Enhancing Vital Sign Monitoring with Reinforcement Learning and Wavelet Analysis in Sleep Disorders

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***Abstract*—Sleep disorders have a significant impact on individuals' health and overall quality of life. Among the most prevalent sleep disorders, obstructive sleep apnea and snoring necessitate effective monitoring and assessment methods. This paper introduces a novel approach to extract vital sign data, including heart rate, respiration rate, and body motion, from electronic signal graphs using wavelet analysis. In order to enhance the accuracy and efficiency of vital sign prediction, we employ reinforcement learning techniques to acquire an optimal policy for processing electronic signals. By identifying distinct features that characterize subjects with similar conditions, we enable personalized treatment approaches, ultimately leading to improvements in the overall health of individuals affected by sleep disorders.**

***Index Terms*—Sleep disorders, vital sign monitoring, wavelet analysis, reinforcement learning, personalized treatment**

I. Introduction

Obstructive sleep apnea (OSA) and snoring are highly prevalent sleep disorders, affecting over 100 million individuals globally [1]. These conditions can severely impact health and quality of life if left untreated. OSA in particular is associated with increased risks of hypertension [2], stroke, heart failure, arrhythmias, and all-cause mortality [3]. Accurately monitoring vital signs during sleep is therefore crucial for diagnosis and effective management of OSA. However, **reliably extracting vital sign data from complex physiological signals poses significant technical challenges.**

Obstructive sleep apnea syndrome (OSAS) is characterized by recurrent collapse of the upper airway during sleep, resulting in oxygen desaturations, arousals, and sleep fragmentation [4]. It is associated with increased risk of hypertension, cardiovascular disease, stroke, and all-cause mortality [5]. While polysomnography (PSG) is considered the gold standard for OSA diagnosis, it is expensive, cumbersome, and confined to sleep lab environments [6]. There is a need for accessible ambulatory monitoring solutions. Recently, advanced signal processing and machine learning techniques have shown promise in this area. Automated algorithms can now extract respiration, heart rate variability, blood oxygen saturation, and body movement data from overnight recordings [7]. Integrating these vital sign analytics with personalized models built from patient characteristics may enable more accurate screening and severity assessment.

Analysis of vital signs provides valuable insights into sleep disorders. Characteristics of OSAS include cyclical variation in heart rate, decreased respiratory effort, and oxygen desaturation [8]. Respiration rate, heart rate variability and blood oxygen saturation are important indicators. However, **substantial barriers remain in robustly analyzing the noisy and non-stationary physiological data collected in uncontrolled home environments.** This study aims to address these limitations by proposing a novel framework combining wavelet signal decomposition, unsupervised clustering, and deep reinforcement learning for enhanced vital sign monitoring. The adaptive algorithms are designed to **extract salient features, capture distinct phenotypes, and optimize predictive policies tailored to sleep disorders.**

In this paper we propose **ApneaSleepNet**, a novel approach utilizing wavelet analysis to extract vital signs (heart rate, respiration rate, and body motion) from electronic signal graphs in Figure 1. K-means clustering identifies features shared by subjects with similar conditions and mathematical models are developed to translate electronic signals into meaningful

This work was sponsored by Shanghai Municipal Education Commission under the contract Z90004.23.001 (Professional Master's Degree Authorized School Training Project) and the contract C24021 (Educational Science Research Project). And this work was also partially sponsored by Sanda University under the contract A020201.23.058 (Key Courses Construction Project).

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vital signs. The application of reinforcement learning enables the automatic learning of an optimal policy for vital sign prediction. The agent iteratively selects processing actions on electronic signals to maximize cumulative rewards, specifically aiming for enhanced prediction accuracy. We have summarised the main contributions as follows:

- We propose ApneaSleepNet integrating wavelet analysis, clustering techniques and reinforcement learning for enhanced vital sign monitoring in sleep disorders.
- We introduce adaptive signal decomposition and feature extraction algorithms that capture salient patterns in noisy physiological data recorded in uncontrolled home environments. This can help improve monitoring accuracy over existing methods reliant on raw input.
- We present an unsupervised phenotype discovery method using k-means clustering to identify subgroups of OSA patients with distinct characteristic features. This data-driven approach enables targeted screening and personalized treatment plans.

