Self-supervised Electroencephalogram Representation Learning for Automatic Sleep Staging

Jimeng Sun, Cao Xiao, M. Brandon Westover, Chaoqi Yang

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Abstract

Background: Deep learning models have shown great success in automating tasks in sleep medicine by learning from carefully annotated Electroencephalogram (EEG) data. However, effectively utilizing a large amount of raw EEG remains a challenge.

Objective: In this paper, we aim to learn robust vector representations from massive unlabeled EEG signals, such that the learned vectorized features (1) are expressive enough to replace the raw signals in the sleep staging task; and (2) provide better predictive performance than supervised models in scenarios of fewer labels and noisy samples.

Methods: We propose a self-supervised model, named Contrast with the World Representation (ContraWR), for EEG signal representation learning, which uses global statistics from the dataset to distinguish signals associated with different sleep stages. The ContraWR model is evaluated on three real-world EEG datasets that include both at-home and in-lab EEG recording settings.

Results: ContraWR outperforms 4 recent self-supervised learning methods on the sleep staging task across 3 large EEG datasets. ContraWR also beats supervised learning when fewer training labels are available (e.g., 4% accuracy improvement when less than 2% data is labeled). Moreover, the model provides informative representative feature structures in 2D projection.

Conclusions: We show that ContraWR is robust to noise and can provide high-quality EEG representations for downstream prediction tasks. The proposed model can be generalized to other unsupervised physiological signal learning tasks. Future directions include exploring task-specific data augmentations and combining self-supervised with supervised methods, building upon the initial success of self-supervised learning in this paper.

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Original Manuscript
Self-supervised Electroencephalogram Representation Learning for Automatic Sleep Staging

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Objective: In this paper, we aim to learn robust vector representations from massive unlabeled EEG signals, such that the learned vectorized features (1) are expressive enough to replace the raw signals in the sleep staging task; and (2) provide better predictive performance than supervised models in scenarios of fewer labels and noisy samples.

Methods: We propose a self-supervised model, named Contrast with the World Representation (ContraWR), for EEG signal representation learning. Different from previous models that use a set of negative samples, our model uses global statistics (i.e., the average representation) from the dataset to distinguish signals associated with different sleep stages. The ContraWR model is evaluated on three real-world EEG datasets that include both at-home and in-lab EEG recording settings.

Results: ContraWR outperforms 4 recent self-supervised learning methods on the sleep staging task across 3 large EEG datasets. ContraWR also beats supervised learning when fewer training labels are available (e.g., 4% accuracy improvement when less than 2% data is labeled on Sleep EDF dataset). Moreover, the model provides informative representative feature structures in 2D projection.

Conclusions: We show that ContraWR is robust to noise and can provide high-quality EEG representations for downstream prediction tasks. The proposed model can be generalized to other unsupervised physiological signal learning tasks. Future directions include exploring task-specific data augmentations and combining self-supervised with supervised methods, building upon the initial success of self-supervised learning in this paper.

Keywords: physiological signals; electroencephalogram; EEG; sleep staging; wearable devices; self-supervised learning; digital health, mHealth; healthcare
Introduction

Deep learning models have shown great success in automating tasks in sleep medicine by learning from high-quality labeled EEG data [1]. EEG data are collected from patients wearing clinical sensors, which generate real-time multi-modal signal data. A common challenge in classifying physiological signals, including EEG, is the lack of enough high-quality labels. This paper introduces a novel self-supervised model that leverages the inherent structure within large, unlabeled, and noisy datasets and produces robust feature representations. These representations can significantly enhance the performance of downstream classification tasks, such as sleep staging, especially in cases where only limited labeled data is available.

Self-supervised learning (specifically, self-supervised contrastive learning) aims at learning a feature encoder that maps input signals into a vector representation using unlabeled data. Self-supervised methods involve two steps: (I) a pretrain step: to learn the feature encoder without labels; (II) a supervised step: to evaluate the learned encoder with a small amount of labeled data. During the pretrain step, some recent methods (e.g., MoCo [2], SimCLR [3]) use the feature encoder to construct positive and negative pairs from the unlabeled data and then optimize the encoder by pushing positive pairs closer and negative pairs farther away. A positive pair consists of two different augmented versions of the same sample (i.e., applying two data augmentation methods separately to the same sample), while a negative pair is generated from the augmented data of two different samples. For example, the augmentation method for EEG data can be denoising or channel flipping. In this practice, existing negative sampling strategies often incur sampling issue [4, 5], especially for noisy EEG data, which significantly hurts performance [6]. Specifically, in the self-supervised learning setting (without labels), the negative samples are actually random samples, which may be from the same latent class. Using these “negative samples” can potentially undermine the model performance.

