Boosting Lying Posture Classification with Transfer Learning

Parastoo Alinia[1], Saman Parvaneh[2], Seyed-Iman Mirzadeh[3], Asiful Arefeen[4] and Hassan Ghasemzadeh[5]

***Abstract*— Automatic lying posture tracking is an important factor in human health monitoring. The increasing popularity of the wrist-based trackers provides the means for unobtrusive, affordable, and long-term monitoring with minimized privacy concerns for the end-users and promising results in detecting the type of physical activity, step counting, and sleep quality assessment. However, there is limited research on development of accurate and efficient lying posture tracking models using wrist-based sensor. Our experiments demonstrate a major drop in the accuracy of the lying posture tracking using wrist-based accelerometer sensor due to the unpredictable noise from arbitrary wrist movements and rotations while sleeping. In this paper, we develop a deep transfer learning method that improves performance of lying posture tracking using noisy data from wrist sensor by transferring the knowledge from an initial setting which contains both clean and noisy data. The proposed solution develops an optimal mapping model from the noisy data to the clean data in the initial setting using LSTM sequence regression, and reconstruct clean synthesized data in another setting where no noisy sensor data is available. This increases the lying posture tracking F1-Score by 24.9% for 'left-wrist' and by 18.1% for 'right-wrist' sensors comparing to the case without mapping.**

I. INTRODUCTION

Lying posture tracking provides important clinical information about the patients' mobility [1], risk of developing hospital-acquired pressure injuries [2], and quality of sleep [3]. Therefore, accurate estimation of lying postures during sleep at night, along with the day-time posture/activity recognition, plays a crucial role in monitoring well-being of the individuals. To this end, researchers have proposed several lying posture tracking techniques based on the data collected with wearable and ambient sensors such as infrared camera, accelerometers, pressure sensors, load sensors, and electrocardiogram (ECG) sensors. Preserving the privacy, user-friendliness, and affordability are three key features important to continuous and long-term lying postures monitoring. However, these features have not been carefully taken into consideration in designing prior lying posture monitoring frameworks. For example, camera-based lying posture estimation imposes privacy concerns, multi-sensor wearable systems are uncomfortable to wear, and pressure-mats are costly to deploy at scale. While chest sensor based lying posture detection is highly effective, they often cause disturbance during sleep.

In contrast, wrist-based lying posture tracking is a non-invasive and inexpensive solution with less privacy and wearability concerns compared to multi-sensor wearable and vision-based systems. However, a major challenge with using a wristband device to estimate lying postures is the adverse impacts of noise due to hand motions and body rotations on the performance of the underlying lying posture estimators. In fact, as supported by our experimental results in this paper and shown in Figure 1, while machine learning algorithms can be used to detect lying postures with a performance of 94.2% using a wearable sensor affixed to 'chest' or 'thigh', the classification performance drops to 66.2% when lying postures are inferred using wrist-worn sensors. This observation motivates us to design algorithms that can leverage machine learning knowledge gained in a previous setting such as those models trained with 'chest' and 'thigh' sensors data in order to achieve highly accurate posture detection using 'wrist' sensors.

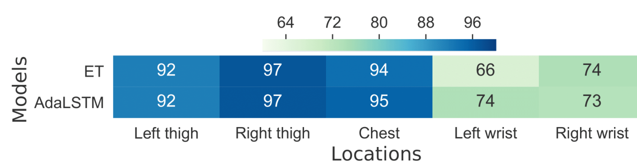

Fig. 1. Comparison between the F1-Score (%) of the Ensemble Tree and AdaLSTM classification models on the Class-Act dataset.

To address the aforementioned challenge, we propose a wrist-based lying posture tracking framework that uses a teacher/learner transfer learning technique to reduce motion-induced noise in the data using knowledge learned from a clean setup. Specifically, we develop an approach to transfer the lying posture detection knowledge from an initial setting (e.g., a network with both 'chest' and 'wrist' sensors), referred to as *source*, to a wearable system with only a wrist-worn sensor, referred to as *target*. While the source setting contains both clean and noisy data, only noisy data are available in the target setting. Our proposed model reconstructs clean data from the noisy sensor readings generated in the target setting by finding an efficient representation of the target data for use with a model trained previously in the source domain. We propose two successful architectures for such a deep mapping approach. Those architectures include an LSTM (Long Short-Term Memory) sequence regression model and an LSTM Encoder-Decoder regression technique.

