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Data Transmission in Wearable Sensor Network for Human Activity Monitoring using Embedded Classifier technique

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ABSTRACT

The recent development of wireless wearable sensor networks has opened up a slew of new possibilities in industries as diverse as healthcare, medicine, activity monitoring, sports, safety, human-machine interface, and more. The battery-powered sensor nodes' longevity is critical to the technology's success. This research proposes a new strategy for increasing the lifetime of wearable sensor networks by eliminating redundant data transmissions. The proposed solution is based on embedded classifiers that allow sensor nodes to determine whether current sensor readings should be sent to the cluster head. A strategy was developed to train the classifiers, which takes into account the impact of data selection on the accuracy of a recognition system. This method was used to create a wearable sensor network prototype for human monitoring of activity Experiments were carried out in the real world to assess the novel method in terms of network lifetime, energy usage, and human activity recognition accuracy. The proposed strategy allows for a large increase in network lifetime while maintaining excellent activity detection accuracy, according to the results of the experimental evaluation. Experiments have also demonstrated that the technology has advantages over state-of-the-art data transmission reduction strategies.

Keywords: Wireless Sensor Network, Wearable Sensors, Activity Recognition, Lifetime, Energy Con- Sumption, Transmission Suppression, Embedded Machine Learning.

I. INTRODUCTION

The majority of wireless wearable sensor networks are made up of many sensor nodes that are attached to the human body or incorporated in garments [1–3]. The sensor nodes can keep track of both body and environment characteristics. Wireless data links are used to communicate between the wearable sensor nodes. There have been several applications of wearable sensor networks considered in the literature so far. Healthcare, location, activity tracking, sport, fitness, augmented reality, safety, rescue, and emergency management are just a few of the potential uses.

The battery-powered sensor nodes' longevity is critical to the success of wearable sensor networks. The limited energy resources of sensor nodes must be efficiently utilised in order to ensure a lengthy network lifetime.

. Data transmission is the most energy-intensive activity of wireless sensor nodes. Data processing, on the other hand, uses a lot less energy. Data transmission reduction can save a lot of energy and extend the life of a network [4–6]. As a result, effective strategies for avoiding unwanted data transmissions in wearable sensor networks are required. Existing data reduction strategies are mostly focused on wireless sensor networks that gather sensor readings, do basic preprocessing activities, and transport the data to a sink or a base station. The sensor network considered in this research, on the other hand, is made up of data from wearable devices as well as data from the surrounding nodes. In order to reduce the transmission of redundant data, if the data is deemed to be close, it will not be submitted. Although these aggregation algorithms reduce the amount of data and save the energy consumption of the node, they cause a loss of node data.

1.1 machine learning algorithms

This paper introduces a method for reducing data transmissions in wearable sensor networks, where a cluster head node collects data from different sensors to recognize human activity in real-time. In this method, the sensor nodes are equipped with binary classifiers that allow them to decide if current sensor readings have to be transmitted to cluster head or not. According to the proposed approach, the data classifiers for sensor nodes are trained with use of machine learning algorithm. An algorithm was elaborated to prepare a training data set, which consists of data readings from sensors and assigned labels. Each label indicates if a given data reading is necessary to correctly recognize the activity of monitored person or not. These labels are determined during tests of a recognition algorithm, which is used by the cluster head node to categorize human activities.

The proposed method was implemented in a prototype of wearable sensor network for activities recognition of persons working in a computer laboratory. The prototype was designed to recognize the human activities, such as sitting, walking, or standing. Moreover, in case of sitting person, it was also recognized where the person is sitting and if the monitor is switched on. During experiments, energy consumption of sensor nodes was measured and lifetime of the wearable sensor network prototype was analysed. Results of the experimental evaluation have enabled detailed comparison of the network lifetime for the proposed approach, and for state-of-the-art transmission reduction methods. Also, the impact of data transmission reduction on accuracy of activity recognition was analysed for the compared methods in real-world experiments.

The paper is organized as follows. Section 2 reviews related works and discusses contribution of this paper. Section 3 presents the proposed approach to reducing data transmission in wearable sensor networks. Experiments and their results are described in Section 4. Finally, conclusions are given in Section 5.

