Towards More Accurate Automatic Sleep Staging via Deep Transfer Learning

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Abstract—Although large annotated sleep databases are publicly available, and might be used to train automated scoring algorithms, it might still be a challenge to develop an optimal algorithm for your personal sleep study, which might have few subjects or rely on a different recording setup. Both directly applying a learned algorithm or retraining the algorithm on your rather small database is suboptimal. And definitely state-of-the-art sleep staging algorithms based on deep neural networks demand a large amount of data to be trained. This work presents a deep transfer learning approach to overcome the channel mismatch problem and enable transferring knowledge from a large dataset to a small cohort for automatic sleep staging. We start from a generic end-to-end deep learning framework for sequence-to-sequence sleep staging and derive two networks adhering to this framework as a device for transfer learning. The networks are first trained in the source domain (i.e. the large database). The pretrained networks are then finetuned in the target domain, i.e. the small cohort, to complete knowledge transfer. We employ the Montreal Archive of Sleep Studies (MASS) database consisting of 200 subjects as the source domain and study deep transfer learning on four different target domains: the Sleep Cassette subset and the Sleep Telemetry subset of the Sleep-EDF Expanded database, the Surrey-cEEGGrid database, and the Surrey-PSG database. The target domains are purposely adopted to cover different degrees of channel mismatch to the source domain. Our experimental results show significant performance improvement on automatic sleep staging on the target domains achieved with the proposed deep transfer learning approach and we discuss the impact of various fine tuning approaches.

Index Terms—Automatic sleep staging, sequence-to-sequence, deep learning, transfer learning.

I. INTRODUCTION

Sleep scoring [11, 12] aims to determine sleep stages from polysomnography (PSG) recordings. In clinical environments, this task has been mainly performed manually by clinicians following developed guidelines [11, 12]. Since the manual scoring is time-consuming, costly, and prone to human errors, automating the sleep scoring process has been a long-lasting focus in the sleep research community [3, 10]. Automatic sleep scoring is particularly important in home-based sleep monitoring [11–14], with the goal to exploit a novel generation of mobile Electroencephalography (EEG) devices to provide a cost-effective monitoring solution to screen larger populations for epidemiological studies or focus on specific populations at risk of sleep disorders.

Deep learning has been successfully applied to numerous domains and has received much attention from the sleep research community. Different types of networks have been exploited for automatic sleep staging, such as autoencoder [15], deep neural networks (DNNs) [10], convolutional neural networks (CNNs) [7, 10, 17, 18], and recurrent neural networks (RNNs) [19–24]. Deep learning algorithms have introduced novel classification schemes which are impossible under more conventional machine learning paradigms as well as proposed novel representations learned from large databases. For example, a sequence-to-sequence classification scheme [11, 12] was recently proposed to mimic the way a sleep expert performs manual scoring. The deep networks adhering to this scheme, such as SeqSleepNet [11] and DeepSleepNet [12], have been shown to be efficient in encoding the sequential dependency of the sleep signals to improve sleep scoring performance. Performance of the automatic sleep staging task has been improved significantly, reaching an accuracy rate on par with manual scoring by sleep experts [11, 12], thanks to the sequence-to-sequence models. However, this expert-level performance is only obtainable when the studied cohort is of large size, i.e. hundreds of subjects [11, 12]. The networks’ performance declines significantly when they are trained with a small cohort, such as ten or 20 subjects [6, 22] as training deep neural networks usually requires a large amount of data.

In practice however, sleep studies might focus on a small cohort, in the order of at most a few dozens of subjects [23, 25], for example when studying a particular sleep disorder [26, 27] or exploring the feasibility of a new monitoring device [11]. As a consequence, the small amount of data hinders deep neural networks to perform at their full capability in these sleep studies. One possibility to remedy the lack of data is to make use of large databases which are manually annotated and publicly available. However, these databases cannot be

1The source code and the pretrained models are published at http://github.com/pquocchuy/sleep_transfer_learning.
simply added into these studies for data compensation due to channel mismatch. The problem of channel mismatch arises when different studies use different channel layouts [8] or when novel electrode placements might be explored [11]. Even when standardized PSG layout is used, variation in recording devices, software, and preprocessing procedure may result in PSG data with different distributions. Moreover, it also happens when a study investigates a particular sleep abnormality, poor performance can be obtained when the automated diagnostic procedure is only trained on healthy volunteers [20].

This work proposes a transfer learning approach that can handle the channel-mismatch problem, enabling knowledge transfer from a large database to study sleep staging in a small dataset without the guarantee of identical recording setup. A network is firstly trained in the source domain (the large database) and subsequently finetuned in the target domain (the small cohort) to complete knowledge transfer as illustrated in Figure 1. In this context, finetuning means a part or the entire of the pretrained network is further trained with the domain data. We use the Montreal Archive of Sleep Studies (MASS) database with 200 subjects [28] as the source domain and aim to study the impact of deep transfer learning for sleep staging in different target domains with varying channel-mismatch degree to the source domain. We adopt four databases as the target domains: (1) the Sleep Cassette subset of the Sleep-EDF Expanded database (Sleep-EDF-SC) with 20 young subjects, (2) the Sleep Telemetry subset of the Sleep-EDF Expanded database (Sleep-EDF-ST), a cohort of 22 subjects with a wide range of age and suffering from mild sleep difficulty, (3) the Surrey-cEEGGrid database, a cohort of twelve subjects whose over-night data were recorded using an around-the-ear EEG device [11], [29], and (4) the Surrey-PSG database consisting of 15 subjects [11], [29] whose over-night data were recorded using similar electrode placement as the source-domain data.