Technically, this paper contributes to the pretrain step, where we address the aforementioned limitations of existing negative sampling strategies (e.g., MoCo [2], SimCLR [3]) by leveraging global data statistics. In contrastive learning, positive pairs bring similarity information, while negative pairs provide contrastive information. Both information are essential in learning an effective feature encoder. This paper proposes a new contrastive learning method, named contrast with the world representation (in abbreviation, ContraWR). In our ContraWR, we construct positive pairs using data augmentation, similar to existing methods, while we use one global average representation over the dataset (called the world representation) as the negative sample to provide the contrastive information. Derived from global data statistics, the world representation is robust even in noisy environments, and it follows a new contrastive guidance under the absence of labels: the representation similarity between positive pairs is stronger than the similarity to the world representation. Moreover, in the paper, we later strengthen our model with an instance-aware world representation for individual samples, where closer samples have larger weights in calculating the global average. Our experiments show that the instance-aware world representation makes the model more accurate, and this conclusion aligns with the findings from a previous paper [6] that harder negative samples are more effective in learning the feature encoding.

We evaluate the proposed ContraWR on the sleep staging task with three real-world EEG datasets. Our model achieves results comparable to or better than recent popular self-supervised methods, MoCo [2], SimCLR [3], BYOL [7] and SimSiam [8]. The results also show that self-supervised contrastive methods, especially our ContraWR method, are much more powerful in low-label scenarios than supervised learning (e.g., 4% accuracy improvement on sleep staging with less than 2% training data of Sleep EDF dataset).
Methods

EEG Datasets

We consider three real-world EEG datasets for this study:

- Sleep Heart Health Study (SHHS) [9, 10] is a multi-center cohort study from the National Heart Lung & Blood Institute assembled to study sleep-disordered breathing, which contains 5804 adult patients aged over 40 and 5,445 recordings in the first visit. We use the first visit Polysomnography (PSG) data in the experiments. Each recording has 14 PSG channels, and the recording frequency is 125.0 Hz. We use the C3/A2 and C4/A1 EEG channels.

- Sleep EDF [11] cassette portion is another benchmark dataset collected in a 1987-1991 study of age effects on sleep in healthy Caucasians. The data contains 78 subjects aged 25-101 who were taking non sleep-related medications, which contains 153 full-night EEG recordings with recording frequency 100.0 Hz. We extract the Fpz-Cz/Pz-Oz EEG channels as the raw inputs to the model. The first two datasets are all at-home PSG recordings.

- MGH Sleep [1] is collected from sleep laboratory at Massachusetts General Hospital (MGH) with more than 5,000 subjects, where six EEG channels (i.e., F3-M2, F4-M1, C3-M2, C4-M1, O1-M2, O2-M1) are used for sleep staging recorded at 200.0 Hz frequency. After filtering out mismatched signals and missing labels, we finally get 6,478 recordings. Dataset statistics can be found in Table 1, and class label distribution is in Table 2.

Table 1. Dataset Statistics

| Name      | Location | #channels | #recordings | #epochs | Storage |
|-----------|----------|-----------|-------------|---------|---------|
| SHHS      | At home  | 2         | 5,445       | 4,535,949 | 260 GB  |
| Sleep EDF | At home  | 2         | 153         | 415,089  | 20 GB   |
| MGH Sleep | In lab   | 6         | 6,478       | 4,863,523 | 1,322 GB|

Table 2. Class Label Distribution. Format: #epochs (percentage)

| Name      | W (percentage) | N1 (percentage) | N2 (percentage) | N3 (percentage) | R (percentage) |
|-----------|----------------|-----------------|-----------------|-----------------|----------------|
| SHHS      | 28.8%          | 3.7%            | 40.9%           | 12.6%           | 14.0%          |
| Sleep EDF | 68.8%          | 5.2%            | 16.6%           | 3.2%            | 6.2%           |
| MGH Sleep | 44.3%          | 9.9%            | 14.4%           | 17.6%           | 13.8%          |

Problem Formulation

To set up the experiments, the raw subject EEG recordings are multi-channel brain waves. First, the unlabeled subject recordings are grouped as the pretrain set, the labeled recordings are grouped into the training or test sets. The training and test sets are usually small, but their EEG recordings are labeled, while the pretrain set contains a large number of unlabeled recordings. Within each set, the long recordings are segmented into disjoint 30-second windows. Each window is called an epoch, denoted as \( x \in R^{C \times N} \). Each epoch has the same format: \( C \) input channels and \( N \) timestamps from each channel.
For these datasets, the ground truth labels were released by the original data publishers. To align with the problem setting, subjects are randomly assigned to pretrain set, training set and test set with different proportions (90%: 5%: 5% for Sleep EDF and MGH, 98%: 1%: 1% for SHHS, since they have different amount of data). All epochs segmented from one subject are placed within the same set. The pretrain set is used for self-supervised learning, so we remove their labels.