II. Literature Review

In the literature, various approaches have been proposed for data transmission reduction in wireless sensor networks. The state-of-the-art methods can be categorized into four main categories, i.e., data aggregation, data compression, adaptive sampling, and data prediction methods. This section includes a concise review of the existing approaches to data transmission reduction, and focuses on their applications in wearable and body area sensor networks. In this context, the contribution of this paper is explained at the end of this section.

2.1 Data Aggregation

Data aggregation methods were designed for multi-hop transmissions, where inter- mediate nodes can merge several messages received from neighbouring sensor nodes, and send them towards the sink node as a single packet [7–9]. As a result, the number of packets transmitted in the network is reduced. Moreover, in case when the sensor nodes are densely deployed, and can observe the same phenomenon, the aggregation methods allow the intermediate nodes to eliminate redundant messages. This approach increases transmission delay as the data have to be buffered before aggregation and transmission, when the intermediate node receives messages from different sources.

In [10] a data aggregation method was introduced to reduce power consumption in wearable sensor networks for physical movement monitoring and quality evaluation of postural control system during walking. The development of the method was motivated by the fact that larger packets have a lower energy consumption per bit. Based on this observation, a routing protocol was introduced, which finds effective routes for data aggregation. The authors have suggested that by transmitting aggregated data though longer paths, a smaller total energy consumption can be achieved than in case of the shortest path communication. However, the longer transmission path results in larger delay. Thus, this approach is not suitable for real-time applications.

III. Proposed Methodology

The objective of the considered wireless sensor network is to recognize human activities at in successive time steps (t). In this network, the wearable sensor nodes attached to a person establish a cluster, where one of the nodes acts as cluster head, i.e., receives data from the other nodes and uses them to recognize the user's activity. The cluster head to a sink node periodically report the recognized human activity.

The method presented in this section allows us to reduce the number of data trans- missions from sensor nodes to cluster head. According to this method, the sensor nodes use classifiers to decide if sensor data are necessary for activity recognition and have to be transmitted, or not. The decision made by sensor node i with use of binary classifier C can be described with the following formula:

$$d_{i,t} = C(S_{i,t}, M_i), (1)$$

where $d_{i,t} = 1$ means that the data collected at time step t by sensor node i have to be transmitted to cluster head and $d_{i,t} = 0$ denotes that the data transmission can be skipped. This decision is made by the classification algorithm C, based on data set $S_{i,t}$ and model M_i. The models M_i are trained using a machine-learning algorithm, according to the procedure which is presented in Section 3.3. The set $S_{i,t}$ consists of preprocessed sensor readings collected by sensor node i at time step t. Construction of the classification algorithm C depends on the machine learning algorithm used for training the model M_i.

For instance, if the model is trained with use of the random forest algorithm then it has the form of a collection of decision trees, and algorithm C has to calculate the decision based on those decision trees. The operations performed by sensor node are summarized in Algorithm 1. It should be noted that the method described in this section can be implemented for various sets of sensors, with use of different machine learning algorithms. Here, for seek of generality, the term "machine learning algorithm" is used, which can refer to neural network, decision tree, random forest, support vector machine, etc. Similarly, the data set mentioned here can be composed of different sensor readings. Thus, size of the processed and transmitted data is not determined. Implementation details of the proposed method, for a prototype of wearable sensor network, are discussed in Section 4.

Algorithm 1 Operation of sensor node i

Input: classification model Mi

1: for each time step t do

2: collect data Si,t from own sensors

3: classify collected data - determine di,t = C(Si,t, Mi)

4: if di,t = 1 then

5: send Si,t to cluster head

6: end if

7: end for

As shown in Algorithm 2, the cluster head (node i∗) collects its own sensor readings and waits for data transmitted from the other nodes in its cluster. The available data are then used to recognize current activity of the monitored person. Since the proposed method assumes that only selected data are sent to the cluster head node, an activity recognition algorithm R is needed, which can deal with incomplete data sets. In general, the activity recognition task, performed by cluster head, is expressed as follows:

$$\hat{a}_t = R(S_t, M), \quad (2)$$

where M is an activity recognition model trained with use of a machine learning algorithm and St denotes a set of data transmitted to the cluster head from sensor nodes a time step t:

$$S_t = \{S_{i,t} : d_{i,t} = 1\}. \quad (3)$$

The problem of reducing data transmission at time step t is defined as follows:

Minimize_ card(St) subject to a^t = at, (4) where at is the actual human activity, and card( ) denotes cardinality of the set. Note that card(St) corresponds to the number of sensor nodes that have to send data at time step t.