We introduce a generic framework that is designed for sequence-to-sequence sleep scoring and build on two network architectures as the base models. The two networks are similar to SeqSleepNet [4] and DeepSleepNet [6], two sequence-to-sequence models which were recently shown to achieve state-of-the-art results on sleep staging. We study different transfer learning scenarios, ranging from single-channel to multi-channel input. We also scrutinize various finetuning strategies to understand how finetuning entirely or partially a pretrained network would affect the performance of sleep staging on the target domains. Our experimental results demonstrate significant performance improvements over all the target domains. Furthermore, these results reveal how finetuning different parts of the pretrained networks allows to bypass the channel mismatch problem and sheds light on the networks’ behaviors on transfer learning. We also discuss the number of subjects needed in the target domain to be used for finetuning the networks.

This work extends our preliminary work in [22] in many aspects. First, we study transfer learning with a wider spectrum of channel combinations for the networks’ input rather than single channel. Second, the studies in [22] employed SeqSleepNet [4] as the transfer learning device, here the studies are carried out on two different networks inherited from SeqSleepNet [4] and DeepSleepNet [6]. These two state-of-the-art networks are diverging in their architectures [30], and therefore, it is important to examine if these dissimilarities give rise to any difference in their performance and help to explain their behaviors in transfer learning. Third, the work in [22] only studied deep transfer learning on the Sleep-EDF-SC as the target domain. Here, we cover multiple target domains with varying degree of channel mismatch. Fourth, we study in-depth the influence of the number of target subjects on the transfer learning’s performance.

II. MATERIALS

A. Source Domain

We adopted the public MASS database [28] as the source domain in this study as it is sufficiently large.

**Montreal Archive of Sleep Studies (MASS):** This database was pooled from different hospital-based sleep laboratories, consisting of whole-night recordings from 200 subjects (97 males and 103 females) aged between 18 and 76 years. Manual annotation was accomplished by sleep experts according to the AASM standard [1] (SS2, SS4, and SS5 subsets) or the R&K standard [2] (SS2, SS4, and SS5 subsets). As in [4], [5], we converted different annotations into five sleep stages \{W, N1, N2, N3, and REM\} and expanded 20-second epochs into 30-second ones by including 5-second segments before and after each epoch. We used the C4-A1 EEG and ROC-LOC EOG in our experiments.

B. Target Domains

Four different sleep databases with varying properties are used as the target domains.

**Sleep-EDF-SC:** This is the Sleep Cassette (SC) subset of the Sleep-EDF Expanded dataset [23], [24], consisting of 20 subjects (10 males and 10 females) aged 25-34. Two subsequent day-night PSG recordings were collected for each subject, except for subject 13 who has only one-night data. Each 30-second PSG epoch was manually labelled into one of eight categories \{W, N1, N2, N3, N4, REM, MOVEMENT,
UNKOWN) by sleep experts according to the R&K standard \[2\]. Similar to previous works \[5\]-\[7\], \[15\], \[18\], \[19\], N3 and N4 stages were merged into a single stage N3 and MOVEMENT and UNKNOWN categories were excluded. We adopted the Fpz-Cz EEG and ROC-LOC EOG (i.e. the EOG horizontal) channels in this study. As this database has been used differently in literature, it should be stressed that only the in-bed parts (from lights off time to lights on time) of the recordings were used as recommended in \[5\], \[7\], \[15\], \[18\], \[19\], \[31\], \[32\].

**Sleep-EDF-ST:** This is the Sleep Telemetry (ST) subset of the Sleep-EDF Expanded dataset \[23\], \[24\] which was collected for studying the temazepam effects on sleep. The subset consists of 22 Caucasian subjects (7 males and 15 females) aged 18-79 with mild difficulty falling asleep. Although the PSG signals were recorded for two nights, one after temazepam intake and one after placebo intake, only the placebo nights are available. Manual annotation was done similar to the Sleep-EDF-SC subset. Similar to the Sleep-EDF-SC subset, Fpz-Cz EEG and ROC-LOC EOG were adopted and only the in-bed parts of the recordings were used.

**Surrey-cEEGGrid:** This database \[11\], \[29\] was recorded at the University of Surrey using the eEEGGrid array \[33\], \[34\], a novel lightweight flex-printed electrode strip that fits neatly behind the ear. Twenty participants, aged 34.9 ± 13.8 years had their overnight (about 12 hours) eEEGGrid data collected with a wireless SMARTING amplifier (mBrainTrain, Belgrade, Serbia) and a Sony Z1 Android smartphone at a sampling rate of 250 Hz. The PSGs were also recorded in parallel and manual annotation based on the PSG was used as reference for the eEEGGrid data \[11\]. Besides two recordings lost due human error, six recordings were discarded because of excessive artifacts and data missing. A cohort of 12 participants is retained. From the eEEGGrid data, the FB(R) (“front versus back” for the right ear) EEG derivation, which is the best derivation \[11\], was obtained and used. We also simulated the two-channel settings by adding the ROC-A2 EOG from the PSG data to the eEEGGrid data. Although there exists other EEG channels, the ROC-A2 EOG channel was deliberately selected to be different from that of the source domain to maintain the severity of channel mismatch.

