participants performing 7 activities. Sampling frequency of the accelerometer: 52 Hz [31]. Data are formatted in the CSV format. Data are separated by participant. Each file contains the information of sequential number, x acceleration, y acceleration, z acceleration, label. Labels are codified by numbers 1: working at computer, 2: standing-up, walking and going up\down stairs, 3: standing, 4: walking, 5: going up\down stairs, 6: walking and talking with someone and 7: talking while standing.

B. Feature Extration

We have explored eleven statistical features. These are variance of x-axis, y-axis, z-axis of accelerometer data; mean of x-axis, y-axis, z-axis of accelerometer data; skewness; kurtosis; maximum value; minimum value; and median absolute deviation (MAD).

Mean value summarizes the data attributes for the three axes of accelerometer data. Variance is used to identify any sharp details of time series data. If we consider $X = x_1, x_2, x_3, \dots, x_n$ are the series of sensor data then the mean value will be, $\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n}$. Here, n is the number of training instances. The variance of any random variable X is the expected value of the squared deviation from the mean of X: $\mu = E[X]$ and $Var(X) = E[(X-\mu)^2]$.

Skewness calculates the skewing rate or asymmetry of the probability distribution of a random variable about its mean value. For a symmetrical dataset, the skewness will be equal to 0. Hence, for a normal distribution, we can have a skewness of 0.

Kurtosis measures the flatness of a distribution. It can define as an average value of the variation of the time series data. Also, the peak of a frequency-distribution curve is denoted by Kurtosis feature. It measures whether the data are peaked or flat relative to a normal distribution. It also measures tailedness of the probability distribution of a real-valued random variable and degree of asymmetry of the sensor signal distribution.

Maximum value and minimum value are computed for the accelerometer data. Maxima (Max) and Minima (Min) provides the maximum and minimum values of a particular signal. Median absolute deviation (MAD) is computed as a feature.

We considered 1-person-left-out cross-validation approach while computing the feature vectors. Our aim is to handle missing values during activity recognition in multi-sensory networks. There are three levels for handling missing values in such a network; raw data, feature level and classifier. Incomplete data is common in wireless sensor network and may arise due to hardware failures, synchronization, packet collisions, signal strength fading, or environmental interference. For sensor network we consider time series sensor data. A more realistic assumption is that data is missing at random (MAR). The key aspect about MAR is that the values of the missing data can somehow be predicted from some of the other variables being studied. Possible variations are: 'NaN', 'NA', 'None' and others. In our research, we consider random missing data and replace missing value with NA. This data missing is following data missing at random pattern.

We have trained the model with clean data. Then we have added random percentage of missing data in testing module and buildup model with these missing data. For this research, we split the sensor data for both training and testing. For data segmentation, we have considered overlapping windowing approach while computing features. Overlapping plays a vital role when the signals in each interval are not independent of the signals of the other intervals.

C. Classification

For classification, we can apply numerous classification method based on data type, amount of data, similarities of activities, amount of activities and number of classes, etc. In this paper, we have explored, Support Vector Machine (SVM) and Random Forest classifiers. We exploited Support Vector Machine, which is a well-explored classifier for various recognition tasks. We also exploited the Random Forest classifier. It is also a popular and powerful classifier [10-11]. This classifier is good with regression and multiclass classification. It can provide better recognition rate in multiclass scenarios [12]. This classifier can have multiple decision trees. These are developed randomly based on various sampled instances of training data and these are trained independently [12]. On the other hand, class labels of various decision trees are anticipated by combining the multiple classifiers' predictions [13].

If any missing values remain in the training of decision trees, these missing data could interrupt in proper classification of the decision trees. That is why, the presence of missing data in the training part may produce inaccurate decision tree induction and demonstrate misclassification [12, 13]. Even though a decision tree has some kind of missing values, the combining the multiple classifiers' predictions from many decision trees can decrease the impact of missing values. Therefore, Random Forest can demonstrate better performance even any presence of missing data.