Algorithm 2 Operation of cluster head (node i∗)

Input: recognition model M

1: for each time step t do

2: collect data Si∗,t from own sensors

3: wait for data St transmitted from sensor nodes

4: recognize activity a^t = R(Si∗,t ∪ St, M)

5: send a^t to sink

6: end for

The classification models Mi, should allow sensor nodes to made decisions di,t that determine solution of minimization problem (4). This objective is achieved by appropriate training of the classification models. Application of this proposed method involves the following steps:

1. Collect training data.
2. Divide the training data into two samples.
3. Train recognition model M using the first data sample.
4. Prepare data for training classification models Mi based on the second data sample.
5. Train classification models Mi.

A training data set, collected at the first step, has to include pre-processed sensor readings from all sensor nodes (S) and information about activities of the monitored persons (A) for a representative period. Activities are recognized by a human observer. The sensor readings are prepossessed to eliminate noise, aggregate the raw data and reduce their size. Subsequently, the training data set (S, A) is divided into samples (S', A') and (S", A"). Finally, the training procedures (steps 3–5) are performed as discussed in the following subsections.

Block diagrams in Figures 1 and 2 illustrate the outline of the proposed method. Figure 1 depicts the training of recognition and classification models. Usage of the trained models during operation of sensor network is presented in Figure 2. It should be noted that left part of Figure 2 corresponds to Algorithm 1, and the right part relate to Algorithm 2.

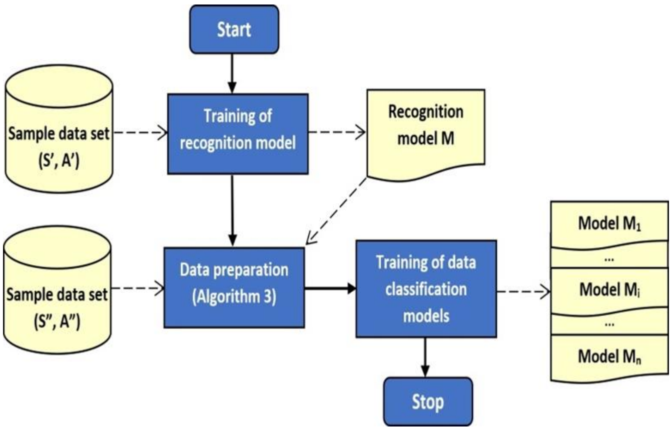

Figure 1. Block diagram of the proposed method: training stage.

IV. Results and Discussion

The objective of the conducted experiments was to verify effectiveness of the proposed method, when implemented in the wearable sensor network for human activity monitoring. The activity recognition was considered as a typical application of the wearable sensors. During experiments, the energy consumption of sensor nodes was measured to enable evaluation of the network lifetime. In parallel, the accuracy of activity recognition was investigated. The results obtained for the proposed method were compared with those of the state-of-the-art data prediction methods that use neural networks [30] and naive algorithm [39].

4.1 Experimental Testbed

The prototype of wearable sensor network used for the experiments was built of four sensor nodes. Each node contains an ARM microcontroller (STM32F103C8T6) and communication module based on ZigBee technology (xBee S2C). Three of them are addi- tionally equipped with the accelerometer (MPU-9250) and the light sensor (ALS-PT19). These sensor nodes are used as the wearable devices attached to a person, as shown in Figure 3. The fourth node acts as the sink and collects the information about recognized activities of the monitored person.

Initial experiments were conducted to compare the accuracy of human activity recognition for various machine learning algorithms (classifiers). The compared algorithms include: probabilistic neural network (PNN), support vector machines (SVM), k-nearest neighbours algorithm (k-NN), random tree (RT), and random forest (RF). During these tests the data reduction was not executed, i.e., all collected sensor readings were taken into account. The initial tests were carried out using implementations of the machine learning algorithms that are available in the WEKA package. Results of this comparison (Figure 2) clearly demonstrate that the data collected by the proposed wearable sensor network enables recognizing the human activities with a high accuracy. Parameters of the compared machine learning algorithms were selected empirically based on our prelimi- nary experiments.