[1]Parastoo Alinia is an Applied Machine Learning Scientist at Amazon, Atlanta, GA 30305, USA

[2]Saman Parvaneh is a Data Scientist at Edwards Lifesciences, Irvine, CA 92614, USA

[3]Seyed-Iman Mirzadeh is a PhD student in Computer Science, Washington State University, Pullman, WA 99163, USA

[4]Asiful Arefeen is a PhD student in Biomedical Informatics, Arizona State University, Phoenix, AZ 85004, USA

[5]Hassan Ghasemzadeh is an Associate Professor of Biomedical Informatics, Arizona State University, Phoenix, AZ 85004, USA

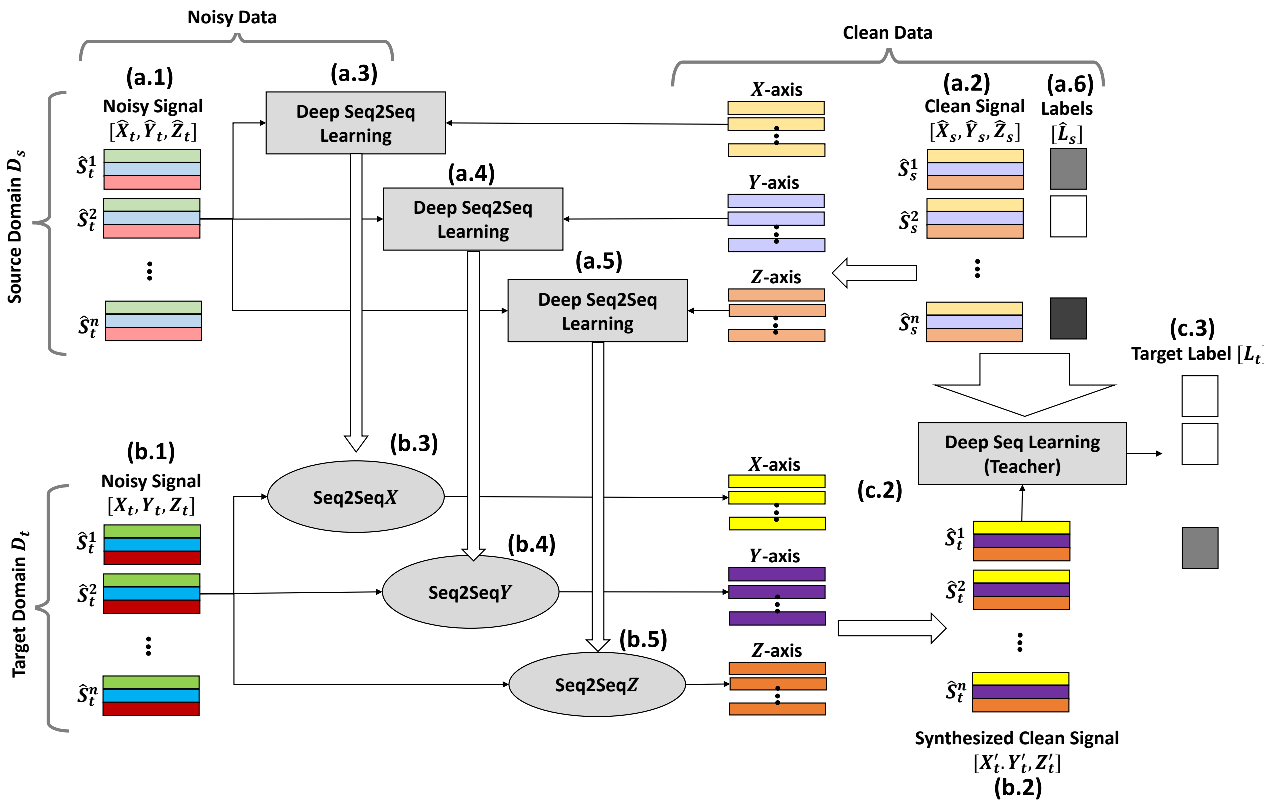

Fig. 2. Overview of the Teacher/Leaner Transfer Learning approach.