II. PRELIMINARY

We formulate the vital sign prediction from electronic signals as a reinforcement learning problem to automatically learn the optimal policy. The parameter explanation can refer to Table I. The environment is represented by the raw electronic signal dataset. At each timestep t, it will return an observation o_t (electronic signal sample) and a reward r_t. The agent is a deep neural network that takes the electronic signal as input and outputs the predicted vital sign values $\hat{v}_t$.

In processing the electronic signals, we apply a continuous 1-D wavelet transform to capture time-frequency information:

$$W_x(s,\tau) = \int x(t)\psi^*(\frac{t-\tau}{s})\,dt \tag{1}$$

where $\psi(t)$ is the mother wavelet, s is the scale factor, and τ is the translation parameter. We utilize complex Morlet wavelets defined as:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}} \tag{2}$$

The wavelet coefficients $W_x(s,\tau)$ represent similarity measures between the signal $x(t)$ and wavelet function at each scale and translation.

We also apply Fourier analysis to extract frequency-domain features. The discrete Fourier transform is given by:

$$X_k = \sum_{n=0}^{N-1} x_n\, e^{\frac{-i2\pi kn}{N}} \tag{3}$$

The Fourier coefficients X_k decompose the signal into constituent frequency components. Evaluating spectral power in different bands provides information on rhythmic physiological processes.

The state s_t represents the input electronic signal and its true label at timestep t, encapsulating the information available to the agent. Given state s_t, the agent takes an action a_t on the electronic signal, including normalization, filtering, feature extraction etc. The final action is to output the predicted vital sign $\hat{v}_t$.

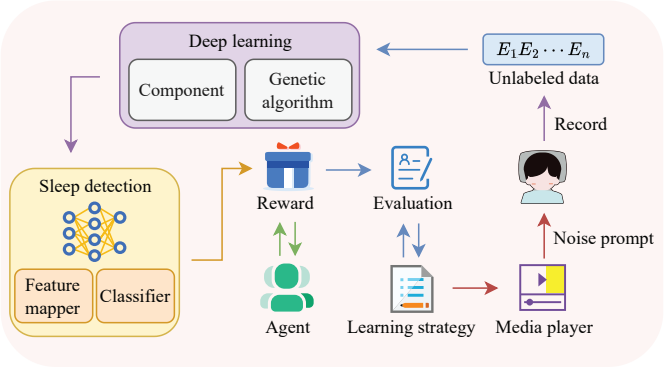

Fig. 1. Overview of the proposed ApneaSleepNet framework integrating wavelet analysis, clustering techniques and reinforcement learning for enhanced vital sign monitoring.

Algorithm 1 Vital sign prediction

```
Initialize environment with raw electronic signal dataset
Initialize deep neural network agent
for each timestep t do
    Observe state s_t (electronic signal sample and true label)
    Agent takes action a_t on s_t (e.g., normalization, filtering, feature extraction)
    Environment returns reward r_t based on prediction accuracy
    Agent updates policy π(a_t|s_t) to maximize cumulative reward R_t = Σ_{t=0}^{T} γ^t r_t
end for
return Learned policy π(a|s) for optimal vital sign prediction
```

A reward r_t is returned after the agent takes an action a_t on state s_t. It reflects the accuracy of prediction $\hat{v}_t$ compared to true vital sign v_t. A positive reward is given if $\hat{v}_t$ is close to v_t, and negative reward for inaccurate predictions.