During experiments 60% of the data were used for training and 40% for testing. The test was executed 10 times for different divisions of the data into train and test sets. The error bars presented in Figure 2 correspond to maximum and minimum results of these tests, while columns depicts the average value.

The PNN was trained using the constructive training algorithm, based on dynamic decay adjustment [47]. When using this algorithm, the PNN is dynamically constructed during training and the number of required hidden neurons is automatically adjusted. The PNN is built of neurons with a Gaussian activation function and models the probability distribution of each considered class through a combination of these Gaussians. The training algorithm adjusts each Gaussian function by taking into account two parameters ($\Theta+$ and $\Theta-$) to avoid conflicts between different classes. The parameter settings used in this study are $\Theta+ = 0.4$ and $\Theta- = 0.2$.

The training of SVM aims at constructing hyper planes defined in a multidimensional space that separate training data points belonging to different classes. To this end a training algorithm is used, which solves an optimization problem [48]. The iterative training procedure finds optimal hyper planes with maximum distance to the nearest training data point of any class. The experiments were performed using C-SVC version of the SVM classifier [49] with radial basis function kernel.

The k-NN classifier [50] evaluates distances between a test data point and all training data points in a multidimensional feature space. Based on the calculated distances, the nearest k training data points are selected. The classification result is determined as the class, which is most common among the k selected training data points. This algorithm was used during experiments with parameter k = 3, and the Euclidean distance was considered.

The RT algorithm [51] builds a decision tree using a random procedure. Each node of the tree is split using the best split among a subset of randomly chosen attributes. The tree constructed by the RT algorithm considers K random attributes at each node. In this study the parameter K = 5 was used.

The highest accuracy was achieved for the RF algorithm. Thus, this algorithm was selected for further experiments. The RF algorithm [52] creates a set of decision trees from randomly selected parts of training data and features. Each of the multiple decision trees classifies data independently and votes for the selected class. Finally, the votes from all decision trees are aggregated to decide the output class. The classification algorithm picks the class having the majority of votes from decision trees.

The number of trees for RF algorithm was set to 10. As illustrated in Figure 3, for more than 10 trees, the increase of recognition accuracy is not significant (below 0.006%), while the larger number of trees involves longer computational time and increased con- assumption of memory resources. The dotted lines in Figure 3 correspond to the maximum and minimum result of 10 tests, while the solid line represents the average value. An additional advantage of the random forest algorithm is its suitability for implementation in the prototypes of sensor nodes. It should be noted that several approaches to implementation of the random forest classifier for embedded devices are available in the literature [53–55]. In this study the random forest algorithm was used for activity recognition as well as for data classification to decide which data have to be transmitted.

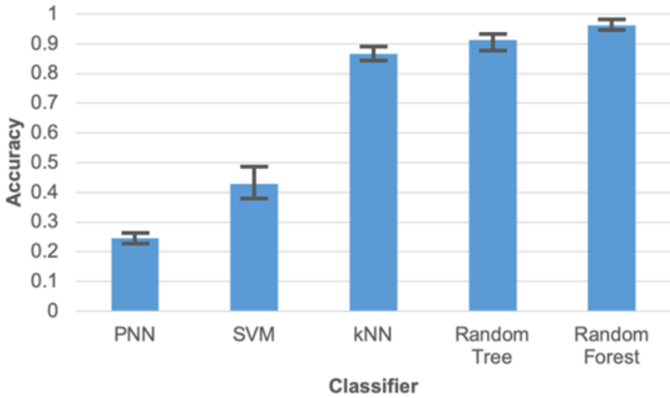

Figure 2. Accuracy of human activity recognition for compared machine learning algorithms.

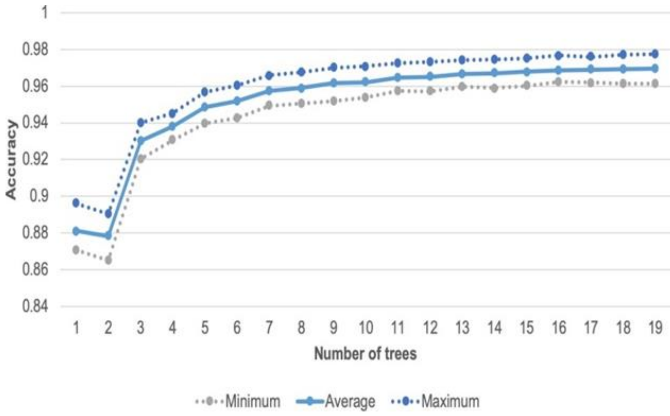

Figure 3. Accuracy of human activity recognition for different number of trees.

