CWMformer: A Novel Framework for Long-Term Fatigue Conditions Measurement and Prediction of Construction Workers with A Wearable Optical Fiber Sensor System

Qing Wang, *Member*, *IEEE*, Ke Li, *Student Member*, *IEEE*, Xiuyuan Wang, Xiang Wang, Jing Qin, *Senior Member*, *IEEE*, and Changyuan Yu, *Senior Member*, *IEEE*, *Fellow*, *OSA*

***Abstract*—Construction workers face numerous dangers and high-intensity environments at work. Monitoring their vital signs and fatigue is crucial for ensuring their health and safety, preventing accidents, and improving work efficiency. Optical fiber sensors are widely used due to their small size, lightweight, and strong resistance to electronic interference. These sensors are particularly useful for detecting and monitoring the vital signs of construction workers. Heart rate variability (HRV) is the variation in consecutive heartbeat intervals and is a marker of autonomic nervous system activity, influenced by various factors. Fatigue significantly impacts HRV and overall cardiovascular health, making HRV a useful tool for assessing fatigue conditions. Monitoring HRV helps identify fatigue conditions. However, existing optical fiber sensors have drawbacks such as signal loss, distortion during long-term transmission, and high manufacturing and maintenance costs. They may also produce missing or anomalous data due to sensor failures and other unforeseen factors, making long-term fatigue measurement challenging, especially when direct contact with the skin causes discomfort. To address these issues, we propose a novel optical fiber sensor system based on a fiber interferometer integrated with smart clothing. In addition, we propose a robust deep learning framework called CWMformer, which processes and analyzes raw vital signs of construction workers, predicts long-term fatigue conditions, and matches them with HRV more accurately. Our experiments show an average mean absolute percentage error (MAPE) of 2.126 and *p*-value of 0.0213, indicating the feasibility and effectiveness. This study presents a novel and practical application for smart healthcare monitoring of construction workers.**

***Index Terms*—Heart rate variability, construction workers, fatigue conditions, optical fiber sensor, fiber interferometer, smart clothing, deep learning.**

I. INTRODUCTION

During the past few years, the optical fiber communication industry has been leaping forward. An optical fiber communication system has been reported with several characteristics, such as larger channel bandwidth, lower cost, and more reliable information service [1]-[4]. Moreover, the optical fiber sensors have been extensively employed for a wide variety of applications, especially in medical monitoring [5]-[8]. Currently, the incidence and mortality of high-risk diseases often show an upward trend. The development of the clinical field is changing significantly, and its focus has gradually shifted from simple human disease treatment to monitoring health [9]. The evaluation and the results of prevention work have a pivotal position in the prevention and control of diseases. Taking patients as an example, many vital signs such as blood oxygen saturation, pulse frequency, blood pressure (BP), heartbeat, respiratory and body temperature have been regarded as key health signs of human physiological activities. The monitoring of life signs not only helps to accurately evaluate the daily health status of the subject, but also provide strong support for the early discovery and intervention of the disease [10], [11]. However, the current common monitoring methods of monitoring life signs, such as the test of the five-lead, have certain limitations. This method requires direct contact with the human skin to collect signals of life signs, which will bring inconvenience to patients in many different scenes [12]-[15]. Moreover, it has poor performance in terms of efficiency and accuracy. To solve these problems, the application of fiber sensors has become a feasible and effective way. Optical fiber sensor has various advantages and can obtain vital signs more accurately and conveniently [16], [17].

Long-term monitoring the vital signs and fatigue of construction workers is of great significance and necessity to protect health of construction workers, improve construction safety, and improve construction efficiency [18], [19]. First of all, the construction industry is a high-risk industry, and workers may encounter various accidental injuries during the construction process. By monitoring vital signs of construction workers in real time, abnormal situations can be detected in time and countermeasures can be taken quickly to avoid accidents [20]. Secondly, construction workers have high-intensity work and high physical exertion, making them prone to fatigue, heat stroke and other health problems [21]. By monitoring the fatigue of construction workers, we can understand the rest status of workers, arrange their work and rest time reasonably, ensure that workers have adequate rest and recovery, and reduce safety accidents caused by fatigue [22], [23]. Thirdly, long-term poor monitoring quality will affect the physical and mental health of construction workers, lead to a decrease in work efficiency, and even cause occupational diseases. By monitoring the fatigue of workers, fatigue-associated problems can be discovered in time and improvement measures can be taken to improve construction

