Sleep Posture Classification Using Bed Sensor Data and Neural Networks*

Moein Enayati, Marjorie Skubic, James M. Keller, Mihail Popescu, and Nasibeh Zanjirani Farahani

Abstract— **Sleep posture has been shown to be important in monitoring health conditions such as congestive heart failure (CHF), sleep apnea, pressure ulcers, and even blood pressure abnormalities. In this paper, we investigate the use of four hydraulic bed transducers placed underneath the mattress to classify different sleep postures. For classification, we employed a simple neural network. Different combinations of parameters were studied to determine the best configuration. Data were collected on four major postures from 58 subjects. We report the results of classification for different combinations of these four postures. Both 10-Fold and Leave-One-Subject-Out (LOSO) Cross-validations (CV) were used to evaluate the accuracy of our predictions. Our results show that there are multiple configuration settings that make classification accuracy as high as 100% using k-Fold CV for all postures. Maximum classification accuracy after applying LOSO is 93% for a two-class classification of separating Left vs. Right lateral positions. The second-best classification accuracy with LOSO is 92% for the classification of lateral versus non-lateral.**

I. Introduction And Related Works

With the recent advances in health care, the average lifespan of elderly people is increasing. This increases the necessity of better and more accessible monitoring tools specialized for the needs and conditions of this population. One major aspect of elderly life, is the large amount of time they spend in bed. Human beings usually spend one third or one-quarter of their daily life in bed [1] while elderly usually stay in bed more than that. If their sleeping posture and movements are measured and evaluated quantitatively over a period of time, not only can nurses assist them better, but also the health monitoring systems can be used to detect health issues.

There is a two-way relationship between health and sleep posture. Some sleep disorders may appear due to the decline or changes in health condition. For example, [2] reported that for patients with Congestive Heart Failure (CHF), the amount of time spent in the right lateral position is significantly more than the amount of time spent in the left lateral position. This strategy might help them to avoid the discomfort caused by the enlarged apical heartbeat or further hemodynamic or autonomic compromise. On the other hand, some health problems might appear due to or influenced by, sleep posture e.g. bedsores. Bedsores or pressure ulcers may appear on any part of the body, as a result of long-term lying on the bed with the same posture [3]. Also, by modification of sleep position and preventing supine sleep, [4] reported improvement of sleep-disordered breathing for positional Obstructive Sleep Apnea (OSA) patients. About 20~40% of the elderly population are suffering from sleep apnea and hypopnea syndrome (SAHS), and more than half of the patients remain undiagnosed [5].

In sleep studies, neurophysiological signals and polysomnography (PSG) are used due to their accuracy [6]. Sleep studies are usually expensive, and the patients are asked to stay overnight in hospitals. In-home sleep monitoring systems would help researchers to analyze sleep conditions in a natural setting such as patient's own home. Long-term care facilities may also take advantage of sleep-related information on the treatment plans for their residents. As a result, we see an increase in demand for low cost and efficient monitoring systems for elderly [7].

In polysomnography, different devices such as accelerometers, gyroscopes, and magnetometers are being placed on the chest, wrist or feet of the subject. Although these sensors can accurately measure the thoracic respiration, heartbeat, as well as body posture, they all need to be worn during sleep, making an inconvenient sleep experience for the subjects. Noninvasive methods such as camera-based techniques are main ways of monitoring in-bed postures. As an example, the use of 3D depth cross-sectional scans of the body is explored in [8]. The main issues with the camera-based approaches are privacy concerns and limitations in obtaining images at night.

The majority of recent noninvasive methods for in-bed posture recognition use high-density pressure mats to identify the structure of the whole body. [9] uses a dense grid of 42x192 pressure sensors, with sampling rate at 1 frame every 3 seconds, to classify the Supine, Prone, Left and Right postures. [10] uses a total of 6144 square sensors within a region of 33 × 73 inches, for their limb clustering algorithm. Conductive textile sheet [11] and static charge sensitive bed [1] are also being used for posture detection

Although most of these methods reported high recognition accuracy, usually hundreds of pressure sensors are required in a mat for detailed data acquisition. Recent approaches are seen to decrease the number of sensing array elements. In [12], 48 conductive sensors were placed between the mattress and the bed sheet. They reported 80.76% accuracy for their classification task. [3] uses 16 long-narrow Force Sensing Resistor (FSR) sensors. Additionally, [13] had only four sensors i.e. two piezoelectric and pressure sensors are used for data acquisition. They reported 89.9% accuracy for three postures i.e. lying back, lying left, and lying right, with 5-fold cross-validation and on 120 hours of data collected from one subject.