A high accuracy of human activity recognition was achieved using the sensor network with three wearable nodes. Figure 9 compares this result with the accuracy obtained in case when the input data for activity recognition algorithm are collected from one sensor node only. It should be noted that the experiments were performed by using the random forest algorithm for activity recognition. The Labels A, B, and C in Figure 9 identify the sensor nodes. ABC denotes the sensor network of three nodes. Sensor node A was placed on the person's chest, node B on the waist, and node C on the leg. Based on the chart in Figure 9, it can be observed that the accuracy obtained for separate sensor nodes are significantly lower than for the sensor network. This observation confirms that the use of network with three sensor nodes is justified. The meaning of error bars in Figures 9 and 10 is the same as discussed above for Figure 2.

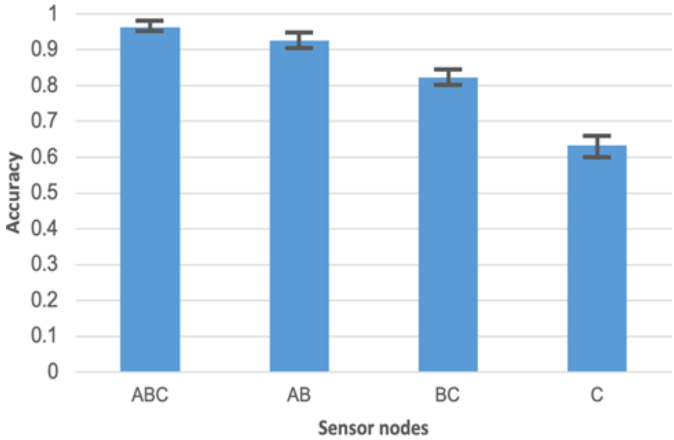

Figure 4. Comparison of activity recognition accuracy for sensor network and separate sensor nodes.

The results shown in (Figure 10b,c) relates to the situation when the accuracy of activity recognition is at the same level (average of 0.95%) for the three compared methods

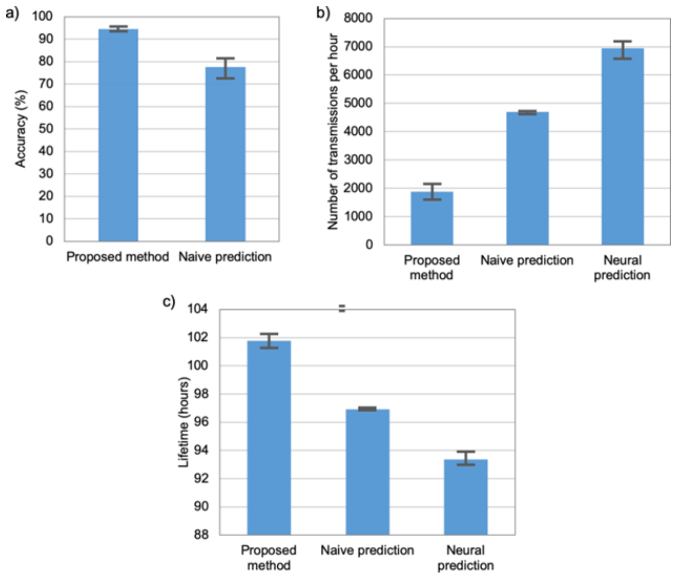

Figure 5. Comparison of accuracy (**a**), transmission number (**b**), and network lifetime (**c**).

V. CONCLUSION

The experimental results presented in this paper confirm that lifetime of the activity recognition system with wearable sensor network can be significantly extended by using the embedded classifiers that detect useful sensor readings. The introduced approach allows us to effectively eliminate the data transmission that are not necessary for performing the given recognition task. This reduction of data transmission preserves high recognition accuracy. In this study, the presented method was applied for human activity recognition, however it can be easily adapted for different applications of wearable sensor networks that involve the use of recognition algorithms for other purposes. It is also suitable for application in Internet-of-Things environment. Comparison with state-of-the-art solutions have shown that the proposed method achieves better trade-off between the accuracy and transmission reduction. 75% of data transmissions from sensor nodes were eliminated, while the accuracy level of 95% was kept.