IV. EVALUATION OF EXPERIEMENT RESULTS

1. Results on clean data performance in two benchmark datasets:

In the clean HASC and Single Chest dataset there are six and seven activity classes present. Figure 2 shows the activity classes for HASC dataset with number of activities count for each activity class. Figure 3 shows different activity classes for Single Chest dataset with activity count record. We have evaluated the clean data performance for these two datasets. We have found 94% accuracy with random forest classifier for Single Chest dataset and it becomes 80% accuracy with SVM. In the HASC clean dataset also performance is good with random forest classifier and it is 89%. By SVM we have found 80% accuracy in HASC dataset.

2. Results with having missing data in two Benchmark Datasets:

In this paper, we have exploited two machine learning approaches to build a model and train the dataset by calculating feature values. In this performance evaluation experiment, we have explored activities of the HASC dataset and the Single Chest dataset in conditions: (i) activity classification without any missing data; (ii) activity classification with missing data in the testing part when training is good quality data.

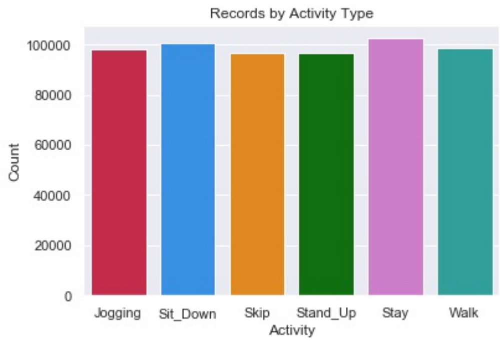

Fig 2. Activity record count in HASC clean dataset.

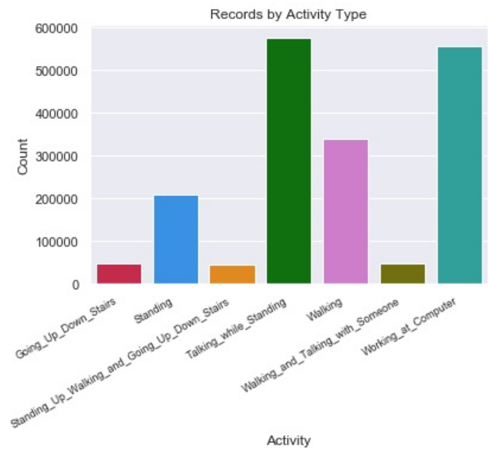

Fig 3. Activity record count in Single Chest clean dataset.

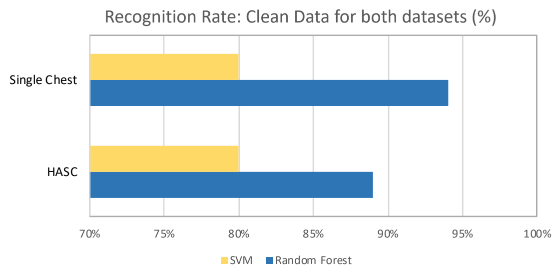

Fig 4. Recognition performance for both datasets

In our performance comparison study, we have compared the results of same missing percentage data evaluation result in both datasets at a same time. For creating random missing percentage in the datasets, we have created different incremental missing percentage (from 2~20%). Afterwards, we have compared the accuracy in terms of missing rate with two classifiers for both datasets. Figure 5 shows the performance of random forest classifier with different missing rate.

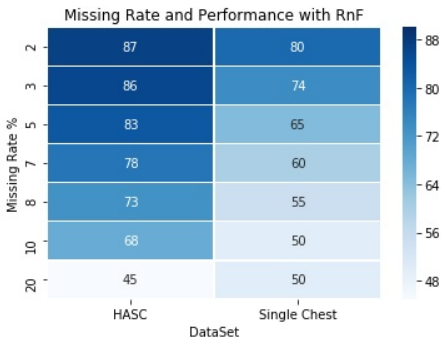

Fig 5. Random Missing data performance with RnF

Our results show that having 2% of missing data in the datasets not decrease performance so much. Having random missing data over 8% decrease performance drastically in HASC dataset but for Single Chest it is considerable up to 3% missing data. Over 10% of missing data is not considerable in any environment.