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On the other hand, different classification algorithms have been applied by researchers for the estimation of in-bed sleep postures, including Bayesian classification [3], K-nearest neighbors [9] and SVM [14]. [9] reported the accuracy of 98% by applying KNN and SVM. Hierarchical inference model with the binary SVM classification also tested by [14]. They reported the high accuracy of 91% after applying PCA. Despite the ease of application, Neural Networks have been used only in a handful of papers. For example, [1] used neural networks to estimate pose and motion, to assist the patients using their Intelligent Bed Robot System (IBRS).

This paper focused on evaluating different parameter settings for the application of neural networks in sleep posture detection using the data acquired from an in-home setting of only four hydraulic bed sensors. Section II of this paper presents a brief overview of the system and the data collected for the experiments. Data preprocessing and feature extraction will be described in Section III. In section IV we will discuss the classification method, the parameters and the experiments were done for validation. The experiment will be discussed in Section V and their results would come in Section VI. Finally, Section VII provides a brief summary of the work, along with avenues for future investigation.

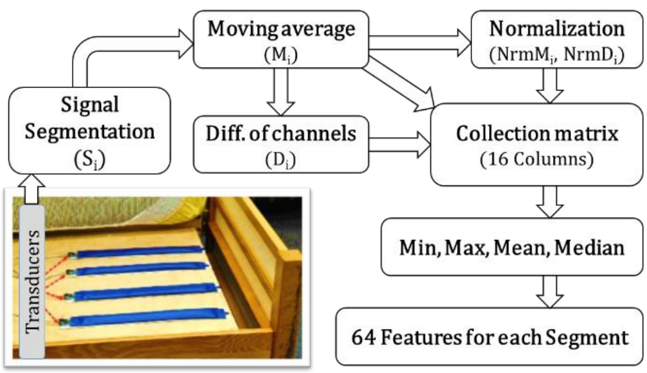

Figure 1. The workflow of data preparation for the classification task, from bed-data acquisition to feature extraction. Our bed sensor consists of four hydraulic transducers placed underneath the bed mattress.

I. Sensor And Data

In this paper, we use a hydraulic bed sensor designed for capturing ballistocardiogram (BCG) signals [15]. It is composed of a set of four water tubes each fitted with a pressure sensor (Fig. 1) which are placed under the bed mattress for the purpose of non-invasive heart motion measurement. The four-channel signal is sampled at 100 Hz and in its raw format, it contains a DC bias (the weight of the body lying on the bed). We simply ran moving averages to remove the high-frequency part of the signal. Variations in the DC values for the four channels are known to be correlated to the location of the person on the bed.

A total of 58 young healthy subjects were recruited and asked to lie still on each of the main postures for one minute. The exact definition of Supine, Prone, Left Lateral and Right Lateral, was somewhat subjective and left for the subjects' interpretation. The data collection procedure was approved by University of Missouri Institutional Review Board (MUIRB). A separate file containing four data channels has been created for each subject and per posture. In order to create the dataset, all channels were divided into multiple segments of equal length. Features extracted from each segment are used for signal segmentation, as described in algorithm I.

Algorithm I Signal segmentation

Goal: Segmentation of data acquired from one subject on a specific posture.
Requires: Ti, Signal acquired from each transducer for the entire length.
ST, Segmentation length. Could be 5, 10, 15, or 20 seconds.

```
function signal_segmentation(T1, T2, T3, T4)
    ST = 15*Fs;                                  % Segment length in Seconds
    for i=1:4 do
        Si = reshape( Ti, len(Ti)/ST, ST);  % Cut the signal
    end
end
```

II. Feature Extraction

Authors of [16], [6] reported the use of a set of statistical features including mean, standard deviation, minimum and maximum of sensor values and also the kurtosis of the frame values. They reported high accuracy rates for using statistical features especially being applied to a limited number of sensors. Consequently, we also based our classification on a set of simple statistical features as shown in Fig. 1 and described in algorithm II. All channels were divided into equal length segments S_i. Length of the segments varies between configurations (e.g. 15 seconds). Then a set of 16 simple statistical features were extracted from each signal, in the following manner. A moving average M_i is computed for each channel, resembling the DC value of that channel over time. Then, the difference of the adjacent channels was computed as $D_i = M_i - M_{i+1}$. We then normalized both computed vectors of M_i and D_i, using formulas 1 and 2 where we subtract the mean value in order to center the data and then divide by the global range of that segment.