(Corresponding author: Changyuan Yu)
Q. Wang and X. Wang are with the Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong (e-mail: qing-wq.wang@connect.polyu.hk, xiuyuan.wang@connect.polyu.hk).
K. Li is with the School of Fashion and Textile, The Hong Kong Polytechnic University, Hong Kong (e-mail: ke0414.li@connect.polyu.hk).
X. Wang is with the Department of Engineering, University of Cambridge, United Kingdom (e-mail: xw438@cam.ac.uk).
J. Qin is with the School of Nursing, The Hong Kong Polytechnic University, Hong Kong (e-mail: harry.qin@polyu.edu.hk).
C. Yu is with the Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong, and also with the Shenzhen Research Institute, The Hong Kong Polytechnic University, Shenzhen, Guangdong 518057, China (e-mail: changyuan.yu@polyu.edu.hk).

workers' quality of life and work efficiency [24]. In addition, long-term monitoring the vital signs of construction workers and fatigue can provide data support for construction companies to formulate scientific labor organization and work and rest systems [25]. Enterprises can reasonably arrange construction plans based on monitoring data to avoid overwork of construction workers and improve construction efficiency [26]. Recent advancements in optical fiber sensors for human health monitoring, particularly fatigue condition monitoring, have been notable [27]. These sensors utilize light interference, scattering, and absorption, offering advantages over traditional electrical sensors, such as resistance to electromagnetic interference and enhanced electrical safety. Wearable fiber sensors are categorized into silicon and polymer fibers. Silicon fibers offer ultra-low-loss optical transmission but require structural design improvements for better mechanical properties [28]. Polymer fibers, on the other hand, provide excellent biocompatibility and stretchability, making them suitable for embedded sensing [29]. Optical fiber sensors exhibit high sensitivity and a good linear response, capable of monitoring body temperature, limb movement, and deformation with stability and speed. They are used in applications like joint posture, respiratory rate, and heart rate monitoring, and even in remote robotic arm control, highlighting their potential in human-computer interaction. However, challenges remain in system integration and ensuring long-term optical mechanical stability for reliable signal performance and monitoring [30].

Heart rate variability (HRV) has been reported as a physiological measure that quantifies the change of successive heartbeat time intervals [31]. It is considered as a reliable indicator of autonomic nervous system activity. Besides, it shows a correlation with a wide variety of health and well-being aspects. The integration of HRV monitoring with fatigue detection and the human-cybernetic interfaces (HCI) has achieved significant attention [32]. Fatigue detection involves monitoring and analyzing a wide variety of parameters during working for the evaluation of fatigue patterns and conditions. HRV is a valuable biomarker in terms of fatigue-associated conditions and disorders, such as insomnia, sleep apnea, and sleep disturbances. By measuring HRV, it is possible to identify abnormalities or deviations from normal patterns, which can facilitate disorder diagnosis and management [30]. The HCI is the system enabling interaction between human and machines, including computers, smart system, and artificial intelligence (AI), ranging from simple input devices to advanced technologies, like smart healthcare monitoring system [33], [34]. In the context of fatigue detection, HCI devices, such as healthcare monitoring systems, can be employed to capture HRV data. The above-mentioned devices can continuously monitor HRV and transmit the data to a central server or cloud-based platform for analysis [35]. Furthermore, the integration of HRV monitoring with HCI contributes to remote monitoring and telemedicine applications. Healthcare professionals can access HRV data remotely while providing personalized recommendations or interventions to subjects with fatigue, improving the accessibility and convenience of healthcare services. Overall, the integration of HRV monitoring, fatigue detection, and the HCI holds great potential for advancing the field of healthcare monitoring [36], [37]. It can enable objective and continuous monitoring of facilitate early detection and intervention for disorders, and enhance the overall management of fatigue conditions.