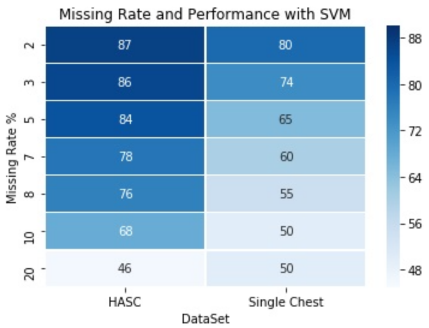

Fig 6. Random Missing data performance with SVM

In Fig. 6, we can find that the performance of missing data handling capability is almost same for both RnF and SVM classifiers. In this case, evaluation performance is not varying so much on different classifiers but it is mostly depending on having missing percentage in the datasets. Over 8% missing data evaluation with SVM classifier in HASC dataset also decrease performance and more then 10% missing data drastically reduce performance which is not considered in terms of accuracy. For this case also, Single Chest dataset perform better up to having 3% random missing data in the dataset.

V. Discussions and Motivation

The clean HASC and Single Chest datasets demonstrates some evaluation based on 11 features combination. We can notice that random forest (RnF) classifier provides better recognition result than the SVM classifier when data is fully clean. Having different percentage of incremental random missing data, both RnF and SVM classifier perform almost same. It is not varying so much based on classifiers. Result varies based on percentage of missing data in the datasets. Our results show that having missing data from 2~7 % can be considered in terms of accuracy. However, more then 8% missing data reduce recognition performance drastically. In terms of dataset, we have compared the performance for having same percentage of missing data. We have observed that HASC dataset recognition performance is always good having any percentage of missing data. However, with clean dataset evaluation time, Single Chest perform highest result which is 94% accuracy. To find out the core issue, we analyze the sampling rate of each datasets during data collection time. The sampling rate is the number of samples per second. It is the reciprocal of the sampling time, i.e. 1/T, also called the sampling frequency. HASC dataset sampling frequency is 100 Hz whereas Single Chest dataset sampling frequency of the accelerometer is 52 Hz. It can be say that higher sampling frequency is good during having noisy data environment in realistic case.

We have tested in different percentage missing data level. We observe that when we added even 5% missing data in testing module then recognition rate is 83% by using RnF in HASC dataset whereas it becomes 65% in Single Chest dataset. By using SVM also it is 84% in HASC dataset but 65% in Single Chest dataset. Even recognition performance in Single Chest dataset reduce to 55% when 8% random missing data is present in the dataset. On the other hand, for HASC dataset it is 73 and 76% using RnF and SVM. Finally, we notice that for HASC dataset up to 8% missing data is considerable but for Single Chest dataset, more than 3% missing data reduce performance.

In realistic scenario, if we know the score of missing rate and the missing pattern in the data then we can eliminate the cause of high missing rate. Our evaluation shows that when we have collected raw data over 100 Hz sampling frequency, then missing impact is less then 52 Hz sampling frequency data collection result. After knowing the missing percentage in the dataset, we can estimate how much accuracy can fall having certain percentage of missing data. Assessing the missing data rate is important for network design. If we can presume or predict the pattern and rate of missing data in a network for the purpose of human activity understanding, we can design the algorithm for activity recognition accordingly. For example, if we can predict that missing data up to 8% is manageable or reasonable, then we can design our recognition algorithm and the decision-making process based on this. Therefore, if missing data is more than 8%, we cannot consider the machine learning-based activity recognition and wait for a situation when the missing data rate will be below this. And missing data situation in a network is not a regular issue: some networks may be more vulnerable to have missing data, or some networks may miss data very randomly and less frequently. On those cases, we can estimate the missing data pattern and missing rate, and design our network or algorithms to develop the activity recognition system. Based on our study and evaluation, we can conclude that these research findings are very important for future healthcare center, hospitals, smart homes, smart city or smart hospitals. With the advent of Internet of Things and smart city concepts in healthcare, we are confident that these research outcomes will be beneficial for human activity recognition.