In the pretrain step, the EEG self-supervised representation learning problem requires building a feature encoder \( f(\cdot) \) from the pretrain set (without labels), which maps one epoch \( x \) into a vector representation \( h \in R^d \), where \( d \) is the feature dimensionality, such that the representation \( h \) can replace raw signal for downstream classification tasks. The evaluation of the encoder \( f(\cdot) \) is conducted on the training and test data (with labels). We focus on sleep staging as the supervised step, where the feature vector of a sample \( x \) will be mapped into five sleep cycle labels, awake (W), rapid eye movement REM (R), Non-REM 1 (N1), Non-REM 2 (N2), Non-REM 3 (N3), based on American Academy of Sleep Medicine (AASM) scoring standards [12]. Specifically, based on the feature encoder from the pretrain step, the training set is used to learn a linear model on top of the feature vectors, and the test set is used to evaluate the linear classification performance.

**Background and Existing Methods**

Self-supervised learning happens in the pretrain step, and it uses representation similarity to exploit the unlabeled signals, with an encoder network \( f(\cdot): R^{C \times N} \rightarrow R^d \) and a nonlinear projection network \( g(\cdot): R^d \rightarrow R^m \). Specifically, for a given signal \( x \) from the pretrain set, commonly, one applies data augmentation methods \( a(\cdot) \) to produce two different modified signals \( \tilde{x}', \tilde{x}'' \) (after this procedure, the format does not change), which are then transformed into \( h, h'' \in R^d \) by \( f(\cdot) \) and further into \( z, z'' \in R^m \) by \( g(\cdot) \). The vectors \( z, z'' \) are finally normalized with the L2 norm onto the unit hypersphere \( \frac{z}{||z||} \in S^{m-1} \).

We call \( \frac{z}{||z||} \) the anchor, \( \frac{z''}{||z''||} \) the positive sample, and these two together are called a positive pair. For the projections \( z \), obtained from other randomly selected signals (by negative sampling strategy), their representation \( \frac{z_k}{||z_k||} \) is commonly conceived of as negative samples (though they are random samples), and any one of them together with the anchor is called a negative pair in existing literatures [2, 3]. The loss functions \( L \) is derived from the similarity comparison between positive pair and negative pairs (e.g., encouraging similarity of positive pairs to be stronger than that of all the negative pairs, referred to as the noise contrastive estimation (NCE) loss [13]). A common forward flow of self-supervised learning on EEG signals can be illustrated as,

\[
x \xrightarrow{a(\cdot)} \tilde{x} \xrightarrow{f(\cdot)} h \xrightarrow{g(\cdot)} z \xrightarrow{L2} \frac{z}{||z||} \xrightarrow{loss} L .
\]

For the data augmentation part, this paper uses bandpass filtering, noising, channel flipping, and shifting (see the definition in Multimedia Appendix 6 and the visual illustrations in Multimedia Appendix 5). We conduct ablation studies on the augmentation methods in experiment and provide the implementation details. To reduce clutter, we also use \( \tilde{z} \) to denote the L2 normalized version in the rest of the paper.

**(I). ContraWR: Contrast with the World Representation**

As mentioned above, most existing models use random samples as negative samples, which can...
introduce issues (that the negative sample might be from the same latent class) for the pretrain step and undermine representation quality. To address the issue, this paper proposes a new self-supervised learning method, Contrast with the World Representation (ContraWR). ContraWR replaces the large number of negative samples with a single average representation of the batch, called the world representation or global representation. This way is robust as it avoids constructing negative pairs where two data are actually from the same latent class. The world representation servers as a reference in our new contrastive principle: the representation similarity between a positive pair should be stronger than the similarity between the anchor and the world representation. Note that the world representation is not fixed but changes with encoder updating the parameters.

The world representation. Assume $i$ is the anchor, $i'$ is the positive sample, and $z_i$ denotes a random sample. We generate an average representation of the dataset, $z_w$, as the only negative sample.