$$NrmM_i = \frac{M_i - mean(M_{1\ldots4})}{\max(M_{1\ldots4}) - \min(M_{1\ldots4})} \quad (1)$$

$$NrmD_i = \frac{D_i - mean(D_{1\ldots4})}{\max(D_{1\ldots4}) - \min(D_{1\ldots4})} \quad (2)$$

Finally, we put all these 16 vectors in a form of a columnar matrix. By applying four functions of Min, Max, Mean, and Median on the columns of this matrix we made our feature set of size 64 (=16x4).

Algorithm II Feature extraction

Goal: Extracting features from one signal segment in the time
Requires: Si, Signal acquired from each of the four transducers

```
function feature_extraction(S1, S2, S3, S4)
    W = 5*Fs;                    % Window size in Seconds
    for i=1:4 do M(i) = moving_mean(S(i), W);          % DC bias
    for i=1:4 do D(i)  = M(i)-M(i+1);                  % Diff. channels
    for i=1:4 do NrmM(i) = (M(i)-mean(M(:)))/range(M(:));
                 NrmD(i)  = (D(i) - mean(D(:))) /range(D(:));
    Matrix   = [M(:,:), D(:,:), NrmM(:,:), NrmD(:,:)];  % Collection
    Features = [min(Matrix), max(Matrix),               % Statistical func.
                mean(Matrix), median(Matrix)];
end
```

With a total of 64 features per sample point, for 58 subjects and over 4 sleeping postures, we ran multiple experiments to investigate the best configuration settings. We applied Matlab's PCA function called *pcares*, to sort the features in the original domain. And then we selected the first

4 or first 16 features for classification tasks. For the principal component analysis (PCA) we compared the set of best 16 features to the set of best 4 features.

PCA is one of the most widespread methods in data analysis. It consists of applying orthogonal transformations to variables that are assumed to be possibly correlated, in order to make them linearly uncorrelated, aiming to preserve the most variations between the data variables and avoid redundancy. Hence the first principal component is the one that accounts for the most data variability, while the second account for less variance, and is orthogonal to the previous one, etc. The resulting uncorrelated variables form then an orthogonal basis set.

III. Classification Procedure

The classification process was performed using a feedforward neural network. We explored some parameters of the neural network itself, including the number of hidden layers and the number of nodes per layer, the activation function of each layer, and the amount of regularization. We used Matlab's implementation for our neural network as an easy to use API, which gives us the ability to manually set all these parameters (Fig. 2).

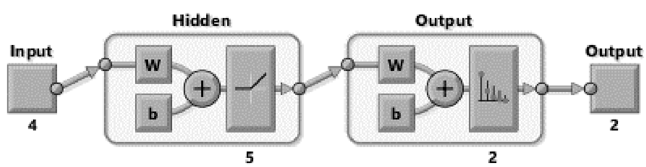

Figure 2. An example of a Neural Network with one layer of 5 nodes. For input, it uses 4 features after PCA, and generated 2-class labels as output.

For the number of hidden layers, we used both 1 and 2 layers. We then changed the number of nodes per layer, to be either 5, 10, 20, or 30 neurons to change the complexity of the model. Also, for the activation function, we applied the hyperbolic tangent sigmoid function (*tansig*) which is a faster implementation of tanh function. We also used the Positive linear function (*poslin*) which is Matlab's implementation of the rectified linear unit (ReLu), as described in Fig. 3.

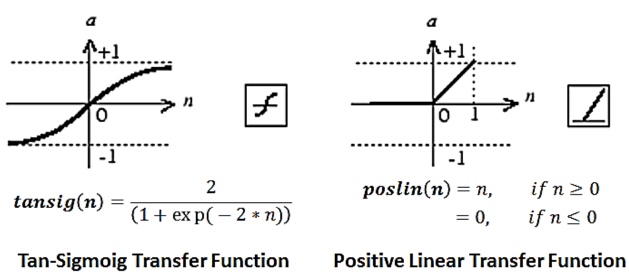

Figure 3. Schematic definition and formulation of the two transfer functions that we compared.