The model ensemble used in this study for activity recognition is suitable for the wear- able sensor network, in which a few nodes are used to monitor the person. Future works will be devoted to other types of the sensor network, where a larger number of sensor nodes is connected in one cluster, and different ensemble learning methods will be used. For instance, a separate recognition sub-model can be trained based on data from each sen- sor node. In this case, after receiving data from sensor nodes, the recognition is performed independently using many sub-models in parallel. Subsequently, a common decision is made in a voting procedure, by taking into account the recognition results obtained from individual sub-models. This method requires only n sub-models to be trained, where n corresponds to the number of sensor nodes. Another possibility is to consider group of sensor nodes to simplify the model.

VI. REFERENCES

[1]. Giannini, P.; Bassani, G.; Avizzano, C.A.; Filippeschi, A. Wearable Sensor Network for Biomechanical Overload Assessment in Manual Material Handling. Sensors 2020, 20, 3877. [CrossRef]

[2]. Xu, Z.; Zhao, J.; Yu, Y.; Zeng, H. Improved 1D-CNNs for behavior recognition using wearable sensor network. Comput. Commun. 2020, 151, 165–171. [CrossRef]

[3]. Ghasemzadeh, H.; Amini, N.; Saeedi, R.; Sarrafzadeh, M. Power-aware computing in wearable sensor networks: An optimal feature selection. IEEE Trans. Mob. Comput. 2014, 14, 800–812. [CrossRef]

[4]. Jarwan, A.; Sabbah, A.; Ibnkahla, M. Data transmission reduction schemes in WSNs for efficient IoT systems. IEEE J. Sel. Areas Commun. 2019, 37, 1307–1324. [CrossRef]

[5]. Płaczek, B.; Bernas´, M. Uncertainty-based information extraction in wireless sensor networks for control applications. Ad Hoc Netw. 2014, 14, 106–117. [CrossRef]

[6]. Lewandowski, M.; Bernas, M.; Loska, P.; Szymała, P.; Płaczek, B. Extending Lifetime of Wireless Sensor Network in Application to Road Traffic Monitoring. In International Conference on Computer Networks; Springer: Cham, Switzerland, 2019; pp. 112–126.

[7]. Liu, X.; Yu, J.; Li, F.; Lv, W.; Wang, Y.; Cheng, X. Data Aggregation in Wireless Sensor Networks: From the Perspective of Security. IEEE Internet Things J. 2020, 7, 6495–6513 [CrossRef]

[8]. Dehkordi, S.A.; Farajzadeh, K.; Rezazadeh, J.; Farahbakhsh, R.; Sandrasegaran, K.; Dehkordi, M.A. A survey on data aggregation techniques in IoT sensor networks. Wirel. Netw. 2020, 26, 1243–1263. [CrossRef]

[9]. Feng, C.; Li, Z.; Jiang, S.; Jing, W. Delay-constrained data aggregation scheduling in wireless sensor networks. Int. J. Distrib. Sens. Netw. 2017, 13. [CrossRef]

[10]. Ghasemzadeh, H.; Jafari, R. Data aggregation in body sensor networks: A power optimization technique for collaborative signal processing. In Proceedings of the 2010 7th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON), Boston, MA, USA, 21–25 June 2010; IEEE: Piscataway, NJ, USA, 2010; pp. 1–9.

[11]. Shen, B.; Fu, J.S. A method of data aggregation for wearable sensor systems. Sensors 2016, 16, 954. [CrossRef]

[12]. Raj, A.S.; Chinnadurai, M. Energy efficient routing algorithm in wireless body area networks for smart wearable patches. Comput. Commun. 2020, 153, 85–94.