VI. CONCLUSIONS

The data missing scenario commonly happens during real-world data collection time and in realistic situations. Studies are going on for Sensor-based or wearable sensor-based activity recognition. There are challenges to overcome, especially in missing data in the network. There are few works related to consider random missing data in this arena. Hence, in this paper, we explore recommend better features for accelerometer-based data analysis to recognize various actions. In this paper, we study optimum missing data percentage in data situations. This work can be useful for elderly care center where missing data is crucial for accurate activity recognition. Here, we compare the recognition performance in the presence of different levels of random missing data. We explore two benchmark datasets which is HASC dataset and Single Chest dataset. Two classifiers are considered for recognition study: Random Forest and SVM. Among them, under various experiments of missing data level, both classifiers performance almost same. However, performance varies in different datasets. Sampling frequency of data collection time is one of the issues which we can more elaborate in future. In future, we need to evaluate the performance in missing data environment as increasing the dataset, classify more activities, and perform another algorithm which can perform better result.

REFERENCES

[1] T. Hossain, H. Goto, and S. Inoue, "Improving Activity Recognition for Missing Data," EAI International Conference on Mobile Computing, Applications and Services (MobiCASE) Student Workshop, 2018.

[2] J. Yin, Q. Yang, and J. J. Pan, "Sensor-Based Abnormal Human-Activity Detection", IEEE Trans. on Knowledge and Data Engineering, vol. 20, no. 8, 2008.

[3] Z. Hajihashemi and M. Popescu, "Detection of Abnormal Sensor Patterns in Eldercare", 4th IEEE Int. Conf. on E-Health and Bioengineering, 2013.

[4] J. Ko, C. Lu, M. B. Srivastava, J. A. Stankovic, A. Terzis, and M. Welsh, "Wireless Sensor Networks for Healthcare", Proceedings of the IEEE, vol. 98, no. 1, pp. 1947-1960, 2010.

[5] A. Kumar and C. V. Raj, "A Comprehensive Survey of QoS-Aware Routing Protocols in Wireless Body Area Networks", Int. J. of Advanced Research in Computer and Communication Engineering, vol. 6, no. 1, 2017.

[6] N. Kawaguchi, N. Ogawa, Y. Iwasaki, K. Kaji, T. Terada, K. Murao, S. Inoue, Y., Kawahara, Y. Sumi, and N. Nishio, "HASC Challenge: Gathering Large Scale Human Activity Corpus for the Real-World Activity Understandings", ACM AH, pp. 27:1-27:5, 2011.

[7] N. Ogawa, K. Kaji, and N. Kawaguchi, "Effects of Number of Subjects on Activity Recognition - Findings from HASC2010corpus", 1st Int. Workshop on Frontiers in Activity Recognition using Pervasive Sensing (IWFAR2011), pp. 48-51, 2011.

[8] Y. Yu, F. Han, Y. Bao, and J. Ou, "A Study on Data Loss Compensation of WiFi-based Wireless Sensor Networks for Structural Health Monitoring", IEEE Sensors J., 2015.

[9] L. Kong, M. Xia, X.Y. Liu, M.Y. Wu, and X. Liu, "Data Loss and Reconstruction in Sensor Networks," IEEE INFOCOM, pp. 1654-1662, 2013.

[10] K. Richards, Machine Learning for Beginners, Chapter 7: Algorithm.

[11] L. Breiman, "Random forests", Machine Learning, vol. 45, pp. 5-32, 2001.

[12] Z. Cui, W. Chen, Y. He, and Y. Chen, "Optimal action extraction for random forests and boosted trees", ACM Int. Conf. on Knowledge Discovery and Data Mining (SIGKDD), pp. 179-188, 2015.

[13] Z. Qi, H. Wang, J. Li, and H. Gao, "Impacts of Dirty Data: an Experimental Evaluation" ArXiv:1803.06071v1 [cs.DB] March 2018. https://arxiv.org/pdf/1803.06071.pdf

[14] Md. Atiqur Rahman Ahad, Computer Vision and Action Recognition: A Guide for Image Processing and Computer Vision Community for Action Understanding, ISBN: 978-94-91216-20-6, Springer, 2011.