Regularization was another parameter to explore, which addresses the over-fitting problem in training the neural networks. In over-fitting, the network "memorizes" the training examples, instead of learning a general pattern. Having very few training samples, or too many free parameters (weights of the network) without using regularization may cause overfitting. We tried three values of 0, 0.1 and 0.5 for the regularization.

Another gap in the literature was related to the validation of the classification accuracy. Despite some papers which did not mention their validation approach, most of the researchers in this field used k-Fold CV, and there are few papers in which the Leave-One-Subject-Out (LOSO) validation was used [11]. Based on the typical assumption of having independent and identically distributed (i.i.d) dataset, many of the machine learning researchers use the k-Fold CV to evaluate their classification tasks. In each fold of the k-Fold CV, $1/k$ of all sample points will be selected randomly and tested against the rest of the samples. However, in human activity recognition ,we do not always have i.i.d dataset. In fact [17] reported having non-negligible grouping of data points by subjects. In contract, in LOSO samples of one subject will be tested against the model being trained by all samples from other subjects together, as described by algorithm III.

Algorithm III LOSO CV

Goal: Leave-One-Subject-Out Cross-Validation
Requires: **N,** Number of subjects
Fn, Set of 64 feature extracted from subject *n*.
fTrain, function used to train the neural network
fTest, function used to test the neural network

```
function LOSO_CrossVal([F1, F2, …, F58])
    net = feedforward(hiddenSizes, ActivationFn, Regularization);
    for i=1:58 do
        test_FeatureSet = Fi;                    % Test Features, current user
        train_FeatureSet = F - Fi;               % All other samples to train
        net = train(net, train_FeatureSet)       % Train the network
        acc(i) = test(net, test_FeaturesSet)     % Test the network
    end
    % Evaluate the overall(mean) accuracy
end
```

We used both of these cross-validation methods to make sure our proposed system is capable of classifying, not just random test samples from all subjects combined (as defined in the 10-Fold cross-validation), but also it is able to learn a general pattern from part of the population and use it for classification of a new unseen subject (claimed in LOSO).

IV. Experiments

In this paper, each classification process consists of setting multiple parameters started by defining the length of signal segments, followed by the number of features selected after PCA, setting the number of hidden nodes, activation function and the amount of regularization for neural network, and finally ended by deciding the type of cross-validation method to evaluate that specific classification task accuracy. Selecting a subset of posture data helps us to explore different class label problems such as classification of "Lateral vs Non-Lateral", or "Supine vs. Prone".

We used four values for the segmentation length (5,10,15, and 20 seconds), three values for the number of features selected after PCA (4, 16, 64 features), three values for the regularization (0, 0.1, and 0.5), two different activation functions (tansig, poslin), and eight configurations for the number of layers and neurons in the neural network (one layer of 5,10,20 or 30 nodes, or two layers by adding 5 nodes to the second layer). We applied all these configurations on 6 posture-based problem settings (e.g. Supine vs. Non-Supine which are reported in the second column of Table I) and

TABLE I. SHOWS AN OVERVIEW OF THE AGGREGATED RESULTS BY CHANGING ONE PARAMETER AT A TIME.

Classification problem		Splitting Time (S.)				Num. Features			Regularization			Num. Hidden Layer Nodes							
		5	*10*	*15*	*20*	*4*	*16*	*64*	*0*	*0.1*	*0.5*	*5*	*10*	*20*	*30*	*10_5*	*20_5*	*30_5*	*5_5*
k-Fold	L vs. NL	91	90	89	87	85	91	93	94	94	92	84	88	91	92	90	92	92	85
	LL vs. RL	95	93	93	92	92	94	95	78	76	63	92	93	93	94	93	94	95	92
	S vs. NS	84	81	79	76	75	80	84	83	82	78	74	79	82	83	80	83	84	75
	S vs. P	86	82	80	76	77	81	85	78	77	68	75	80	83	84	81	83	84	77
	S vs. P vs. L	77	77	73	70	66	75	81	92	91	85	67	73	78	80	74	78	80	67
	S vs. P vs. LL vs. RL	76	70	73	70	65	75	79	82	81	77	65	71	76	78	72	75	78	65
	k-Fold total	***85***	***82***	***81***	***78***	***77***	***83***	***85***	***84***	***83***	***77***	***76***	***80***	***84***	***85***	***81***	***84***	***85***	***77***
Leave One Subject Out	L vs. NL	87	87	86	86	83	88	88	89	89	89	83	86	88	88	87	88	88	83
	LL vs. RL	89	89	89	89	89	90	88	70	70	61	89	89	89	89	89	89	89	89
	S vs. NS	71	72	72	72	71	73	72	72	72	72	71	73	73	73	72	72	72	70
	S vs. P	72	73	72	72	72	73	72	68	69	64	72	73	73	73	73	72	72	70
	S vs. P vs. L	67	68	67	66	63	69	69	88	88	84	63	67	69	69	66	68	69	63
	S vs. P vs. LL vs. RL	67	66	68	67	62	69	70	72	72	72	63	67	69	70	66	69	70	62
	LOSO Total	***76***	***75***	***76***	***74***	***73***	***77***	***75***	***76***	***76***	***73***	***73***	***75***	***77***	***77***	***75***	***76***	***76***	***73***