II. Related Studies

Sensor-based lying posture tracking has been proposed using different modalities of wearable or ambient sensors. The lying posture tracking techniques based on ambient sensors used load cell sensors [4], pressure sensors [5], [6], and infrared cameras [7]. The camera-based lying posture tracking solutions suffer from privacy concerns [8]. Although using pressure mats [9] and load sensors is non-invasive and does not impose major privacy concerns to the end-user, the technologies based on such sensor modalities are expensive and often times require sensor calibration. On the other hand, wearable sensors that have been used for lying posture tracking include accelerometers [10] and electrocardiogram wave forms [11]. There also exists multi-modal lying posture tracking systems [12], [13], which are more challenging to deploy in real-life settings because of the complexities involved in the processing of multi-modal data and data fusion difficulties. With respect to the number of the sensors, wearable sensor-based lying posture tracking can be categorized into single-sensor and multi-sensor. Multi-sensor technologies are developed based on the data captured from multiple sensors on different locations of the body, and usually are proposed based on the relative angular axes of the sensors to each other. Major shortcoming of such systems includes acceptability of the technology due to user discomfort for long-term use while sleeping. Another drawback associated with multi-sensor systems is the rotation and displacement of the sensors during sleep, which reduces the accuracy of the orientation-based lying posture tracking. The focus of this paper is on designing a system that requires a single-sensor for long-term deployment for lying posture tracking.

III. Methodology

Transfer learning is applying the knowledge learned in one setting (referred to as ısource domain) to another setting that is nonidentical but related to the initial one (referred to as ıtarget domain) to improve the performance of the learning task in the target domain. The sensor data captured in the source domain is called the source dataset, and the sensor data captured in target domain is referred to as the target dataset [14].

With respect to the availability of the labeled data, transfer learning techniques have been categorized into informed, when there is label in the target domain, uninformed, when there is no label in the target domain, supervised, when there is labeled data in the source domain, and unsupervised, when there is no label data available in the source domain. Therefore, the informed supervised transfer learning is defined as the case with some labeled data in both target and source domains. Uninformed supervised is referred to the case when labeled data is available only in the source domain. Finally, uninformed unsupervised is when there is no label available in either of target or source domains. The other case in this categorization, which is the focus of this paper, is when there is no training data directly available. Instead, a pre-trained classifier (also referred to as *teacher*) is used simultaneously with the new classifier (also referred to as *learner*) to transfer the labels for the target data samples. The teacher/learner transfer learning techniques has not been explored as much as the other approaches, however, they have great potential to improve the performance of the classifier/regressor in the target domain using the source knowledge.

In short, we propose a teacher/learner transfer learning approach to address the decline in the performance of the lying posture tracking system when the sensor is worn on the locations that are prone to noise and extra movements such as wrists.

The teacher/learner deep transfer learning approach consists of four main steps as described below.

- Sequence to sequence (Seq2Seq) learning: Learning a sequence to sequence mapping for each axis of the accelerometer. The models identify an optimal mapping between the noisy tri-axial accelerometer signal and a single axis of the clean data in the source domain. (Figure 2 a.1–a.5).
- Teacher classifier: Training a deep classifier on the clean data and lying posture labels in the source domain (2-a.6)
- Clean data synthesize: Reconstructing each axis of the clean signal given the noisy tri-axial signal in the target domain, using the learned sequence to sequence mapping models (seq2seq) in the first step (2-b.1–b.5)
- Label Prediction: Predicting the lying posture of synthesized clean signal sequences using the teacher classifier (2-b.6)

Algorithm 1 Proposed Algorithm

Input: D_t, *unlabeled target dataset,* $\{D_s,\ L_s\}$, *labeled source dataset.*
Result: *Labeled target dataset,* $\{D_t,\ L_t\}$
Source domain:
1: *Learn a sequence to sequence regression model between the target and source datasets;* ▷ (section III-A)
2: *Learn a teacher classifier* Cl_s *on the clean source dataset and corresponding labels* $\{D_s,\ L_s\}$; ▷ (section III-B)
Target domain:
3: *Reconstruct clean data sequences in the target given the sequence to sequence regression model and the clean data sequences from the source;* ▷ (section III-C)
4: *Predict labels* L_t *in the target domain based on the teacher classifier and the synthesized clean data sequences from the previous step;* ▷ (section III-C)