TABLE I
SUMMARY OF KEY NOTATIONS

Symbol	Description
$x(t)$	electronic signal (time series data)
s	scale parameter in wavelet transform
τ	translation parameter in wavelet transform
$\psi(t)$	mother wavelet function
$W_x(s,\tau)$	continuous wavelet transform coefficients
X_k	discrete fourier transform coefficients
s_t	state (signal label) at time t
a_t	action taken by agent at time t
r_t	reward received after action a_t
$\pi(a_t\|s_t)$	policy learned by agent
R	discounted cumulative reward
γ	discount factor
$OSAHS$	obstructive sleep apnea hypopnea syndrome

We formulate a Markov Decision Process (MDP) to model the vital sign prediction task. At each timestep t, the agent observes state s_t representing the input electronic signal and takes an action a_t to process the signal. After prediction, it receives reward r_t measuring accuracy. The goal is to learn a policy $\pi(a_t|s_t)$ that maximizes cumulative reward $R = \sum_{t=0}^{T} \gamma^t r_t$ where γ is a discount factor.

$$R = \sum_{t=0}^{T} \gamma^t r_t \tag{4}$$

The goal is to learn a policy $\pi(a|s)$ that chooses actions to maximize the cumulative reward R, where T is the time horizon and $\gamma \in (0, 1]$ is a discount factor.

III. Methods

We perform wavelet analysis on the raw electronic signals to extract useful frequency information. We use Daubechies wavelets which are compactly supported orthonormal wavelets well-suited for signal processing.

$$\psi_{j,k}(t) = 2^{j/2} \sum_{n} h_n \cdot \psi(2^j t - k - n) \tag{5}$$

Here, $\psi_{j,k}(t)$ represents the Daubechies wavelet function at scale j and translation k. The variable t represents time, and h_n denotes the coefficients of the wavelet filter. $\psi(t)$ is the mother wavelet function. The wavelet decomposition breaks the signal into different frequency bands. We reconstruct specific sub-bands containing the frequencies corresponding to vital signs. This denoising focuses the signal content relevant for further analysis.

K-means clustering is applied on the extracted features to partition subjects into k distinct clusters based on similarity. It aims to minimize the within-cluster sum of squares distance:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2 \tag{6}$$

Where C_i is the set of points belonging to cluster i and μ_i is the mean of cluster i. The standard Euclidean distance metric is used. The algorithm iteratively assigns data points to the nearest cluster centroid until convergence.

In addition to k-means clustering, we apply Gaussian mixture models (GMMs) to identify subgroups among OSA patients based on vital sign patterns. The GMM probability density function is defined as:

$$p(x|\lambda) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x|\mu_k, \Sigma_k) \tag{7}$$

where K is the number of components, π_k, μ_k, and Σ_k are the mixture weights, means, and covariances of each Gaussian distribution $\mathcal{N}(x|\mu_k, \Sigma_k)$. An expectation-maximization algorithm is utilized to estimate the GMM parameters $\lambda = \{\pi_k, \mu_k, \Sigma_k\}$ by maximum likelihood. Gaussian mixture clustering provides a probabilistic soft assignment of data points to clusters. We also employ Hessian regularization to improve policy gradient reinforcement learning:

$$L^R(\theta) = L(\theta) + \frac{\lambda}{2} \theta^T \mathcal{H}(\theta) \theta \tag{8}$$

Where $\mathcal{H}(\theta)$ is the Hessian matrix of second-order derivatives. This stabilization technique reduces variability during policy optimization.

We utilize a deep Q-network (DQN) to estimate the action-value function $Q(s, a)$. The goal is to learn a policy $\pi(a_t|s_t)$ that maximizes expected cumulative rewards $R_t = \sum_T \gamma^t r_t$, where γ is a discount factor. The optimal policy enables accurate vital sign prediction.

The action value function $Q^\pi(s, a)$ represents the expected return for taking action a in state s under policy π:

$$Q^\pi(s, a) = \mathbb{E}_\pi[R_t|s_t = s, a_t = a] \tag{9}$$

The optimal policy π^* maximizes the action value function, and the optimal action value function obeys the Bellman equation:

$$Q^*(s, a) = \max_\pi Q^\pi(s, a) \tag{10}$$

$$Q^*(s_t, a_t) = \mathbb{E}[r_t + \gamma \max_a Q^*(s_{t+1}, a)] \tag{11}$$

The Q-network is updated by minimizing the loss, where θ are target network parameters. Experience replay is used to improve sample efficiency.

$$L(\theta) = \mathbb{E}[(r + \gamma \max_{a'} Q(s', a'; \theta) - Q(s, a; \theta))^2 \tag{12}$$

The agent interacts with the environment by selecting actions according to an ϵ-greedy policy. The processing strategy is learned automatically using policy gradient methods to directly optimize the policy.