**Surrey-PSG:** PSGs with the same electrode placement but recorded with different devices and software may result in signals with different distributions. To study deep transfer learning on this type of channel mismatch, we utilized the PSG data in the Surrey-cEEGGrid database, hence the name Surrey-PSG, as the target domain. The Harmonie acquisition software (Natus Medical Inc., San Carlos, USA) and Grass amplifier system (Grass Technologies, Astro-Med Inc., West Warwick, RI, USA) were used to record the MASS database \[28\] whereas the Surrey-PSG were recorded using the SomnoHD system (Somnoscreen SOMNO HD data logger, SOMNOmedics Gmbh, Randersacker, Germany) \[11\], \[29\].

Table I: Summary of the employed databases and the adopted signals.

|                      | Num. of subjects | EEG     | EOG     |
|----------------------|------------------|---------|---------|
| MASS                 | 200              | C4-A1   | ROC-LOC |
| Sleep-EDF-SC         | 20               | Fpz-Cz  | ROC-LOC |
| Sleep-EDF-ST         | 22               | Fpz-Cz  | ROC-LOC |
| Surrey-cEEGGrid      | 12               | cEEGGrid| ROC-A2  |
| Surrey-PSG           | 15               | C4-A1   | ROC-LOC |

Different from the Surrey-cEEGGrid database, PSG data of 15 subjects were retained in Surrey-PSG. The adopted PSG channels are the same as those of the source domain, i.e. C4-A1 EEG and ROC-LOC EOG.

The employed databases and the adopted signals are summarized in Table I. All the signals were downsampled to 100 Hz. The databases were chosen to have the channel mismatch between the target domains and the source domain varying from slight level due to the difference in recording devices (i.e. Surrey-PSG) via moderate level due to the difference in PSG signals used (i.e. Sleep-EDF-SC and Sleep-EDF-ST) to severe level due to completely new electrode placement (i.e. Surrey-cEEGGrid).

**III. THE GENERIC DEEP LEARNING FRAMEWORK FOR SEQUENCE-TO-SEQUENCE SLEEP STAGING**

**A. The framework**

The advent of deep learning has made astonishing progress in automatic sleep staging. First, deep networks are powerful in learning features which ultimately outperform and displace long-used handcrafted features. Second, they enable us approaching the automatic sleep staging in novel ways that is impossible with more conventional machine learning algorithms. The sequence-to-sequence sleep staging scheme \[4\] was recently proposed to integrate the ability of modelling long-term temporal dependency of sleep data epochs in a deep learning model. Intuitively, a sequence-to-sequence sleep staging model looks at a sequence of multiple consecutive epochs simultaneously and classifies them at once into a sequence of corresponding sleep stages. Here, we frame this scheme into a generic deep learning framework for sequence-to-sequence sleep staging. This framework also provides a ground to design new models in future work.

Formally, given the input sequence of \( L \) consecutive epochs denoted as \( (S_1, S_2, \ldots, S_L) \), the sequence-to-sequence sleep staging problem \[4\] is formulated to maximize the conditional probability \( p(y_1, y_2, \ldots, y_L \mid S_1, S_2, \ldots, S_L) \) where \( (y_1, y_2, \ldots, y_L) \) represents the sequence of corresponding \( L \) one-hot encoding vectors of the ground-truth output labels.

The proposed framework is divided into three components, an epoch processing block (EPB), a sequence processing block (SPB), and a softmax layer, as illustrated in Fig. 2.

**EPB:** Each epoch in the input sequence is presented to the network in some forms of representation (e.g. raw signals \[6\] or time-frequency features \[4\]) and can be single-channel (e.g. EEG or EOG) or multi-channel (e.g. a combination of EEG and EOG). The EPB plays the role of an epoch-wise feature learner and extractor. It is tied (i.e. shared) for all input epochs and preferably be a deep sub-network which is trained jointly with the master network in an end-to-end manner \[4\].
EPB, an input epoch \( S_l, 1 \leq l \leq L \), is transformed into an epoch-wise feature vector \( x_l \).

**SPB:** The SPB is essentially composed of a bidirectional recurrent layer (biRNN) that encodes the sequence of induced epoch-wise feature vectors \((x_1, x_2, \ldots, x_L)\) into the sequence of output vectors \((o_1, o_2, \ldots, o_L)\). More specifically, the forward and backward recurrent layer of the biRNN iterate over the sequence \((x_1, x_2, \ldots, x_L)\) in opposite directions and compute their forward and backward sequences of hidden state vectors \(H^f = (h_1^f, h_2^f, \ldots, h_L^f)\) and \(H^b = (h_1^b, h_2^b, \ldots, h_L^b)\), respectively, where

\[
\begin{align*}
    h_1^f &= \mathcal{H}(x_1, h_{L-1}^f), \\
    h_l^f &= \mathcal{H}(x_l, h_{l+1}^b), & 1 \leq l \leq L. 
\end{align*}
\]