Algorithm 1 summarizes the steps in the proposed method. The input to the algorithms is the labeled dataset containing clean sequences (chest sensor data with known lying postures), and the unlabeled dataset in the target (wrist sensor data). The algorithm finds an optimal mapping model between the noisy target sequences of data and the clean ones in the source domain. It learns a teacher classification model that achieves high prediction accuracy for the lying postures given clean data sequence. In the target domain, where clean data is not available, the clean synthesized data sequences, reconstructed using the mapping model from the source domain and noisy data sequences, serve as proxy to the clean data and fed as input. Finally, the algorithm applies the teacher classifier to make decision on the synthesized data and predicts the labels in the target domain.

The remaining of this section will discuss each step of the proposed method.

A. Sequence to Sequence Learning

LSTM networks have shown promising results on time series classification tasks [15]. These models captures long-distance dependencies from sequential data through the integration of memory cells and RNNs [16]. Bidirectional long short-term memory (bi-LSTM) networks were introduced as an extension to the LSTM networks. The bi-LSTM architecture consists of two LSTMs that train in two directions; therefore, it is capable of extracting long-term data dependencies in both forward and backward directions [17]. We propose two mapping models based on the architecture of the LSTM networks to address the above-mentioned problem: (1) LSTM sequence to sequence (Seq2Seq) regression model; and (2) LSTM Encoder-Decoder model.

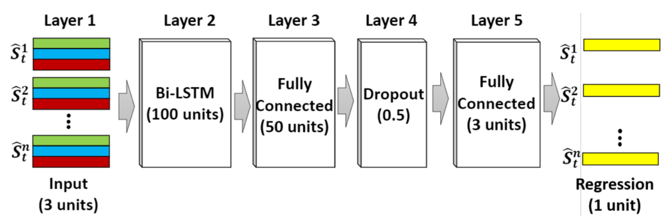

Fig. 3. Architecture of LSTM sequence to sequence regression model.

*1) **LSTM Seq2Seq Regression**:* Figure 3 demonstrates the architecture of the proposed LSTM sequence to sequence Regression model, also referred to as DeepReg. The input to this model comprises the episodes of source raw accelerometer data (sequences of raw accelerometer sensor data), and the output is the target raw accelerometer data. The proposed model contains 6 layers including an input layer, a bi-LSTM layer with 100 hidden units, a drop out layer with 0.5 dropout ratio, a fully connected layer with three hidden units, and a regression layer with 1 output unit that correspons to the output signal. The LSTM Seq2Seq regression aims to minimize the root mean squared error (RMSE) between the corresponding input and output sequences, therefore, is a suitable model for the purpose of this study.

We set the maximum number of the epochs equal to 100, *Adam* as the optimizer, mini-batches to be short sequences of 20 samples, learning and decay rate to 0.01 and 0.99 respectively for training the neural network through back-propagation.

*2) **LSTM Seq2Seq Encoder-Decoder**:* LSTM Encoder-Decoder consists of an encoder that extracts a latent representation of the input sequences of data in the target domain, and a decoder that reconstructs the sequences of the data in another setting (e.g., source) from the latent representation.

The proposed model contains 11 layers including the input layer with 3 units for the tri-axial input signal and the output layer which is a regression layer with one hidden unit for the output single axis signal. The encoder side consists of two bi-LSTM layers with 100 and 50 hidden units respectively to extract lower level features from the input data, a drop out layer with 0.5 dropout rate for regularization of the low-level features, and another bi-LSTM layer with 25 hidden units to extract high-level features as the embedding features. The decoder unit contains a bi-LSTM layer with 25 units, a drop out layer with 0.5 dropout rate, two bi-LSTM layers with 50 and 100 hidden units respectively, and a fully connected layer with 3 hidden units.