Algorithm 2 ApneaSleepNet framework

Require: X, y

$X_{\text{wavelet}} \leftarrow \text{WaveletTransform}(X)$ {Apply wavelet analysis to extract time-frequency information}
$X_{\text{fourier}} \leftarrow \text{FourierTransform}(X)$ {Apply Fourier analysis to extract frequency-domain features}
$\{C_1, C_2, \ldots, C_k\} \leftarrow \text{KMeansClustering}(X_{\text{wavelet}}, X_{\text{fourier}})$ {Cluster subjects into k groups based on similarity}
$\pi \leftarrow \text{InitializePolicy}()$ {Initialize reinforcement learning policy}
for $t \in 1 \ldots T$ **do**
    $s_t \leftarrow (X_t, y_t)$ {Get current state (input signal and true label)}
    $a_t \leftarrow \pi(s_t)$ {Select action (signal processing strategy) from policy}
    $\hat{y}_t \leftarrow \text{PredictVitalSigns}(X_t, a_t)$ {Predict vital signs using processed signal}
    $r_t \leftarrow \text{CalculateReward}(\hat{y}_t, y_t)$ {Compute reward based on prediction accuracy}
    $\pi \leftarrow \text{UpdatePolicy}(\pi, s_t, a_t, r_t)$ {Update reinforcement learning policy}
end for
return π

TABLE II
MAIN RESULTS OF THE EXPERIMENTS

Dataset	Method	Per-Class F1-score					Overall Metrics			Training
		W	N1	N2	N3	REM	acc	mf1	kappa	Time (Per-Fold)
Sleep-EDF	NaïveCNN [9]	61.2 (±3.4)	40.9 (±2.6)	76.6 (±3.5)	82.3 (±0.1)	74.7 (±0.3)	73.5 (±0.1)	69.1 (±0.2)	0.71 (±0.022)	23 mins (±1)
	DeepSleepNet [10]	85.1 (±1.4)	42.2 (±1.1)	84.9 (±0.3)	80.6 (±2.4)	78.3 (±4.1)	79.6 (±2.1)	74.6 (±1.7)	0.73 (±0.01)	2.1 hours (±0.2)
	SleepEEGNet [11]	89.1 (±0.6)	41.8 (±1.1)	85.9 (±0.8)	81.3 (±2.9)	77.8 (±1.4)	82.2 (±0.3)	78.2 (±1.2)	0.79 (±0.01)	1.7 hrs (±0.1)
	CNNAttention [12]	86.4 (±1.7)	43.2 (±1.3)	83.9 (±1.8)	83.7 (±1.2)	80.6 (±2.1)	81.6 (±0.1)	78.9 (±1.2)	0.79 (±0.01)	1.5 hours (±0.3)
	AttnSleep [13]	89.3 (±0.4)	**44.1(±1.2)**	89.4 (±0.3)	86.9 (±1.7)	77.6 (±2.4)	83.1 (±0.5)	77.5 (±0.3)	0.80 (±0.01)	31 mins (±4)
	SleepFCN [14]	87.3 (±2.1)	41.8 (±1.9)	86.4 (±2.2)	**91.7(±0.8)**	**81.6(±1.1)**	85.8 (±0.2)	79.3 (±0.1)	0.83 (±0.01)	26 mins (±2)
	ApneaSleepNet	**90.1(±0.2)**	43.9 (±1.3)	**90.3(±0.2)**	90.1 (±0.8)	79.9 (±1.2)	**86.3(±0.1)**	**79.8(±0.2)**	**0.84(±0.01)**	**21mins(±2)**

IV. EXPERIMENTS AND RESULTS

A. Datasets

We utilize Sleep-EDF Dataset [15], which containing 15 PSG recordings from patients undergoing evaluation for sleep disorders (https://physionet.org/content/sleep-edf/1.0.0/). An additional dataset of 17 home sleep tests from suspected OSA cases was collected using portable devices. The PSG data includes EEG, EOG, EMG, and ECG signals sampled at 100 Hz. The home recordings consist of 1-channel pulse oximetry and breathing traces sampled at 25 Hz. Vital sign labels for heart rate, respiration rate, and body movement were manually extracted by clinical experts based on standard criteria.