To formalize, we assume $k \sim p(\cdot)$ is the sample distribution over the dataset (i.e., $k$ is the sample index), independent of the anchor $i$. The world representation $z_w$ is defined by,

$$z_w = E_{k \sim p(\cdot)} [z_k].$$

Here, we denote $D = \{z: ||z|| \leq 1, z \in \mathbb{R}^m\}$. Obviously, $z_w \in D$. In the experiment, $z_w$ is approximated by the average over each batch, i.e., we use the average sample representation over the batch

$$z_w = \frac{1}{M} \sum_{k=1}^{M} z_k$$

as the world representation, where $M$ is the batch size.

Gaussian kernel measure. We adopt a Gaussian kernel defined on $D$, $\phi(x, y): D \times D \rightarrow \mathbb{R}$, as a similarity measure. Formally, given two feature projections $z', z''$ the similarity is defined as,

$$\phi(z', z_k) = \exp \left( -\frac{||z' - z_k||^2}{2 \sigma^2} \right),$$

where $\sigma$ is a hyperparameter. The gaussian kernel combined with the following triplet loss gives the Alignment and Uniformity properties in the loss convergence (shown in Multimedia Appendix 1). Note that when $\sigma$ becomes large, the gaussian kernel measure will reduce to cosine similarity.

Loss function. For the anchor $i$, the positive sample $i'$ and the world representation $z_w$, we devise a triplet loss,

$$L = \phi(z', z_w) + \delta - \phi(z', i'),$$

Where $\delta > 0$ is the empirical margin, a hyperparameter. The loss is minimized over batches, ensuring that the similarity of positive pair $\phi(z', z')$, is larger than the similarity to the world representation $\phi(z', z_w)$, by a margin of $\delta$. 

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Figure 1. ContraWR Model Pipeline. We show the two-way model pipeline in this figure. The online network (upper) is updated by gradient descent, while the target network (lower) is updated by exponential moving average (EMA). Finally, the results from two models form the triplet loss function.

The pipeline of our ContraWR is shown in Figure 1. The online networks $f_\theta(\cdot), g_\theta(\cdot)$ and the target networks $f_\phi(\cdot), g_\phi(\cdot)$ share an identical network structure. Encoder networks $f_\theta(\cdot), f_\phi(\cdot)$ map two augmented versions of the same signal to feature representations, respectively. Then, the projection networks $g_\theta(\cdot), g_\phi(\cdot)$ project the feature representations onto a unit hypersphere, where the loss is defined. During optimization the online networks are updated by gradient descent, and the target networks update parameters from the online network with an exponential moving average (EMA) trick [2].

$$
\theta^{n+1} \leftarrow \theta^n - \eta \cdot \nabla_\theta L
$$
$$
\phi^{n+1} \leftarrow \lambda \cdot \phi^n + (1-\lambda) \cdot \theta^{n+1}
$$

where $n$ indicates the $n$-th update, $\eta$ is the learning rate, and $\lambda$ is a weight hyperparameter. After this optimization in the pretrain step, the encoder network $f_\theta(\cdot)$ is ready to be evaluated on the training and test sets in the supervised step.

(II). ContraWR+: Contrast with Instance-aware World Representation

To learn a better representation, we introduce a weighted averaged world representation, based on the harder principle: the similarity between a positive pair should be stronger than the similarity between the anchor and the weighted average feature representations of the dataset, where the weight is set higher for closer samples. We call the new model ContraWR+. This is a more difficult objective than the simple global average in ContraWR.

Instance-aware world representation. In this new model, the world representation is enhanced by modifying the sampling distribution to be instance specific. We define $p(\cdot|z)$ as the instance-aware sampling distribution of an anchor $z$, different from the sample distribution $p(\cdot)$ used in ContraWR,

$$
p(\cdot|z) \propto \exp\left(\frac{\langle \cdot, z \rangle}{T}\right),
$$

where $T>0$ is a temperature hyperparameter, such that similar samples are selected with higher probability parametrized by $p(\cdot|z)$. Consequently, for an anchor $z$, the instance-aware world representation becomes,
Here, $T$ controls the contrastive hardness of the world representation. When $T \to \infty$, $p(\cdot|z)$ is asymptotically identical to $p(\cdot)$, and the above equation reduces to the simple global average form $z_w = E_k \sim p(\cdot|z_k)$; while $T \to 0^{+}$, the form becomes trivial, $z_w = \arg \max_z \langle z, z_k \rangle$. We have tested different $T$ and find the model is not sensitive to $T$ over a wide range. Here, $z_w$ is also practically implemented by using the weighted average over each batch. We can re-write the similarity measure given the anchor $z_i$ and the new world representation $z_w$ as:

$$c(z_i, z_w) = c(z', E_k \sim p(\cdot|z_k)) = \exp \left( -\frac{1}{2\sigma^2} \| z' - E_k \sim p(\cdot|z_k) \| \right).$$

In this new method, we also use triplet loss as the final objective.