We have used a L_2 regularization technique to prevent over-fitting the training data and again set the maximum number of the epochs equal to 100, *Adam* as the optimizer, mini-batches of size 20 samples, initial learning and decay rate to 0.01 and 0.99 respectively to train the network. Mini-batch sizes have been kept small to shorten the amount of padding and make the training more suitable for CPU.

The Encoder-Decoder model also aims to minimize the RMSE between the input X and output data $\hat{X}$, therefore, is a suitable model for the purpose of this study.

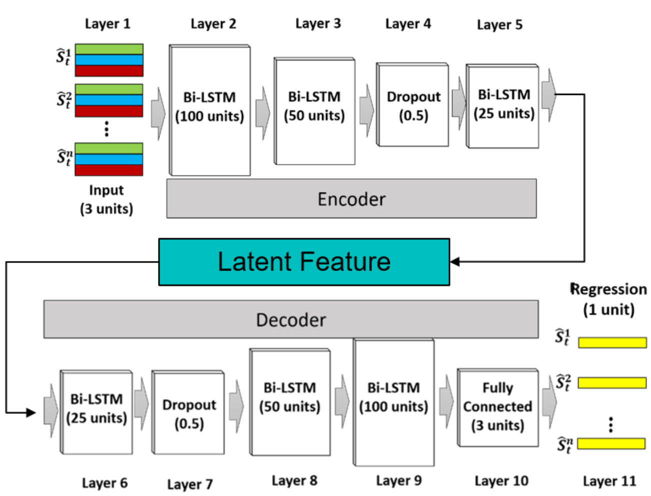

Fig. 4. Architecture of the LSTM Encoder-Decoder mapping model.

B. Deep Teacher Classifier

We train a deep LSTM sequence classification model on the clean dataset in the source domain. The inputs to the model are lying posture sequences and the output is the lying posture including supine, prone, left side, and right side. We have designed AdaLSTM, an LSTM Network with an adaptive learning rate method with decaying learning rate schedule. AdaLSTM receives the sequences of raw accelerometer sensor data as the input and estimates one label for each sequence. The input episodes/sequences of raw accelerometer data have been fed to a Bi-LSTM layer with ten hidden units. The training process of the bi-LSTM includes back-propagation processes in two directions with the objective of minimizing the error. Three fully connected layers multiply the output of the Bi-LSTM layer (e.g., sequence of tri-axial accelerometer data) by the matrix of weights and add it to the vector of bias. The output of the fully connected layer is fed to a softmax layer. We compute the cross-entropy loss for multi-class classification based on the likelihood of the softmax function. The number of the epochs have been set to 100, initial learning and decay rate to 0.01 and 0.99 respectively. This time we chose the mini-batches to be of size 27 and *Adam* optimizer for training the network.

C. Data Synthesis and Lying Posture Estimation

Only noisy sequences of data (e.g., left wrist sensor readings) will not result convincing outcome in high level lying posture estimation. To improve the precision, we use the sequence to sequence mapping models, which are learned during training, on the noisy sequences of data $\{\hat{S}_t^1, \hat{S}_t^2, ...\hat{S}_t'^n\}$, which are collected from a new user not in the training dataset, and reconstruct synthesized clean sequences $\{S1_t, S2_t, ...\S_t^n\}$ (e.g., chest sensor readings).

We apply the teacher model (AdaLSTM) on the synthesized clean signal sequences. The classifier AdaLSTM estimates one label (e.g., supine, prone, left side, or right side) for each synthesized sequence. The estimated label l_t^i for the synthesized sequence S_i^t is set as the label of noisy sequence $\hat{S}_t^i$.

IV. Dataset and Experiment

A. Datasets

We perform training and validation of the models on integration of two publicly available datasets-

(1) ***Class-Act dataset*** [18] which contains human posture and activity classification data from 12 healthy participants (7 females and 15 males, ages between 20 and 36). The participants wore nine accelerometer sensors sampled at 50 Hz on nine different body locations including chest, left and right thigh, left and right ankle, left and right arm, left and right wrist during the activities. Class-Act was collected based on three pre-defined protocols with different combinations of activities or postures in a controlled manner. The activities were walking, sitting, standing, lying supine, lying prone, lying on the left side, kneeling, and crawling.