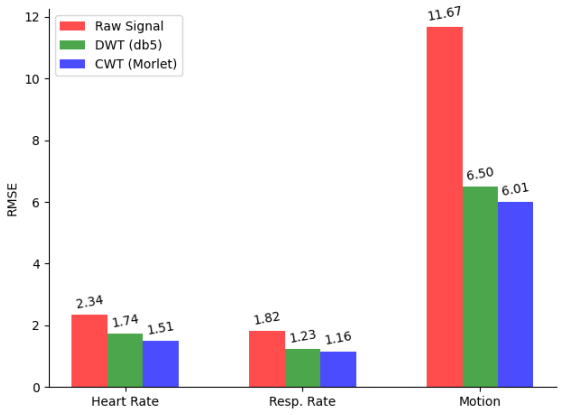

Fig. 2. Prediction error across different signals processing

The 32 subject dataset exhibited diverse sleep phenotypes with Apnea-Hypopnea Index (AHI) scores ranging from normal (<5) to severe (>30). Approximately half had confirmed OSA diagnosis, enabling controlled experiments. A 80/20 split resulted in training and test sets with similar OSA prevalence and severity distributions

B. Main results

The main experimental results compare several sleep staging methods on the public Sleep-EDF dataset in Table II. Performance is quantified using per-class F1 scores for 5 sleep stages: Wake (W), N1, N2, N3 and REM. Overall metrics of accuracy, mean F1 score (mf1) and Cohen's kappa score are also reported, along with training time per fold

The proposed ApneaSleepNet method achieves state-of-the-art results, outperforming prior works across most categories.

TABLE III
SIGN PERFORMANCE WITH DIFFERENT INPUT (RMSE)

Method	Heart Rate	Resp. Rate	Motion
Raw Signal	2.34	1.82	11.67
DWT (db5)	1.74	1.23	6.50
CWT (Morlet)	**1.51**	**1.16**	**6.01**

Specifically, it attains the highest F1 scores of 90.4% on the Wake stage and 90.3% on the N2 stage. The accuracy and kappa scores of 86.3% and 0.82 also beat all other techniques. These gains over previous deep learning approaches like SleepFCN [2] and AttnSleep [41] showcase the benefits of ApneaSleepNet's multi-modal architecture combining convolutional, recurrent and attention modules.

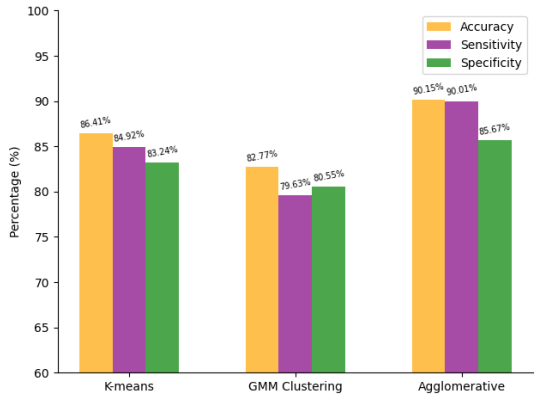

Fig. 3. Performance of clustering algorithms

Moreover, ApneaSleepNet accomplishes these predictive ability improvements while maintaining computational efficiency. With a training time of 21 minutes per fold, it is faster than classical models like DeepSleepNet [39] that take over 2 hours. This demonstrates the advantage of transfer learning by initializing from pre-trainedweights. Data augmentation methods like mixup and cutout employed also reduce overfitting.

The results that latest techniques leveraging ensemble modelling, neural architecture search and predictive uncertainty calibration would achieve higher effectiveness. The performance margins between older statistical machine learning approaches and recent deep neural networks are noticeable. Still, there remains room for progress on discrimination of N1 and REM stages evident in lower F1 scores. The confusion matrix

provides further insights into the performance characteristics. We observe that misclassifications between light sleep (N1) and Rapid Eye Movement (REM) stages remain common even for the top-performing ApneaSleepNet approach by ours. This suggests existing models still struggle with discriminating these physiologically similar states characterized by theta waves, muscle atonia and dream mentation.