[13]. Lin, J.W.; Liao, S.W.; Leu, F.Y. Sensor data compression using bounded error piecewise linear approximation with resolution reduction. Energies 2019, 12, 2523. [CrossRef]

[14]. Pacharaney, U.S.; Gupta, R.K. Clustering and compressive data gathering in wireless sensor network. Wirel. Pers. Commun. 2019, 109, 1311–1331. [CrossRef]

[15]. Liu, J.; Chen, F.; Wang, D. Data compression based on stacked RBM-AE model for wireless sensor networks. Sensors 2018, 18, 4273. [CrossRef] [PubMed]

[16]. Wu, C.H.; Tseng, Y.C. Data compression by temporal and spatial correlations in a body-area sensor network: A case study in pilates motion recognition. IEEE Trans. Mob. Comput. 2010, 10, 1459–1472. [CrossRef]

[17]. Yu, L.; Xiong, D.; Guo, L.; Wang, J. A compressed sensing-based wearable sensor network for quantitative assessment of stroke patients. Sensors 2016, 16, 202. [CrossRef]

[18]. Natarajan, V.; Vyas, A. Power efficient compressive sensing for continuous monitoring of ECG and PPG in a wearable system. In Proceedings of the IEEE 3rd World Forum on Internet of Things (WF-IoT), Reston, VA, USA, 12–14 December 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 336–341.

[19]. Huang, H.; Hu, S.; Sun, Y. Energy-efficient ECG compression in wearable body sensor network by leveraging empirical mode decomposition. In Proceedings of the 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), Las Vegas, NV, USA, 4–7 March 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 149–152.

[20]. Lou, P.; Shi, L.; Zhang, X.; Xiao, Z.; Yan, J. A Data-Driven Adaptive Sampling Method Based on Edge Computing. Sensors 2020, 20, 2174. [CrossRef]

[21]. Cai, W.; Zhang, M. Spatiotemporal correlation–based adaptive sampling algorithm for clustered wireless sensor networks. Int. J. Distrib. Sens. Netw. 2018, 14. [CrossRef]

[22]. Nguyen, L.; Ulapane, N.; Miro, J.V. Adaptive sampling for spatial prediction in environmental monitoring using wireless sensor networks: A review. In Proceedings of the 2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA), Wuhan, China, 31 May–2 June 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 346–351.

[23]. Miskowicz, M. Send-on-delta concept: An event-based data reporting strategy. Sensors 2006, 6, 49–63. [CrossRef]

[24]. Diaz-Cacho, M.; Delgado, E.; Barreiro, A.; Falcón, P. Basic send-on-delta sampling for signal tracking-error reduction. Sensors 2017, 17, 312. [CrossRef]

[25]. Mesin, L. A neural algorithm for the non-uniform and adaptive sampling of biomedical data. Comput. Biol. Med. 2016, 71, 223–230. [CrossRef]

[26]. Rezaie, H.; Ghassemian, M. An adaptive algorithm to improve energy efficiency in wearable activity recognition systems. IEEE Sens. J. 2017, 17, 5315–5323. [CrossRef]

[27]. Augustyniak, P. Adaptive Sampling of the Electrocardiogram Based on Generalized Perceptual Features. Sensors 2020, 20, 373. [CrossRef] [PubMed]

[28]. Shu, T.; Chen, J.; Bhargava, V.K.; de Silva, C.W. An energy-efficient dual prediction scheme using LMS filter and LSTM in wireless sensor networks for environment monitoring. IEEE Internet Things J. 2019, 6, 6736–6747. [CrossRef]

[29]. Ganjewar, P.; Barani, S.; Wagh, S.J. A hierarchical fractional LMS prediction method for data reduction in a wireless sensor network. Ad Hoc Netw. 2019, 87, 113–127. [CrossRef]

[30]. Dias, G.M.; Bellalta, B.; Oechsner, S. A survey about prediction-based data reduction in wireless sensor networks. Acm Comput. Surv. 2016, 49, 1–35. [CrossRef]

[31]. Suh, Y.S. Send-on-delta sensor data transmission with a linear predictor. Sensors 2007, 7, 537–547. [CrossRef]

[32]. Feng, X.; Zhenzhen, X.; Lin, Y.; Weifeng, S.; Mingchu, L. Prediction-based data transmission for energy conservation in wireless body sensors. In Proceedings of the 2010 The 5th Annual ICST Wireless Internet Conference (WICON), Singapore, 1–3 March 2010; IEEE: Piscataway, NJ, USA, 2010; pp. 1–9.