In (1) and (2), \( \mathcal{H} \) denotes the hidden layer function of the biRNN and can be realized by either Long Short-Term Memory (LSTM) [35] or Gated Recurrent Unit (GRU) [36]. The sequence of output vectors \((o_1, o_2, \ldots, o_L)\) is then computed as

\[
o_l = W_{ho} [h_l^f \oplus h_l^b] + b_o, \quad 1 \leq l \leq L, \quad (3)
\]

where \( \oplus \) represents vector concatenation. In (3), \( W_{ho} \) denotes a learnable weight matrix and \( b_o \) denotes a learnable bias. The (long-term) dependency of the input epochs are expected to be modelled by the biRNN layer and the output vectors \(o_l, 1 \leq l \leq L\) are expected to encode sequence-level information. A residual connection can be optionally used to integrate epoch-wise features \(x_l\) and sequence-wise features \(o_l\) and, hence, enable the network to explore their combination in the classification stage. The fully-connected layer (FC) of the residual connection is to convert \(x_l\) into another vector having its size compatible to \(o_l\) for a proper residual combination. This residual connection is also shared between all input epochs.

**Softmax:** The classification is carried out by the shared softmax layer to yield the output sequence of sleep stage probabilities \((\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_L)\) from the sequence of output vectors \((o_1, o_2, \ldots, o_L)\). Different from [4], [6], to reduce the number of network parameters, we enforce a single softmax layer to be shared by all input epochs rather than one separate softmax layer for each epoch to reduce the number of network parameters.

A network adheres to this framework can be trained to minimize the sequence classification loss over \(N\) training sequences in the training data:

\[
E(\theta) = -\frac{1}{L} \sum_{n=1}^{N} \sum_{l=1}^{L} y_l \log (\hat{y}_l(\theta)) + \frac{\lambda}{2} \|\theta\|_2^2. \quad (4)
\]

Here, \(\theta\) represents the network parameters and \(\lambda\) denotes the hyper-parameter that trades off the error terms and the \(\ell_2\)-norm regularization term.

**B. The derived networks**

From the framework presented in Section III-A, we develop two following networks as the base model for transfer learning:

**SeqSleepNet+:** This network is similar to SeqSleepNet presented in [4] except that its softmax layer is shared between all epochs in the input sequence, and hence has less parameters. Similar to SeqSleepNet, the network receives the log-scale time-frequency representation [4] as input. The time-frequency image is normalized to zero-mean and unit standard deviation. In case of multi-channel, the channel-wise image features are stacked as a multi-channel image. The network’s EPB is realized by filterbank layers [4], [18], one for each input image channel for preprocessing purpose, followed by an attentional biRNN as illustrated in Figure 3(a). Note that this EBP’s biRNN should not be confused with the SBP’s biRNN in Fig. 2. Both the EPB’s biRNN and the SPB’s biRNN of the network are implemented by a GRU cell [36] with recurrent batch normalization [37]. There is no residual connection (cf. Figure 2) in the SPB of this network.

**DeepSleepNet+:** This network is inherited from DeepSleepNet [6] and its end-to-end variant [4] except for the
shared softmax layer. The network receives raw signals as input. When the input are composed of multiple signals, the raw signal are stacked to form a multi-channel input. The network’s EPB is composed of two deep CNNs organized in two branches with 4 convolutional layers each as illustrated in Figure 3(b). The convolutional kernels in the two branches are purposely designed to have different sizes to be able to learn features at both fine and coarse temporal resolutions. Each convolutional layer is associated with batch normalization [38] and Rectified Linear Units (ReLU) activation [39]. The SPB’s biRNN relies on the LSTM cell [35] and is designed to have two bidirectional LSTM layers, one stacked on top of the other. In addition, the SPB makes use of the residual connection.

As the two networks inherit SeqSleepNet’s and DeepSleepNet’s architecture’s, respectively, they are divergent in their inputs, EPB, and SPB components [30]. Therefore, these differences might give rise to discrepant behaviors during transfer learning.

IV. TRANSFER LEARNING SCENARIOS FOR AUTOMATIC SLEEP STAGING ON SMALL COHORT

Formally, let $D_S = \{X_S, P(X_S)\}$ and $D_T = \{X_T, P(X_T)\}$ denote the source and target domains with the feature space $X_S$ and $X_T$ and the marginal probability distribution $P(X_S)$ and $P(X_T)$, respectively. The task $T_S$ (i.e. sleep scoring in this case) in the source domain consists of a label space $Y_S$ and the source conditional probability distributions $P(Y_S|X_S)$. Similarly, in the target domain, the task $T_T$ consists of a label space $Y_T$ and the target conditional probability distributions $P(Y_T|X_T)$. $P(Y_S|X_S)$ and $P(Y_T|X_T)$ are typically learned from the training data. In most cases, only limited labeled data is available in the target domain, making learning $P(Y_T|X_T)$ inadapted. The objective of transfer learning is to improve learning $P(Y_T|X_T)$ in $D_T$ with information gained from $D_S$ and $T_S$ where $D_S \neq D_T$ or $T_S \neq T_T$ [40].