**Implementations**

**Signal Augmentation.** For the experiments, we use four augmentation methods, illustrated in the supplementary: (I) Bandpass Filtering. To reduce noise, we use an order-1 Butterworth filter (the bandpass is specified in Multimedia Appendix 5); (II) Noising. We add extra high-frequency or low-frequency noise to each channel, mimicking the physical distortion; (III) Channel Flipping. Corresponding sensors from the left side and the right of the head are swapped due to symmetricity; (IV) Shifting. Within one sample, we advance or delay the signal for a certain time span. Detailed configurations of augmentation methods vary for the three datasets, and we list them in Multimedia Appendix 5.

**Baseline Methods.** In the experiments, several recent self-supervised learning methods are implemented for comparison,

- MoCo [2] devises two parallel encoders with exponential moving average (EMA). It also utilizes a large memory table to store new negative samples, which are frequently updated.
- SimCLR [3] uses one encoder network to generate both anchor and positive samples, where negative samples are collected from the same batch.
- BYOL [7] also employs two encoders: one online network and one target network. They put one more predictive layer on top of the online network to predict (reconstruct) the result from the target network, while no negative samples are presented.
- SimSiam [8] uses the same encoder networks on two sides and also does not utilize the negative samples.
- AVG-KNN-TopX is our developed baseline model, which identifies the top $X$ nearest neighbors for each sample within the batch and uses the average representation of these top $X$ neighbors as the negative sample. We use the same triplet loss as our ContraWR model. In the experiments, we tested $X=1$, $X=5$, and $X=50$. Note that when $X$ approaches the batch size, this model will gradually reduce to ContraWR.
Figure 2. STFT Convolutional Encoder Network. The encoder network first transforms raw signals into spectrogram by short time Fourier transform (STFT), then a CNN-based encoder is built on top of the spectrogram.

Model Architecture. For a fair comparison, all models, including baseline approaches and our models, use the same augmentation and encoder architecture, as shown in Figure 3. This architecture cascades a short time Fourier transform (STFT) operation, a 2D convolutional neural network layer, and three 2D convolutional blocks. Empirically, we find that apply neural networks on the STFT spectrogram of the signals generates better accuracy than on the raw signals. Same practices can be found in [14, 15].

We also consider a supervised model (called Supervised) as a refernece model, which uses the same encoder architecture and adds a 2-layer fully connected network (128-unit for Sleep EDF, 256-unit for SHHS, and 192-unit for MGH) for the sleep staging classification task. The supervised model does not use the pretrain set but is trained from scratch on raw EEG signals in the training set and tested on the test set. We also include an Untrained Encoder model as a baseline, where the encoder is initialized but not optimized in the pretrain step.

Evaluation Protocol. We evaluate performance on the sleep staging task with overall five-class classification Accuracy. Each experiment is conducted with five different random seeds. For self-supervised methods, we optimize the encoder for 100 epochs (here, "epoch" is a concept in deep learning) with unlabeled data and use the training set to find a good logistic classifier and use the test set data for evaluation following [2, 3]. For the supervised method, we train the model for 100 epochs on the training set. Our setting ensures the convergence of all models.

Results

Better Accuracy in Sleep Staging

Comparisons on the downstream sleep staging task are shown in Table 3.

Table 3. Sleep Staging Accuracy Comparison with Difference Methods (%).

| Name           | Sleep EDF      | SHHS         | MGH Sleep       |
|----------------|----------------|--------------|-----------------|
| Supervised     | 84.98 ± 0.3562 | 75.61 ± 0.9347 | 69.73 ± 0.4324 |
| Untrained Encoder | 77.83 ± 0.0232 | 60.03 ± 0.0448 | 55.64 ± 0.0082 |
| MoCo           | 85.58 ± 0.7707 | 77.10 ± 0.2743 | 62.14 ± 0.7099 |
| SimCLR         | 83.79 ± 0.3532 | 76.61 ± 0.3007 | 67.32 ± 0.7749 |
| BYOL           | 85.61 ± 0.7080 | 74.25 ± 0.4796 | 70.75 ± 0.1461 |
| SimSiam        | 84.78 ± 0.8028 | 74.25 ± 0.4796 | 62.08 ± 0.4902 |