[15] Md. Atiqur Rahman Ahad, Motion History Images for Action Recognition and Understanding, ISBN: 978-1-4471-4730-5, Springer, 2012.

[16] K. Kinsella, and D. R. Phillips, "Global aging: The challenge of success", Pop. Bull, vol. 60, pp. 1-42, 2005.

[17] M. Balazinska, A. Deshpande, M. J. Franklin, P. B. Gibbons, J. Gray, S. Nath, M. Hansen, M. Liebhold, A. Szalay, and V. Tao. Data management in the worldwide sensor web. IEEE Pervasive Computing, vol. 6, no. 2, pp. 30-40, 2007.

[18] L. Gruenwald, H. Chok, and M. Aboukhamis, "Using data mining to estimate missing sensor data," 17th IEEE Int. Conference on Data Mining Workshops (ICDM '07), pp. 207-212, 2007.

[19] Z. Gao, W.Cheng, X. Qiu, and L. Meng, "A Missing Sensor Data Estimation Algorithm Based on Temporal and Spatial Correlation", Int. J. of Distributed Sensor Networks, Hindawi, 2015.

[20] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," Computer Networks, vol. 52, no. 12, pp. 2292-2330, 2008.

[21] C. Alippi, G. Boracchi, and M. Roveri, "On-line reconstruction of missing data in sensor/actuator networks by exploiting temporal and spatial redundancy," IEEE Int. Joint Conference on Neural Networks (IJCNN), pp. 1-8, 2012.

[22] M. Moayedi, Y.K.Foo, and Y.C.Soh, "AdaptiveKalman ltering in networked systems with random sensor delays, multiple packet dropouts and missing measurements," IEEE Trans. on Signal Processing, vol. 58, no. 3, pp. 1577-1588, 2010.

[23] A. K. Fletcher, S. Rangan, and V. K. Goyal, "Estimation from lossy sensor data: jump linear modeling and Kalman ltering," 3rd Int. Symposium on Information Processing in Sensor Networks, pp. 251-258, ACM, 2004.

[24] Y. Vaizman, N. Weibel, G. Lanckriet, "Context Recognition In-the-Wild: Unified Model for Multi-Modal Sensors and Multi-Label Classification", Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., 2018.

[25] B.B. Thompson, R. Marks, and M.A. El-Sharkawi, "On the contractive nature of autoencoders: Application to missing sensor restoration", Int. Joint Conference on Neural Networks, 2003.

[26] N. Jaques, S. Taylor, A. Sano, R. Picard, "Multimodal Autoencoder: A Deep Learning Approach to Filling in Missing Sensor Data and Enabling Better Mood Prediction", Int. Conference on Affective Computing and Intelligent Interaction (ACII), 2017.

[27] A. Saeed, T. Ozcelebi and J. Lukkien, "Synthesizing and Reconstructing Missing Sensory Modalities in Behavioral Context Recognition", Sensors Journal, Sept. 2018.

[28] T. Hossain, H. Goto, M.A.R. Ahad, and S. Inoue, "A Study on Sensor-based Activity Recognition Having Missing Data," Joint 7th Int. Conf. on Informatics, Electronics & Vision, & 2nd Int. Conf. on Imaging, Vision & Pattern Recognition, IEEE, 2018.

[29] A.M. Raisul, M.B.I. Reaz, and M.A.M. Ali, "A review of smart homes – Past, present, and future," IEEE Trans. on SMC: Part C, vol. 42, no. 6, pp. 1190-1203, 2012.

[30] M. Balazinska, A. Deshpande, M.J. Franklin, P.B. Gibbons, J. Gray, S. Nath, M. Hansen, M. Liebhold, A. Szalay, and V. Tao, "Data management in the worldwide sensor web," IEEE Pervasive Computing, vol. 6, no. 2, pp. 30-40, 2007.

[31] P. Casale, O. Pujol, and P. Radeva, "Human activity recognition from accelerometer data using a wearable device", 5th Iberian Conference Pattern Recognition and Image Analysis, Springer-Verlag, pp. 289-296, 2011.