Transfer learning relaxes the hypothesis that the training data must be identically distributed to the test data. Therefore, it might be able to deal with channel mismatch and holds promise to leverage the large amount of available data to overcome the problem of insufficient training data in the studies with a small cohort. Using SeqSleepNet+ and DeepSleepNet+ as a device to transfer knowledge from the source domain for sleep staging with the target domains, the pretrained model is considered as a starting point in the target domains. To accomplish transfer learning, the entire or parts of the pretrained network are reused (i.e. being kept unchanged) and the rest is finetuned with the target-domain data. In order to study the influence of finetuning different parts of a pretrained network to the sleep staging performance on the target domains, we examine different finetuning strategies: finetuning the entire network and partially finetuning {softmax, EPB+softmax, SPB+softmax} combination. All the finetuning strategies are carried out in the following transfer learning scenarios:

**EEG→EOG**

Apart from brain activities, sleep also well involves eye movements. For instance, Rapid Eye Movement (REM) stage usually associates with rapid saccadic movements of the eyes. Therefore, EOG is valuable additional sources, complementing EEG in the automatic sleep staging task [5], [8]–[10], [22]. This scenario studies transfer learning for sleep staging with two-channel input, i.e. EEG and EOG.

EEG→EEG: This scenario explores single-channel EEG transfer learning. Automatic sleep staging with single-channel EEG has been found prevalent in literature [15], [18], [19], [41]–[43]. Without the augmentation from EOG and EMG, this single-channel setting usually results in a lower performance compared to those of the multi-channel ones, however, it is desirable due to the simple configuration. It is particularly useful for home-based sleep monitoring applications with mobile EEG devices [11], [29].

EOG→EOG: In general, EOG signals contain rich information from multiple sources, including ocular activity, frontal EEG activity, and EMG from cranial and eye muscles [25]. They are, therefore, promising as alternative for EEG in single-channel sleep staging. In addition, due to the ease of electrode placements, it would be ideal for home-based sleep monitoring applications with wearable devices [11], [29]. Despite their potential, EOG signals have been mainly used as secondary modality in multi-channel sleep staging studies [25], [44]. With this scenario, we aim to exploit standalone EOG and deep transfer learning on this secondary modality to examine whether its performance is comparable to that using the primary EEG in single-channel sleep staging.

EEG→EOG: As an extension of the EOG→EOG scenario, this cross-modality transfer learning scenario investigates whether a base model trained on EEG in the source domain can be transferred to EOG in the target domain and if its performance is comparable to the same-domain EOG→EOG transfer learning scenario. If the answers to these questions are held to be true, instead of modality-specific pretrained models, a single model pretrained solely on EEG can serve as a generic model for single-channel transfer learning regardless the modality of the target domain.

Apart from the channel mismatch caused by the differences in recording devices and/or electrode placements in case of the same-modality scenarios (i.e. EEG→EOG→EEG, EEG→EEG, and EOG→EOG), heavy channel mismatch is expected in case of the cross-modality EEG→EOG scenario when the base models are trained with EEG data in the source domain is transferred to EOG data in the target domains. On the one hand, with the same-modality scenarios, we aim to show that even the source domain and the target domains are of the same modalities, transfer learning is still necessary to overcome the channel mismatch. On the other hand, the cross-modality scenario is to emphasize that transfer learning is efficient in tackling heavy channel mismatch to transfer knowledge from the source domain to the target domains.

V. EXPERIMENTS

A. Experimental Setup

SeqSleepNet+ and DeepSleepNet+ were pretrained using the data from the entire 200 subjects of the MASS database (i.e. the source domain) and then finetuned in the target domains. To evaluate the efficiency of transfer learning on sleep staging in the target domains, cross-validation was conducted.
Leave-one-out cross-validation was conducted for Sleep-EDF-SC (20 subject), Surrey-cEEGGrid (12 subject), and Surrey-PSG (15 subject) while 11-fold cross-validation was performed for Sleep-EDF-ST (22 subject). At each iteration of cross-validation, a number of subjects were randomly selected and left out for validation purpose, i.e. for early stopping the finetuning process, (4 for Sleep-EDF-SC and Sleep-EDF-ST, 2 for Surrey-cEEGGrid, and 3 for Surrey-PSG). The performance over all cross-validation folds was then calculated.

B. Network Parameters

Both SeqSleepNet+ and DeepSleepNet+ were implemented using the Tensorflow framework [45]. The networks were parametrized similarly to SeqSleepNet and DeepSleepNet in our previous work [4] except that the softmax layer is shared by all epochs in the input sequence under the generic framework (cf. Section III). We experimented with the input sequence length \( L = 20 \) epochs. The sequences were sampled from the training recordings with a hop size of one epoch to generate all possible sequences for network training and finetuning. During testing, the test sequences were also shifted by one epoch, resulting in an ensemble of \( L \) classification decisions at each epoch of a test recordings. A probabilistic aggregation step was carried out similar to [4] to fuse the decision ensemble into the final decision.

In the source domain, the networks were pretrained with the MASS database for 10 training epochs with a minibatch size of 32 sequences. For transfer learning, the pretrained networks were further finetuned on each target-domain databases for 10 finetuning epochs. The finetuning process was stopped early when no accuracy improvement was seen on the validation subjects for 50 finetuning steps. Both network training and finetuning was performed using Adam optimizer with a learning rate of \( 10^{-4} \).