[33]. Mishra, A.; Chakraborty, S.; Li, H.; Agrawal, D.P. Error minimization and energy conservation by predicting data in wireless body sensor networks using artificial neural network and analysis of error. In Proceedings of the 2014 IEEE 11th Consumer Communications and Networking Conference (CCNC) Las Vegas, NV, USA, 10–13 January 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 165–170.

[34]. Mejia, J.; Ochoa-Zezzatti, A.; Cruz-Mejía, O.; Mederos, B. Prediction of time series using wavelet Gaussian process for wireless sensor networks. Wirel. Netw. 2020, 26, 5751–5758. [CrossRef]

[35]. Putra, I.P.E.S.; Brusey, J.; Gaura, E.; Vesilo, R. An event-triggered machine learning approach for accelerometer-based fall detection. Sensors 2018, 18, 20. [CrossRef]

[36]. Pérez-Torres, R.; Torres-Huitzil, C.; Galeana-Zapién, H.A Cognitive-Inspired Event-Based Control for Power-Aware Human Mobility Analysis in IoT Devices. Sensors 2019, 19, 832. [CrossRef]

[37]. Socas, R.; Dormido, S.; Dormido, R.; Fabregas, E. Event-based control strategy for mobile robots in wireless environments. Sensors 2015, 15, 30076–30092. [CrossRef]

[38]. Ullah, F.; Abdullah, A.H.; Kaiwartya, O.; Kumar, S.; Arshad, M.M. Medium Access Control (MAC) for Wireless Body Area Network (WBAN): Superframe structure, multiple access technique, taxonomy, and challenges. Hum. Centric Comput. Inf. Sci. 2017, 7, 34. [CrossRef]

[39]. Aderohunmu, F.A.; Paci, G.; Brunelli, D.; Deng, J.D.; Benini, L.; Purvis, M. An application-specific forecasting algorithm for extending wsn lifetime. In Proceedings of the 2013 IEEE International Conference on Distributed Computing in Sensor Systems, Cambridge, MA, USA, 20–23 May 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 374–381.

[40]. Ignatov, A. Real-time human activity recognition from accelerometer data using Convolutional Neural Networks. Appl. Soft Comput. 2018, 62, 915–922. [CrossRef]

[41]. Murad, A.; Pyun, J.Y. Deep recurrent neural networks for human activity recognition. Sensors 2017, 17, 2556. [CrossRef] [PubMed]

[42]. Zubair, M.; Song, K.; Yoon, C. Human activity recognition using wearable accelerometer sensors. In Proceedings of the 2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia), Seoul, Korea, 26–28 October 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 1–5.

[43]. Zhao, Z.; Wang, J.; Zhao, X.; Peng, C.; Guo, Q.; Wu, B. NaviLight: Indoor localization and navigation under arbitrary lights. In IEEE INFOCOM 2017-IEEE Conference on Computer Communications, Atlanta, GA, USA, 1–4 May 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–9.

[44]. Ravi, N.; Iftode, L. FiatLux: Fingerprinting rooms using light intensity. In Proceedings of the 5th International Conference on Pervasive Computing, Toronto, ON, Canada, 13–16 May 2007.

[45]. Lewandowski, M.; Płaczek, B. An Event-Aware Cluster-Head Rotation Algorithm for Extending Lifetime of Wireless Sensor Network with Smart Nodes. Sensors 2019, 19, 4060. [CrossRef]

[46]. Berthold, M.R.; Cebron, N.; Dill, F.; Gabriel, T.R.; Kötter, T.; Meinl, T.; Ohl, P.; Thiel, K.; Wiswedel, B. KNIME-the Konstanz information miner: Version 2.0 and beyond. ACM Sigkdd Explor. Newsl. 2009, 11, 26–31. [CrossRef]

[47]. Berthold, M.R.; Diamond, J. Constructive training of probabilistic neural networks. Neurocomputing 1998, 19, 167–183. [CrossRef]

[48]. Fan, R.E.; Chen, P.H.; Lin, C.J. Working set selection using second order information for training support vector machines. J. Mach. Learn. Res. 2005, 6, 1889–1918.

[49]. Chang, C.C.; Lin, C.J. LIBSVM: A library for support vector machines. ACM Trans. Intell. Syst. Technol. 2011, 2, 1–27. [CrossRef]

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