*Postures including Lateral(L), Non-Lateral(NL), Left Lateral(LL), Right Lateral(RL), Prone(P), Supine(S), Non-Supine(NS). Values shown in this table are in percentage (%)

evaluated the classification accuracy using two cross-validation methods (10-Fold and LOSO). Since we had 58 subjects, for LOCO CV, the data from 57 subjects were used for training and was tested against the data from the remaining one subject. This procedure repeated for 58 times always leaving samples of a new subject out for testing.

In total, we ran the entire classification process, for 6912 number of different configurations, which often takes weeks for training and cross-validation. To speed up this work, the computation was performed on the high-performance computing infrastructure provided by Research Computing Support Services at the University of Missouri.

V. RESULTS

This study gave us a good idea of what postures the neural network is capable of classifying better and what would be the best setting for each classification problem. We report comparisons between the results of 10-Fold CV versus the LOSO, which shows how well a trained network can classify records from unseen subjects in Table I. The best results were produced with 5 second segmentation time, 16 features, more neurons in the first layer, and no regularization.

Table II shows the average and maximum values of 576 separate runs of the entire procedure from feature extraction to cross-validation. The values are computed by aggregating (Avg. or Max) all available data, to illustrate the average accuracy and ultimate potential of each posture setting (the Max column). The max accuracy columns are related to the single configurations which have the highest cross-validation accuracy among all possible configurations. LOSO tends to have lower average accuracy in comparison to the k-Fold because of the higher number of unseen patterns introduced by the left-out subject. For k-Fold, the maximum accuracy was always above 99%, which means there was at least one configuration setting which ended up in 99% correct classification of the target. For LOSO the best value was 93%, which is again less than the results for the k- Fold.

According to this table, Left Lateral and Right Lateral postures were the easiest to classify, probably due to the fact that the rib cage wall moves in opposite directions for these two postures. This possibly introduces differences in the acquired waveforms of the four transducers. The second highest accuracy is related to the classification of Lateral from non-lateral postures. Again, the same reasoning might be applicable, as the rib cage moves horizontally in the lateral posture while this movement is mostly vertical for the supine and prone postures. By combining Left and right Laterals together (Lateral) and Supine and Prone together (Non-Lateral) we achieved as high as 99% accuracy for k-Fold CV and up to 92% accuracy with LOSO. These values are related to the best configuration settings that we explored in this paper and are reported in Table II.

TABLE II. COMPARING THE BEST, AND AVERAGE CASE OF ALL POSSIBLE CONFIGURATIONS SEPARATED BY THE POSTURE PROBLEM.

Classification problem	Avg. Accuracy		Max Accuracy	
	kfold	*LOSO*	*kfold*	*LOSO*
L vs. NL	89%	86%	99%	92%
LL vs. RL	93%	89%	100%	93%
S vs. NS	80%	72%	99%	79%
S vs. P	81%	72%	100%	80%
S vs. P vs. L	74%	67%	99%	76%
S vs. P vs. LL vs. RL	72%	67%	100%	75%
Grand Total (Avg. or Max)	**81%**	**75%**	**100%**	**93%**

* Lateral(L), Non-Lateral(NL), Left Lateral(LL), Right Lateral(RL), Prone(P), Supine(S)

Table III contains some other examples of the best performing configurations, which lead to high classification rates. Best results usually came from either 0 or 0.1 regularization values. Sixteen features after PCA worked as good as all 64 features in a 10-Fold CV, and worked a little better than all 64 features for the LOSO method.