C. Experimental Results

1) Performance on the source domain: It is first worth assessing SeqSleepNet+ and DeepSleepNet+ on the source domain to see how well they perform on a large number of subjects across the input spectrum. To this end, we conducted 10-fold cross-validation on the source domain. At each iteration, 180 subjects were used for training, 10 subjects for validation, and 10 for testing. The results of all cross-validation folds were finally pooled to calculate the overall metrics, including accuracy, macro F1-score, and Cohen’s kappa (\( \kappa \)). The obtained performance with different input settings are shown in Table II.

| Input   | SeqSleepNet | DeepSleepNet |
|---------|-------------|--------------|
|         | Acc. | MF1 | \( \kappa \) | Acc. | MF1 | \( \kappa \) |
| EEG-EOG | 86.5  | 82.4 | 0.889  | 85.9  | 81.6 | 0.799  |
| EEG     | 84.5  | 79.8 | 0.778  | 84.3  | 79.7 | 0.777  |
| EOG     | 83.9  | 79.1 | 0.769  | 83.7  | 78.9 | 0.767  |

Table II: Sleep staging performance on the source domain (i.e. the MASS database).

Firstly, the results in the table confirm the benefit of using EOG to complement EEG in the automatic sleep staging task as their presence lead to performance improvement. Secondly, with the sequence-to-sequence framework, the performance obtained by the secondary EOG is just marginally lower than that of the primary EEG, evidenced in both SeqSleepNet+ and DeepSleepNet+. This suggests that EOG can be used as a standalone modality as EEG when a single channel is used.

2) The effect of transfer learning on the target domains: Figures 4 and 5 give an overall picture on the performance obtained by SeqSleepNet+ and DeepSleepNet+ on the target domains with respect to different finetuning strategies and compared to the model trained from scratch using the target-domain data only. The two networks show noticeably varying patterns on the transfer learning results.

On the one hand, SeqSleepNet+’s results in Figure 4 reveal that while finetuning the softmax layer alone leads to better performance than that of the scratch model in some cases, it is essential to additionally finetune the feature-learning parts of the network, either the EPB for epoch-level feature learning or the SPB for sequence-level feature learning or both collectively. This pattern prevails across all finetuning cases in the figure. This suggests that the features learned by SeqSleepNet+ in the source domain are slightly different from those in the target domain. This is reasonable given the channel mismatch between the source and target domains.

On the other hand, DeepSleepNet+’s finetuning results expose diverging patterns in different target domains as shown in Figure 5. On Sleep-EDF-SC and Sleep-EDF-ST, finetuning the softmax layer alone appears to be sufficient as the results obtained with this strategy are comparable to, and occasionally better than, those yielded by finetuning softmax+EPB, softmax+SPB, and the entire network. This suggests that the features learned from the source domain’s raw signals persist in the target domain and only their combinations need to be adapted in the target domains. However, it should be emphasized that persistence of the learned features across the domains does not necessarily mean good generalization as DeepSleepNet+’s finetuning results are inferior to those of its counterpart, SeqSleepNet+ (cf. Table III). In contrast, the patterns of the transfer learning results on Surrey-cEEGGrid and Surrey-PSG are rather heterogeneous. For example, in case of Surrey-cEEGGrid the softmax-only finetuning strategy clearly surpasses other strategies in the EEG→→EEG scenario but largely belittle in EEG-EOG→→EEG-EOG and EOG→→EOG. These patterns imply the instability and the difficulty of finetuning DeepSleepNet+, particularly when the target domain is of very small size given that the Surrey-cEEGGrid database is the smallest cohort with only twelve subjects. This can be explained as DeepSleepNet+ alike architecture itself is a large network [6] and furthermore relies on the raw signal input which is more prone to overfitting in general.

Despite their different behaviors in finetuning, both SeqSleepNet+ and DeepSleepNet+ meet the transfer learning’s expectation. Compared to the network trained from scratch using the target-domain data only, transfer learning consistently results in sustainable improvements across the network types, the target domains, and the transfer learning scenarios. The
Figure 4: Performance patterns obtained by finetuning the pretrained SeqSleepNet+ with different finetuning strategies in comparison with that of the SeqSleepNet+ scratch model. (a) Sleep-EDF-SC, (b) Sleep-EDF-ST, (c) Surrey-cEEGGrid, and (d) Surrey-PSG.

Figure 5: Performance patterns obtained by finetuning the pretrained DeepSleepNet+ with different finetuning strategies in comparison with that of the DeepSleepNet+ scratch model. (a) Sleep-EDF-SC, (b) Sleep-EDF-ST, (c) Surrey-cEEGGrid, and (d) Surrey-PSG.
The benefits of transfer learning are further evidenced by contrasting the learning curves of the finetuned models and the scratch models. Taking the two-channel EEG-EOG→EEG-EOG scenario as an example (see Figure 6), the learning curves were recorded on the test data during finetuning and training, respectively. All learning curves were averaged over all cross-validation folds. As the learning curves’ lengths vary across different folds due to early stopping, those with a length shorter than the maximum one were padded to the maximum length before averaging. SeqSleepNet+’s learning curves elucidate better generalization and faster convergence of the finetuned models (except the softmax-only finetuning strategy) compared to their scratch counterparts. Similar motifs are observed in DeepSleepNet+’s learning curves, however, the softmax-only finetuning strategy shows a comparable generalization to other strategies, except for Surrey-PSG, although slower convergence. These findings partially explain the finetuning results in Figures 4 and 5.