(2) ***Combined Class Act and Daily & Sport Activities (DAS) dataset*** [19] which contains data from eight subjects that performed 19 activities of daily living (ADL) for five minutes each. The participants wore five inertial sensor units embedding a tri-axial accelerometer on the chest, right and left wrist, and right and left thigh. The sensors were calibrated to acquire data at a sampling frequency of 25 Hz. We only used lying supine and lying on the right side postures in this study. We combined the lying posture episodes from the Class-Act and DAS datasets for the common sensor locations (i.e., chest, right and left wrists, and right and left thighs). We segmented each episode in DAS dataset into 15 episodes of 500 sample (i.e. 20 seconds).

Since the sampling frequencies for the two datasets are not consistent, we performed under sampling in the Class

Act dataset prior to combining the datasets to maintain the balance.

B. Comparison Methods & Evaluation Metrics

We describe the competing methods against the proposed methods DeepReg, and Encoder-Decoder in Table I.

TABLE I
COMPETING METHODS, THEIR MODELS AND FUNCTIONALITIES.

Method	Model Type	Remarks
Baseline (No Mapping)	AdaLSTM classifier	Applies leave one subject out validation on noisy data
Lasso (Mapping)	Lasso regression	Maps noisy data to clean data
Ridge (Mapping)	Ridge regression	Maps noisy data to clean data
DeepReg (Mapping)	LSTM regression	Synthesizes clean data from the noisy data
Encoder-encoder (Mapping)	LSTM Encoder-Decoder	Synthesizes clean data from the noisy data
Upper-Bound (No Mapping)	AdaLSTM classifier	Trained on clean data using leave one subject out validation

We compare the RMSE between the synthesized target signal and the actual signal as a measure of accuracy for the mapping unit which calculated as below.

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}\Big(\frac{x_i^{s\to t} - x_i^t}{\sigma_i}\Big)^2} \quad (1)$$

where $x_i^{s\to t}$ is the sample i in synthetic target signal that is constructed from the source signal, and x_i^t is the same sample from the actual target signal. Additionally, F1-Score is reported for classification.

V. RESULTS

Results are shown in terms of mapping and classification.

A. Mapping

Figure 5 is a demonstration of the mapping network's role and Table II shows the RMSE between the synthesized clean signal and the actual clean signal in the target setting. The input to each mapping model is the noisy data collected from a sensor on the left wrist or right wrist (learners), and the output is set to the clean data collected from a sensor on the chest, left thigh, or right thigh (teachers), that works simultaneously as the sensor on the learner side. Lower RMSE value means the synthesized data is more similar to the actual data, therefore, higher classification accuracy.

The best performance is achieved by LSTM Encoder-Decoder model when noisy signal is coming from both left wrist (0.36, 0.61, and 0.33) and right wrist (0.44, 0.93, and 0.89).

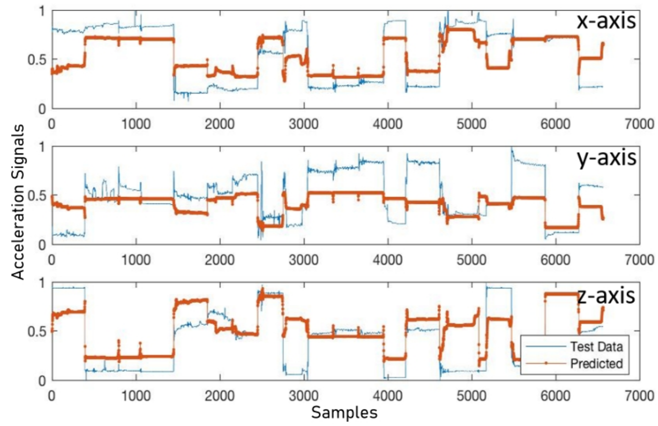

Fig. 5. An example of the constructed signal using the mapping unit. The blue lines show the actual chest sensor signals, and the orange lines are the synthetic chest sensor signals that is constructed from the wrist sensor signals. Both test data and predicted signal are normalized.

TABLE II
RMSE VALUE OF MAPPING THE SENSOR READINGS FROM THE LEARNER (LEFT WRIST AND RIGHT WRIST) TO THE TEACHER (CHEST, LEFT THIGH, AND RIGHT THIGH). RMSE IS ALSO NORMALIZED LIKE TEST/PREDICTED SIGNAL.