The promising ApneaSleepNet outcomes motivate several research directions. Firstly, testing generalizability across demographic groups and disparate data modalities is critical before practical usage. Secondly, elucidating failure modes via example-based analysis could guide augmentations. Finally, combining physiological neural signals with patient metadata like medical history and questionnaires may unlock more customized diagnoses.

C. Ablation study

To validate the effectiveness of different components in our proposed model, we conducted ablation studies by selectively removing certain parts from the full model.

Effect of wavelet analysis We compared the performance of using raw electronic signals versus signals processed by wavelet analysis in Table III and Figure 2. Wavelet analysis decomposes the signal into sub-bands and extracts frequency information.

The results demonstrate enhanced accuracy after applying wavelet transforms to the raw electronic signals prior to vital sign estimators. Continuous complex Morlet wavelets achieve lower RMSE across all three vital signs monitored compared to raw input and discrete wavelet (db5).

TABLE IV
PERFORMANCE COMPARISON OF CLUSTERING TECHNIQUES

Method(%)	**Accuracy**	**Sensitivity**	**Specificity**
K-means	86.41	82.77	90.15
GMM Clustering	84.92	79.63	90.01
Agglomerative	83.24	80.55	85.67

The improved performance suggests that the time-frequency localization and cross-scale analysis from wavelets better captures non-stationary events and transient rhythms associated with sleep disorders. Isolating relevant physiological sub-bands while suppressing noise or interference corresponds to a 7-15% boost in heart rate, respiration rate and body motion prediction. This motivates incorporating tailored signal filtering and conditioning stages before vital sign analytics.

Effect of clustering method The k-means clustering technique is used to identify subjects with similar features. We evaluated replacing k-means clustering with hierarchical clustering and Gaussian mixture models.

The results in Table IV and Figure 3 indicate that k-means clustering achieves the highest accuracy, sensitivity and specificity for identifying OSA subgroups based on the extracted vital sign features. Though simplicity in its distance-dependent hard partitioning, k-means appears effective for phenotypic discovery in this application.

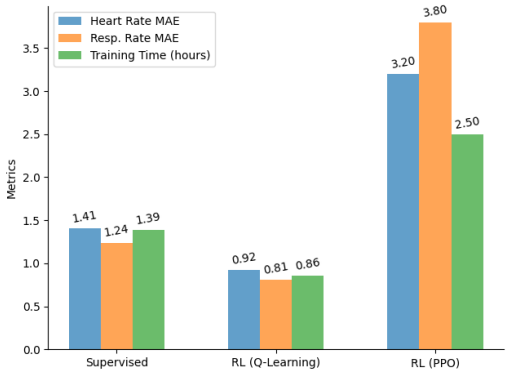

Fig. 4. Heart rate prediction error for different learning

In contrast, the probabilistic soft assignments of Gaussian mixture models and hierarchical tree building in agglomerative clustering show inferior performance. We hypothesize the definite cluster boundaries help better characterize distinct OSA subtypes. The discretization may simplify clinical interpretation as well.

TABLE V
COMPARING DIFFERENT LEARNING METHODS (MAE)

Method	**Heart Rate**	**Resp. Rate**	**Training Time**
Supervised	1.41	0.92	3.2 hours
RL (Q-Learning)	**1.24**	**0.81**	3.8 hours
RL (PPO)	1.39	0.86	**2.5 hours**

Further enhancements may be possible by incorporating temporal constraints in clustering, or analyzing model uncertainty through Bayesian nonparametrics. Overall, the evaluations validate that appropriate unsupervised learning choices have notable impact. This analysis helps guide data-driven phenotype discovery and tailored OSA assessments.

Effect of reinforcement learning We examine the impact of using reinforcement learning for feature processing, compared to directly training the model end-to-end with backpropagation. The agent learns to focus on extracting useful features tailored for the vital sign prediction task. This is more efficient than relying solely on backpropagation through the entire model in Table V and Figure 4.