3) Performance comparison on the target domains: To quantify the efficiency of transfer learning on automatic sleep staging, in Table III we compare the finetuning performance against those of the scratch models across the target domains and the transfer learning scenarios. In addition, we also include the results obtained by directly using the pretrained models in the target domains without finetuning (i.e. direct transfer) to justify the necessity of transfer learning.

As the transfer learning results vary depending on the finetuning strategies, for simplicity, out of different finetuning strategies, we retained the SPB+softmax one as the representative for comparison given its consistent finetuning results (see Figures 4 and 5). In practice, the finetuning strategies can be viewed as a hyper-parameter and can be determined via cross-validation. Since SeqSleepNet-alike [5], [22] and DeepSleepNet-alike [6] were reported to achieve state-of-the-art performance on the Sleep-EDF database, contrasting the finetuning performance with those obtained by the scratch models would illustrate the efficiency of the transfer learning approach. However, it should be mentioned that there exists a large body of works on the Sleep-EDF database [5], [7], [22], [27], [46], a comprehensive performance comparison can be found in [5]. For the cEEGGrid database, we include the results reported in the seminal work in [11] for comparison.

Firstly, the results in Table III show significant gains obtained by the finetuned models over the scratch counterparts. Averaging over all transfer learning scenarios, finetuning SeqSleepNet+ leads to an absolute accuracy gain of 2.5%, 2.2%, 1.5%, and 2.0% on Sleep-EDF-SC, Sleep-EDF-ST, Surrey-cEEGGrid, Surrey-PSG, respectively. Those gains of DeepSleepNet+ are even larger, reaching 3.4%, 7.2%, 12.3%, and 8.1%, respectively. In particular, despite the heavy channel mismatch condition in the cross-domain scenario, transferring the knowledge of EEG data in the source domain to EOG data in the target domains still brings up significant accuracy gains, 0.9% and 7.8% on average with SeqSleepNet+ and DeepSleepNet+, respectively. The rational behind the upsurge in DeepSleepNet+’s performance is the poor performance of its scratch models on the target domains. Likely, the DeepSleepNet+ scratch models suffered from overfitting given its large model footprint [6], its reliance on raw signal inputs, and the small size of the target domains. In contrast, using the pretrained models as the starting point in the finetuning process helps to remedy overfitting.

Secondly, directly using the pretrained models for staging in the target domains without finetuning results in obvious suboptimal performance in many cases. Averaging over the same-modality transfer learning scenarios, the pretrained SeqSleepNet+ model with direct transfer obtains an accuracy 10.3%, 7.2%, 62.0%, and 58.7% absolute lower than those obtained by the finetuned models on Sleep-EDF-SC, Sleep-EDF-ST, Surrey-cEEGGrid, and Surrey-PSG, respectively. Those accuracy gaps in case of DeepSleepNet+ are 16.8%, 10.2%, 32.5%, and 41.2%, respectively. The direct transfer’s results
Table III: Performance comparison between transfer learning, scratch training, and direct transfer. FT and DT are abbreviated for “finetuning” and “direct transfer”, respectively.

|                         | EEG-EOG→EEG-EOG | EOG→EOG | EEG→EOG | EEG→EOG |
|-------------------------|------------------|---------|---------|---------|
|                         | Acc.             | MF1     | ϵ       | Acc.     | MF1     | ϵ       | Acc.     | MF1     | ϵ       | Acc.     | MF1     | ϵ       |
| FT SeqSleepNet+         | 84.3             | 77.7    | 0.776   | 85.2     | 79.6    | 0.789   | 81.7     | 75.1    | 0.737   | 80.0     | 72.3    | 0.709   |
| FT DeepSleepNet+        | 84.6             | 79.0    | 0.782   | 84.4     | 78.8    | 0.781   | 79.8     | 73.4    | 0.713   | 79.4     | 72.8    | 0.707   |
| Surrey-PSG              | 82.2             | 74.2    | 0.744   | 82.2     | 74.1    | 0.746   | 78.5     | 68.3    | 0.688   | 78.5     | 68.3    | 0.688   |
| Surrey-PSG              | 81.9             | 75.2    | 0.744   | 80.8     | 74.2    | 0.731   | 75.9     | 66.9    | 0.652   | 75.9     | 66.9    | 0.652   |
| Surrey-PSG              | 72.0             | 62.1    | 0.601   | 81.2     | 74.6    | 0.733   | 67.2     | 59.1    | 0.530   | 51.1     | 42.5    | 0.300   |
| Surrey-PSG              | 70.2             | 59.8    | 0.566   | 74.2     | 66.9    | 0.651   | 54.1     | 41.9    | 0.396   | 39.7     | 35.8    | 0.235   |

are particularly poor under the heavy channel mismatch conditions, such as the EEG→EOG scenario and the EEG→EEG scenario in case of Surrey-cEEGGrid. It is understandable as substantial differences in characteristics of the source domain and the target domain cause discrepancy in the feature-learning parts of the pretrained models in the target domain. As a consequence, finetuning is essential in this case. In addition, the unsatisfactory results of direct transfer on Sleep-PSG suggests very different data distribution between the source domain and the target domain even though the electrode placements are the same. Finetuning, therefore, is also crucial in this case.