Mapping model	Teacher / Learner	Chest	Left thigh	Right thigh
Lasso Regression	Left wrist	2.15	2.74	5.01
	Right wrist	3.35	8.11	2.93
Ridge Regression	Left wrist	2.95	2.50	6.92
	Right wrist	1.95	2.03	1.89
LSTM Regression	Left wrist	1.12	0.98	2.5
	Right wrist	1.52	2.01	1.0
LSTM Encode-Decode	Left wrist	0.36	0.61	0.33
	Right wrist	0.44	0.93	0.89

TABLE III
LEAVE-ONE-SUBJECT OUT F1-SCORE (%) OF THE LEARNER (LEFT WRIST AND RIGHT WRIST) USING THE KNOWLEDGE FROM TEACHER (CHEST, LEFT THIGH, AND RIGHT THIGH).

Teacher→ Learner	Baseline	Lasso	Ridge	DeepReg	Encoder -Decoder	Upper -Bound
Chest → Left wrist	63.3	65.1	70.5	72.1	88.2	95.0
Left thigh → Left wrist	63.3	65.2	67.2	70.8	90.6	93.7
Right thigh → Left wrist	63.3	50.3	52.1	59.5	60.2	94.0
Chest → Right wrist	69.2	60.9	69.5	76.1	87.3	95.0
Left thigh → Right wrist	69.2	48.8	51.0	63.5	66.4	93.7
Right thigh → Right wrist	69.2	62.3	72.1	71.0	83.3	94.0

B. Lying Posture Classification

Table III shows the lying posture classification F1-Score of the baseline, DeepReg, Encoder-Decoder, Lasso, Ridge and upper-bound methods using the integrated dataset which contains 20 subjects and five sensor locations. The results are leave one subject out validated, therefore, the classifiers are trained on 19 subjects and tested on the remaining one.

The Lasso and Ridge techniques predict the clean sensor data from the noisy data sequences in the target domain; and estimate the labels given the teacher classifier and synthesized clean data. The lasso could improve the F1-score in the scenarios of transferring from the chest sensor to the left wrist to 65.1%, and left thigh sensor to the left wrist to 65.2%. On the other hand, the ridge could enhance more transfer scenarios such that it achieves 70.5%, and 67.2% F1-score of the left wrist when the chest and the left thighs are the teacher sensors. Also, it shows F1-Score of 69.5%, and 72.1% for the right wrist sensor when the teacher sensors are the chest and right wrist respectively. The negative transfer can be observed when transferring for the scenarios of 'left thigh $\leftarrow$ right wrist', and 'right thigh $\leftarrow$ right wrist'.

DeepReg approach increases the F1-Score for the left wrist data to 72.1%, and 70.8% when the chest and the left thigh are the teachers, respectively. DeepReg improves the F1-Score of the right wrist to 76.1% and 71.0% when synthesizing chest data and right thigh data, respectively. The encoder decoder model improves the F1-Score of the left wrist sensor to 88.2% when synthesizing the chest data and 90.6% when synthesizing the left thigh data. The F1-Score of the right wrist data increases to 87.3% and 83.3% when the data coming from chest and the right thigh are set as the teacher in encoder decoder model. However, setting the teacher to the sensor on the opposite side of the body as the learner (e.g., left wrist, and right thigh) impacts the performance of the learner negatively in both DeepReg and Encoder-Decoder approaches. The accuray drops and this phenomena is referred as negative transfer.

VI. Conclusion

We propose a deep feature transfer learning method to improve the performance of the lying posture tracking using wrist-based accelerometer sensor. Our approach extends the knowledge from the source setting - where both noisy and clean data is available - to the target setting - where only noisy data exists - to reconstruct synthesized clean data and classify lying postures. The proposed model utilizes LSTM sequence regression for noisy to clean data mapping in the source setting and improves the F1-Score of lying posture detection by 24.9% when the sensor is worn on the left wrist, and 18.1% when the sensor is worn on the wrist comparing to the case with no mapping. While more experimentation needs to be done, we believe that the results are promising.

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