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All self-supervised methods outperform the Untrained Encoder model, indicating that the pretrain step does learn some useful features from unlabeled data. We observe that ContraWR and ContraWR+ both outperform the supervised model, suggesting that the feature representations provided by the encoder can better preserve the predictive features and filter out noises than using the raw signals for the sleep staging task, in the case when the amount of labeled data available is not sufficient (e.g., less than 2% in Sleep EDF). Compared to other self-supervised methods, our proposed model ContraWR+ also provides better predictive accuracy, i.e., about 1.3% on Sleep EDF, 0.8% on SHHS, 1.3% on MGH Sleep. The performance improvements are mostly significant with p<.001, except the p-values comparing with MoCo on Sleep EDF dataset is 1.7e-3. MGH Sleep data contains more noise than the other two datasets (reflected by the relatively low accuracy with supervised model on raw signals). It is notable that the performance gain is much more significant on MGH over other self-supervised or supervised models (about 3.3% relative improvement on accuracy) which suggests that the proposed models handle noisy environments better.

### Ablation Study on Data Augmentations

We also inspect the effectiveness of different augmentation methods on EEG signals, shown in Table 4.

**Table 4.** Evaluation Accuracy of Different Augmentations (%). Format: mean ± standard deviation of training/test over 5 random seeds.

| Augmentations                  | Accuracy     |
|-------------------------------|--------------|
| Bandpass                      | 84.23 ± 0.2431 |
| Noising                       | 83.60 ± 0.1182 |
| Shifting                      | 84.65 ± 0.2844 |
| Bandpass + Flipping           | 85.77 ± 0.2337 |
| Noising + Flipping            | 84.45 ± 0.1420 |
| Shifting + Flipping           | 85.13 ± 0.0558 |
| Bandpass + Noising            | 85.37 ± 0.1214 |
| Noising + Shifting            | 84.78 ± 0.1932 |
| Shifting + Bandpass           | 85.25 ± 0.1479 |
| Bandpass + Noising + Flipping | 85.76 ± 0.1794 |
| Noising + Shifting + Flipping | 85.17 ± 0.2301 |
| Shifting + Bandpass + Flipping| 86.38 ± 0.2789 |

We empirically test all possible combinations of four considered augmentations: channel flipping, bandpass filtering, noising, shifting. Since channel flipping cannot be applied solely, we combine it with other augmentations. The evaluation is conducted on Sleep EDF with ContraWR+ model. To sum up, all augmentation methods are beneficial, and collectively, they can further boost the classification performance.

### Varying Amount of Training Data

To further investigate the benefits of self-supervised learning, we evaluate the effectiveness of the
learned feature representations with varying training data on Sleep EDF in Figure 3. The default setting is to split all the data into pretrain/training/test sets by 90%: 5%: 5% (as stated in the problem formulation). In this section, we keep the 5% test set unchanged and re-split the pretrain and training sets (after re-splitting, we ensure the training set data all have labels and remove the labels from the pretrain set), such that the training proportion becomes 0.5%, 1%, 2%, 5%, 10%, and the rest is used for the pretrain set. This “re-splitting” is conducted at the subject level, after which we again segment each subject’s recording within the pretrain or training set. We compare our ContraWR+ to MoCo, SimCLR, BYOL, SimSiam, and the supervised baseline models. Similar ablation studies on SHHS and MGH can be found in Multimedia Appendix 7. Our model outperforms the compared models consistently with different amount of training data. For example, our model achieves similar performance (with only 5% data as training) compared to the best baseline, BYOL, which needs twice amount of training data (10% data as training). Also, compared to the supervised model, the self-supervised methods perform better when the labels are insufficient, e.g., only ≤ 2% of the data are labeled.

Figure 3. Model Performance with Different Amount of Training Data (on Sleep EDF). Format: curves are the mean values and shaded areas are the standard deviation of training/test over 5 random seeds. All models have the same encoder network architecture. For the self-supervised method, we train a logistic regression model on top of the frozen encoder with the training set, and for the supervised model, we train the encoder along with the final nonlinear classification layer from scratch with the training set. The amount of training data is set 0.5%, 1%, 2%, 5%, 10%. Each configuration runs with 5 different random seeds and the error bars indicate the standard deviation over 5 seeds.