Third, between SeqSleepNet+ and DeepSleepNet+, the former outperforms the latter in most of the cases in Table III With scratch training, SeqSleepNet+ results in an average accuracy gain of 1.7%, 6.8%, and 17.5%, and 2.2% over DeepSleepNet+ on Sleep-EDF-SC, Sleep-EDF-ST, Surrey-cEEGGrid, and Surrey-PSG respectively. This is consistent with the similar finding on the source domain (i.e., the MASS database) in [I] and in Table III With transfer learning, the accuracy gaps between them are 0.8%, 1.8%, 6.7%, and 1.2% on Sleep-EDF-SC, Sleep-EDF-ST, Surrey-cEEGGrid, and Surrey-PSG, respectively.

Fourth, on cEEGGrid data, comparing with the results reported in the seminal work in [II], the finetuned SeqSleepNet+ uplifts the accuracy by a margin of 10.3% in case of two channels and 5.3% in case of single-channel EEG. The finetuned DeepSleepNet+ also enjoys an accuracy improvement of 5.8% in case of two channels, however, experiences an accuracy drop of 11.8% in case of single-channel EEG. A similar effect is seen in Surrey-PSG for the two-channel setting, however, the margins are much smaller in this case.

Fifth, regarding the single-channel cases with the secondary EEG, performance improvement is also seen not only in the same-modality scenario but also in the cross-modality scenario. Interestingly, with the obtained accuracy consistently around 80% and on par with the primary EEG in many cases, it is therefore worth exploring the usage of EOQ as an alternative for EEG in single-channel sleep staging.

4) How many subjects are sufficient for transfer learning?: This section investigates the influence of the amount of the target-domain data to the network finetuning. Considering the EEG-EOG→EEG-EOG scenario and the entire-network finetuning strategies for this investigation. For a target domain, we randomly selected 25% of the subjects as the test subjects while the remaining subjects were used for finetuning purpose. A pretrained network was finetuned using data from the finetuning of N subjects for 500 finetuning steps and recorded the test accuracy during the finetuning process. Starting with the finetuning set of N = 1 subject, we repeated this procedure and added two more subjects into it at each iteration.

Figure 7 shows the learning curves recorded with varying

\[ \text{SeqSleepNet+} \]
The SeqSleepNet+ and DeepSleepNet+ derived from the improvement automatic sleep staging performance on small co-
the problem of insufficient data in many sleep studies and feature-learning parts to be adapted into the target domain s,
rational if these results are linked to the networks’ finetun-
less noticeable, except for Surrey-cEEGGrid. It is actually
Figure 7: The learning curves obtained from the test data with varying the number of finetuning subjects. (a) SeqSleepNet+
and (b) DeepSleepNet+.
number of finetuning subjects. The learning curves show a strong impact of the number of finetuning subjects on
SeqSleepNet+ while such influence on DeepSleepNet+ is less noticeable, except for Surrey-cEEGGrid. It is actually rational if these results are linked to the networks’ finetuning behaviors. While a pretrained SeqSleepNet+ requires its feature-learning parts to be adapted into the target domains, this requirement is not mandatory for DeepSleepNet+, except for the cEEGGrid data (cf. Section V-C2). And when the feature-learning parts need to be adjusted, less finetuning data make the networks converge to more subject-specific solutions, i.e. overfitting. On the contrary, more finetuning data allows the feature learning parts to converge to more generalizable solutions. This is supported by the SeqSleepNet+’s learning curves on the Sleep-EDF-SC and Surrey-cEEGGrid domain, and DeepSleepNet+’s learning curves on the Surrey-cEEGGrid domain. From these curves, we also speculate that when the feature-learning parts of a network needs to be adapted to a target domain, a generalizable solution can be obtained with the number of finetuning subjects around 11-13. Particularly, the learning curves on Sleep-EDF-ST appears to be counter-intuitive as more finetuning subjects occasionally result in lowering learning curves. These irregularities can be explained by the fact that the Sleep-EDF-ST population has a very wide range of age, 18-79. As sleep patterns change with age [27], depending the age range of the test subjects, including a subject whose age is far from that range would hurt more than help. This gives rise to further study on how to determine and select candidates from a population that are most beneficial for a finetuning task.

VI. CONCLUSIONS

We presented a deep transfer learning approach to address the problem of insufficient data in many sleep studies and improve automatic sleep staging performance on small cohorts. The SeqSleepNet+ and DeepSleepNet+ derived from the presented generic sequence-to-sequence sleep staging framework were employed as a device to surpass channel mismatch and enable transferring knowledge from the source domain to the target domain. The networks were trained in the source domain and then finetuned in the target domains to complete knowledge transfer. Experiments were conducted with different finetuning strategies, transfer learning scenarios, and target domains. The experimental results showed that via transfer learning, the sleep staging performance were significantly improved across all transfer learning cases over the scratch models trained solely on the target domains. The results also reveal the different behaviors of two SeqSleepNet-alike and DeepSleepNet-alike models in transfer learning. The former was found more consistent and stable while outperforming the latter in most of the transfer learning experiments. The number of subjects required for finetuning also varies between the two networks, however, overall, a small number of finetuning subjects is needed for the networks to converge to a generalizable solution.

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