Recently, some optical fiber sensors based on banding loss have been proposed to monitor vital signs of construction workers, such as ballistocardiography (BCG) and electrocardiogram (ECG) signal, with the aim of extracting and detecting heart rate (HR), respiratory rate (RR), HRV, and so on [38], [39]. However, there are three main drawbacks with this sensor as below. First, the sensor based on banding loss can easily fall into breaking in the application process. Besides, the optical fiber interferometer sensor exhibits better sensitivity than the above-mentioned type of sensor. Second, the sensor based on grating has high costs, while it cannot easily be applied in practice [39]. Third, sensors based on electricity are less sensitive to the weak signal of vibration [10]. In addition, under a sophisticated environment, signal with high quality cannot be easily obtained [12]. Moreover, with the development of artificial intelligence, while HRV processing with some proposed machine learning methods has shown promise in a wide variety of applications, HRV and fatigue condition analysis heavily relies on accurate and reliable raw data [40], [41]. And the proposed machine learning methods require high-quality data for effective training and inference, which might not encompass the full range of HRV patterns and variations present in the broader population.

To address the above problems, a novel optical fiber sensor with smart clothing is proposed based on fiber interferometer, which utilizes the interference of light waves within an optical fiber to measure a wide variety of physical quantities. The proposed optical fiber sensor is likely to exhibit great sensitivity, such that precise and accurate measurements can be carried out. In addition, CWMformer, a novel deep learning framework is proposed by us, which can be applied to process the HRV data and detect fatigue conditions better combined with the proposed wearable optical fiber sensor system. Furthermore, the proposed CWMformer framework can be adopted to long-term HRV processing for more effective future fatigue conditions monitoring and prediction.

The main contributions of this paper are summarized as follows:

(1) A novel fiber interferometer-based optical fiber sensor with smart clothing is proposed to monitor vital signs and fatigue conditions of construction workers effectively, and shows its superiority and competitive performance;
(2) To monitor and process the long-term HRV data and fatigue conditions of construction workers, the CWMformer framework is proposed to extract spatial and temporal features of the raw vital signs signal acquired from the optical fiber sensor, analyze and predict long-term fatigue conditions better, and explore the matching relationship between HRV and fatigue conditions of construction workers accurately and effectively;
(3) In the proposed CWMformer framework, the proposed module (MGON) extracts spatial and temporal features from the acquired raw data for graph modeling. Then

the framework introduces a cross dimension-segmented embedding method alongside a two-stage attention module (TDE) to capture correlations across time and dimensions. The framework also employs a hierarchical encoder-decoder module (EDM) to produce the final outputs;

(4) An HRV dataset of construction workers based on the proposed wearable optical fiber sensor system is constructed for the first time, which is collected from over 300 construction workers.

We present the following structure of this paper below. In Section II, an introduction is conducted about some methods and the structure of the proposed framework. In Section III, experiments and the comparison between the proposed framework and other models are illustrated. In Section IV, the results achieved through experiments are analyzed and discussed. And in Section V, the conclusion is drawn and the future works are summarized.

II. METHODOLOGY

A. Proposed Optical Fiber Sensor with Smart Clothing System

In previous study, we proposed a microbend optical fiber sensor system to monitor vital signs signal of perioperative infants, which is based on banding loss [10]. The microbend optical fiber sensor comprises a segment of graded multimode optical fiber firmly secured between a set of microbenders. Its operational principle is rooted in the concept of optical fiber microbending. As the distance varies between the two microbenders, the sinusoidal amplitude of the clamped multimode optical fiber fluctuates in response to the subtle vibrations generated by human respiration, heartbeats, and other movements. This alteration in the spacing between microbenders results in a modulation of light intensity within the microbend fiber, effectively capturing and reflecting the vibrations or motions of body. Fig. 1 shows the basic mechanism of the microbend optical fiber sensor system.