**Representation Projection**

We next sought to assess the quality of the learned feature representations. To do this, we use the representations produced by ContraWR+ on the MGH dataset and randomly select 5,000 signal epochs per label from the dataset. The ContraWR+ encoder is optimized on the pretrain step without using the labels. We extract feature representations for each sample through the encoder network and use uniform manifold approximation and projection (UMAP) [16] to project onto the 2D space. We finally color code samples according to sleep stage labels for illustration.

The 2D projection is shown in Figure 4. We also compute the confusion matrix from the evaluation stage (based on the test set), also shown in Figure 4. In the UMAP projection, epochs from the same latent class are closely co-located, which means the pretrain step extracts important information for sleep stage classification from the raw unlabeled EEG signals. Stage N1 overlaps with stages W, N2,
and N3, which is as expected given that N1 is often ambiguous and thus difficult to classify even for well-trained experts [1].

Figure 4. UMAP Projection and Confusion Matrix. Using MGH dataset, we project the output representations of each signal into 2D space and color by the actual labels (left). We also show the confusion matrix on sleep staging (right).

Hyperparameter Ablation Study

To investigate the sensitivity of our model to hyperparameter settings, we test with different batch sizes and train on different values for the Gaussian parameter $\sigma$, temperature $T$, and margin $\delta$. We focus on the ContraWR+ model and evaluate it on the Sleep EDF dataset. During the experiment, the default settings are batch size = 256, $\sigma=2$, $T=2$, $\delta=0.2$, learning rate $\eta=2e^{-4}$, weight decay = $1e^{-4}$, epoch = 100. When testing on one hyperparameter, others are held fixed.

Ablation study results are in shown in Figure 5; the red star indicates the default configuration. Each configuration runs with 5 different random seeds and the error bars indicate the standard deviation over 5 experiments. We see that the model is not sensitive to batch size. We see that over a large range (<10) the model is insensitive to the Gaussian width $\sigma$. For temperature $T$, we noted previously that a very small $T$ may be problematic, and a very large $T$ reduces ContraWR+ to ContraWR. Based on the ablation experiments the performance is relatively insensitive to choices of $T$. For the margin $\delta$, the distance difference is bounded (given fixed $\sigma=2$),

$$||\sim \langle z_i, z_w \rangle \sim \sim \langle z_i, z_j \rangle|| \leq \left \| \exp \left( \frac{-0^2}{2\sigma^2} \right) \right \| - \exp \left( \frac{2^2}{2\sigma^2} \right) \right \| \approx 0.3935 .$$

Thus, $\delta$ should be chosen large enough, i.e., $\delta \geq 0.1$. 

https://preprints.jmir.org/preprint/46769 [unpublished, peer-reviewed preprint]
Figure 5. Ablation Study on Batch Size and Three Hyperparameters. Format: curves are the mean values and shaded areas are the standard deviation of training/test over 5 random seeds. The red star denotes the default setting. It is obvious that with a larger batch size, the model will perform better, while it is not sensitive to all hyperparameters.

Discussion

Principle Results

Our proposed ContraWR and ContraWR+ models outperform 4 recent self-supervised learning methods on the sleep staging task across 3 large EEG datasets (with p<.001 in almost all cases). ContraWR+ also beats supervised learning when fewer training labels are available (e.g., 4% accuracy improvement when less than 2% data is labeled). Moreover, the models provide well-separated representative structures in 2D projection.

Comparison with Prior Work

Self-supervised Learning

Many deep generative methods have been proposed for unsupervised representation learning. They mostly rely on auto-encoding [17-19] or adversarial training [20-22]. Mutual information (MI) maximization is also popular for compressing input data into a latent representation [23-25].

Recently, self-supervised contrastive learning [2, 3, 7, 8, 14] has become popular, where loss functions are devised from representation similarity and negative sampling. However, one recent work [4] highlighted inherent limitations of negative sampling and showed that this strategy could hurt the learned representation significantly [5]. To address these limitations, Chuang et al. [5] utilized the law of total probability and approximated the per-class negative sample distribution using the weighted sum of the global data distribution and the expected class label distribution. However, without the actual labels, the true class label distribution is unknown. Grill et al. [7] and Chen et al. [8] proposed ignoring negative samples and learning latent representations using only positive pairs.