The lowest performance was obtained for the classification of all four major postures, separately, by the maximum rate of 75% using LOSO. It is noticeable that even for this problem, there is at least one configuration setting which achieves 100% accuracy for k-Fold cross-validation, so it is very important to consider this big difference while comparing results in different methodologies.

VI. SUMMARY AND FUTURE WORK

In this paper, we discussed a low cost and easy to use in-home device for sleep posture classification that could be used to find correlations between sleep patterns and health conditions such as sleep apnea or CHF. Inconvenient wearable devices or expensive dense pressure mats are usually being used in classifying sleep postures in hospitals.

TABLE III. EXAMPLES OF PARAMETER SETTINGS THAT LEAD TO CLASSIFICATION CONFIGURATIONS WITH HIGHER ACCURACY RATES.

Settings	***Splitting Time***	*5*	*5*	*5*	*15*	*15*	*20*	*15*	*10*
	Num. Features	*64*	*64*	*64*	*16*	*16*	*16*	*16*	*4*
	Hidden Sizes	*20*	*30*	*10_5*	*30*	*5*	*30_5*	*5_5*	*30*
	Regularization	*0.1*	*0*	*0*	*0.1*	*0.1*	*0.1*	*0.5*	*0.5*
	Transfer Fun.	*tansig*	*tansig*	*tansig*	*tansig*	*poslin*	*tansig*	*poslin*	*poslin*
k-Fold	L vs. NL	96	99	96	92	90	90	88	87
	LL vs. RL	100	99	98	95	93	93	93	90
	S vs. NS	97	98	96	82	77	77	75	76
	S vs. P	97	100	94	79	78	71	78	77
	S vs. P vs. L	93	99	89	77	72	66	64	66
	S_P_LL_RL	92	100	89	80	72	74	59	62
	k-Fold max	**100**	**100**	**98**	**95**	**93**	**93**	**93**	**90**
LeaveOneSubjectOut	L vs. NL	86	86	88	91	88	87	86	86
	LL vs. RL	88	89	90	91	90	90	92	88
	S vs. NS	70	70	71	73	77	72	74	76
	S vs. P	68	69	72	72	74	73	73	76
	S vs. P vs. L	66	63	66	71	71	67	62	64
	S_P_LL_RL	67	65	69	75	70	72	54	60
	LOSO max	**88**	**89**	**90**	**91**	**90**	**90**	**92**	**88**

*Postures including Lateral(L), Non-Lateral(NL), Left Lateral(LL), Right Lateral(RL), Prone(P).

Here, we proposed a new application for our hydraulic bed sensor, which is already installed in many elderly homes and care facilities for longitudinal heart rate and respiration monitoring [15]. We investigated a variety of different parameter settings to find the potentials and limitations of the bed sensor for posture classification using neural networks.

The bed sensor consists of four hydraulic pressure transducers was placed underneath the mattress to maintain sleeping comfort. We collected one-minute data on each posture of supine, prone, left lateral and right lateral, from 58 subjects. Different configuration settings for feature extraction and neural network were explored, and overall performance and some of the best performing configurations were reported.

Our results confirm that in case we use the 10-Fold cross-validation it is possible to achieve the 100% accuracy for most of posture classification problems. Meanwhile, as it was expected, the accuracy achieved by applying the LOSO CV, is in average less than the 10-Fold CV for the same setting (Table II). This reduced accuracy is due to the fact that in 10-Fold CV the dataset is assumed to be independent and identically distributed (i.i.d) which is not always correct [17].

In general, the highest classification rates were usually related to separating the two lateral postures (left and right) from each other (Table II). We believe this is because the rib cage moves in the opposite horizontal directions in these two postures. Classification of lateral versus non-lateral posture was ordered the second. This can also be correlated to the orthogonal direction of chest movement in these postures.

In future we will use these best configuration settings to initialization the neural networks for posture classification in home and care facilities. Noninvasive posture classification in real home environments would give us opportunities to firstly study the sleep patterns of the residents and correlations to the health conditions, and secondly to improve our estimations of restlessness. It also will open potentials for posture-based segmentation for more accurate estimations of vital signs, as they might be correlated to posture.

We are investigating deep NN structures to improve classification accuracy. Hierarchical classification is yet another powerful, relatively simple to implement and easily expandable method which will be explored in future.

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