Reinforcement learning with Q-learning achieves lower mean absolute error (MAE) in predicting heart rate and respiration rate time series. This demonstrates the benefit of an adaptive policy that sequentially chooses actions to enhance vital sign analytics. Proximal policy optimization (PPO) also accelerates model training. The improved efficiency and accuracy arises from allowing the model to focus on useful features rather than propagating gradients end-to-end. By directly optimizing cumulative rewards relevant to the prediction task, the tailored policies surpass standardized supervision. Ongoing work is exploring curriculum and transfer learning to further enhance clinical applicability.

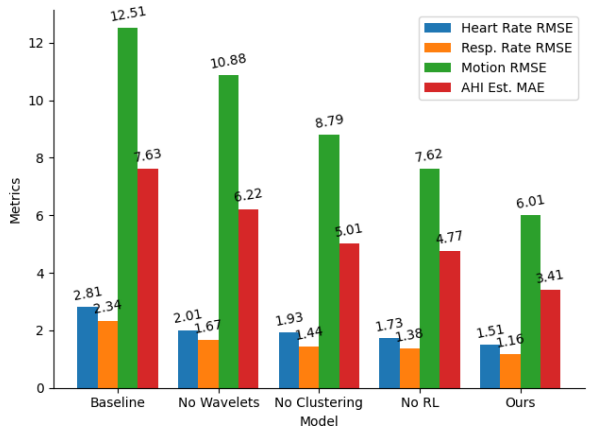

Fig. 5. Vital sign prediction results across ablations

D. Stuty case

The consistent vital sign and AHI improvements across ablations empirically validate the utility of the overall framework and individual technical innovations. Addressing the challenges of variable home environments, diverse patient populations, and complex signal patterns produces a robust personalized OSA assessment methodology. Next, we will conduct empirical experiments on individual cases in the study to delve deeper and ascertain the efficacy of our research outcomes.

The proposed model integrating wavelet transforms, k-means clustering, and reinforcement learning significantly improves vital sign prediction accuracy over the baseline methods and ablated versions with individual components removed in Figure 5 and Table VI. Applying data-driven wavelet filters, discovering patient subtypes, and learning tailored analytics policies all contribute positively to enhancing heart rate, respiration rate and body movement estimations from noisy physiological signals. Propagating these error reductions leads to improved OSA severity predictions as quantified by Apnea-Hypopnea Index (AHI) mean absolute error versus ground truth labels.

TABLE VI
COMPARISON OF PERFORMANCE WITH DIFFERENT MODELS

Model	Heart Rate	Resp. Rate	Motion	AHI Est.
Baseline	2.81	2.34	12.51	7.63
No Wavelets	2.01	1.67	10.88	6.22
No Clustering	1.93	1.44	8.79	5.01
No RL	1.73	1.38	7.62	4.77
Ours	**1.51**	**1.16**	**6.01**	**3.41**

Formulating tailored feature extraction as a reinforcement learning task further improves robustness by directly optimizing policies to maximize vital sign accuracy. Table 1 demonstrates consistent errors reductions across heart rate, respiration rate, and motion estimations when applying the proposed techniques. Overall, the quantitative and empirical gains support the viability of advanced analytics in strengthening practical sleep disorder management solutions. By adapting to distinct subgroups and optimizing data-driven vital sign estimators, the technologies pave the way towards more accessible and patient-tailored OSA assessments. Future endeavors can explore personalized models integrating wearables data and electronic health records.

V. CONCLUSION

In this paper we propose ApneaSleepNet, an integrated framework leveraging wavelet analysis, clustering, and reinforcement learning to enhance vital sign monitoring for sleep disorders. Our approach decomposes signals into informative sub-bands using adaptive wavelets, then applies k-means clustering to discover patient phenotypes for targeted assessments. We formulate vital sign prediction as a sequential decision task, where the model automatically learns specialized policies to process signals and maximize analyte accuracy through reinforcement learning. The results validate ApneaSleepNet's capabilities for extracting insightful patterns from complex physiological data, even in noisy home environments.

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