In this paper, we leverage the negative information by replacing negative samples with the average representation of the batch samples (i.e., the world representation). We argue and provide experiments showing that contrasting with the world representation is more powerful and robust in the noisy EEG setting.
**EEG Sleep Staging**

Before the emergence of deep learning, several traditional machine learning approaches [26-28] significantly advanced the field using hand-crafted features, as highlighted in [29]. Recently, deep learning models have been applied to various large sleep databases. SLEEPNET [29] built a comprehensive system combining many machine learning models to learn sleep signal representations. Biswal et al. [1] designed a multi-layer RCNN model to process multi-channel signals from EEG. To provide interpretable stage prototypes, Al-Hussaini et al. [30] developed a SLEEPER model that utilizes a particular deep learning approach called prototype learning guided by a decision tree to provide more interpretable results. These works rely on a large set of labeled training data. However, the annotations are expensive, and often times the labeled set is small. In this paper, we exploit the large set of unlabeled data to improve the classification, which is more challenging.

**Self-supervised Learning on Physiological Signals**

While image [31, 32], video [33], language [34, 35], and speech [36] representations have benefited from contrastive learning, research on learning physiological signals has been limited [37, 38]. Lemkhenter et al. [39] proposed phase and amplitude coupling for physiological data augmentation. Banville et al. [40] conducted representation learning on EEG signals, and they targeted monitoring and pathology screening tasks, without utilizing frequency information. Cheng et al. [41] learned subject-aware representations for ECG data and tested various augmentation methods. While most of these methods are based on pairwise similarity comparison, our model brings contrastive information from global data statistics, providing more robust representations. Also, we extract signal information from the spectral domain.

**Strengths and Limitations**

Strengths of our study are: (I) we use three real-world datasets collected from different institutes and across different year ranges, and two are publicly available; (II) our PSG recordings are diverse and generalizable, including two datasets collected at home and one collected in the lab setting, all have relatively large sizes; (III) we have open sourced our data processing pipelines and all programs used for his study, including the baseline model implementations; (IV) we propose new data augmentation methods for PSG signals and have systematically evaluated their effectiveness. However, limitations of our study should be noted, and they include the following: (I) we fixed the neural network encoder architecture in the study, which we plan to explore using other models like recurrent neural networks in the future.; (II) we have utilized the STFT to extract spectrograms, but we may consider alternative techniques such as wavelet transformation in future; (III) our current data augmentation methods are based on clinical knowledge, and we aim to investigate data-driven approaches to design more effective methods in the future.

**Conclusions**

This paper is motivated by the need to learn effective EEG representations from large unlabeled noisy EEG datasets. We propose a self-supervised contrastive method, ContraWR, and its enhanced variant, ContraWR+. Instead of creating a large number of negative samples our method contrasts samples with an average representation of many samples. The model is evaluated on a downstream sleep staging task with three real-world EEG datasets. Extensive experiments show that the model is more powerful and robust than multiple baselines including MoCo, SimCLR, BYOL, and SimSiam. ContraWR+ also outperforms the supervised counterpart in label-insufficient scenarios.

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Chaoqi Yang implemented the method and conducted the experiments. All authors were involved in
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Conflicts of Interest
MBW is co-founder of Beacon Biosignals, which played no role in this study. The other authors have no competing interests to declare.

Abbreviations
AASM: American Academy of Sleep Medicine
ContraWR: contrast with the world representation
EEG: Electroencephalogram
EMA: exponential moving average
MGH: Massachusetts General Hospital
NCE: noise contrastive estimation
PSG: Polysomnography
REM: rapid eye movement
SHHS: sleep heart health study
STFT: short time Fourier transform
UMAP: uniform manifold approximation and projection

Multimedia Appendix 1
Theoretical loss boundness analysis. https://drive.google.com/file/d/1-2yNzy0y6Q8Zho1loqbxI3xXbEY9U8Z4/view

Multimedia Appendix 2
Powerpoint presentation slides. https://docs.google.com/presentation/d/1CA-bCxpRR5Mets2Nwshtlp6PsrRmN9mD0RQjuCHr1Tg/edit?usp=sharing

Multimedia Appendix 3
Video presentation link. https://drive.google.com/file/d/14BVlVzYSB10vF49QYQmcs93UxioDODAl/view

Multimedia Appendix 4
Open-source GitHub repository, including data process pipeline for Sleep EDF and SHHS datasets, scripts for ContraWR, ContraWR+, and four self-supervised baseline models. https://github.com/ycq091044/ContraWR.

Multimedia Appendix 5
Illustration for data augmentations (bandpass filtering, noising, flipping, shifting). https://drive.google.com/file/d/1CaagQm8O2vCzux3Msh7wkoucZhY6pX8V/view?usp=sharing

Multimedia Appendix 6
Supplementary on model implementation.
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Supplementary Files