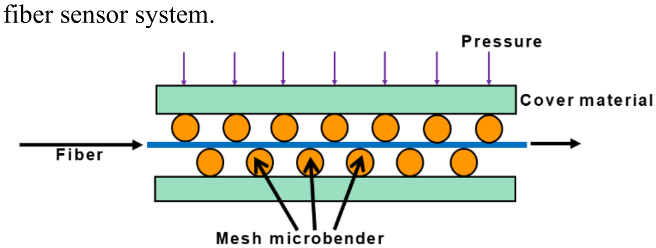


Fig. 1. Basic mechanism of the microbend optical fiber sensor.

In this study, the 1550nm distributed feedback (DFB) laser is regarded as a light source in the optical fiber sensor system. In view of the operation of the optical fiber sensor in accordance with the principle of interference, changes in the external environment may cause random floating sensors. This will cause the working point of the optical fiber interference instrument to prefer the center of offline areas. Random drift at work points can significantly affect the operating status of the interference instrument. Therefore, the 3×3 demodulation method is used to analyze the BCG and ECG signals. To be precise, the interference light is decomposed by a 3×3 coupler into three beams with a 120° phase difference. The light from the DFB laser is transmitted to reference fiber and sensor fibers through the 1×2 coupler. Later, the beam spreading in the reference arm and sensor arms will interfere at the 3×3 coupler. The output light intensity of the interferometer can be computed by employing the equation below

$$I_k = D + I_0 \cos[\varphi(t) - (k-1)(2\pi/3)] \tag{1}$$

where $\varphi(t)$ is the phase difference of light signals, D is the average value of output light intensity, I_0 is the peak intensity of interference fringes, k is the number of the output light path, and k=1, 2, 3.

In practical usage, $\varphi(t)$ encompasses phase alterations resulting from the measured information as well as environmental variations, which can be represented as

$$\varphi(t) = \phi(t) + \psi(t) \tag{2}$$

where $\varphi(t)$ represents the signal to be measured, and $\psi(t)$ is the phase difference caused by environmental changes.

As emitted from the Broadband Source (BBS, SLED-1488/1650-10-FA-B, Shanghai Mai Xuan Laser Co., Ltd.), the signal light sent by Shanghai MAI XUAN LASER was introduced into the interference optical fiber sensor. As shown in Fig. 3, the transmission spectrum was detected by the spectral analyzer (YOKOGAWA AQ6370D), with a resolution of 0.01nm. Four interference inclination is observed at the wavelength 1549.4nm, 1549.72nm, 1550.03nm, and 1550.34nm, respectively. All these inclinations can be used for BCG induction.

According to the equation (1), the three optical intensity signals can be demodulated by the 3×3 coupler demodulation scheme is shown in Fig. 2.

After differentiation and cross-multiplication, the demodulated signal is illustrated as follow

$$N = a(e-f) + b(f-d) + c(d-e) = \frac{3\sqrt{3}}{2} I_0^2 g'(t) \tag{3}$$

In the actual environment, the fluctuation of the intensity of light and the change of polarization state will affect the value of I_0. In order to eliminate these influencing factors, the following mathematical treatment was performed.

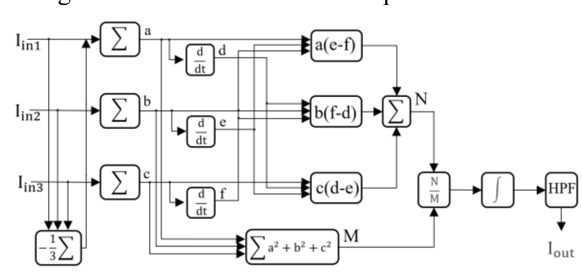


Fig. 2. Demodulation principle of the 3×3 coupler.

First, square the three input signals to obtain

$$M = a^2 + b^2 + c^2 = \frac{3I_0^2}{2} \tag{4}$$

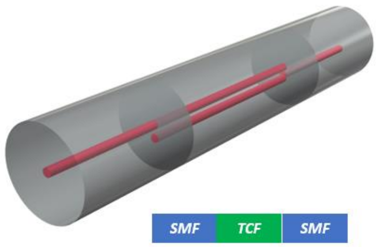
Then divide N by M and eliminate I_0^2 to get

$$P = \frac{N}{M} = \sqrt{3}\varphi'(t) \tag{5}$$

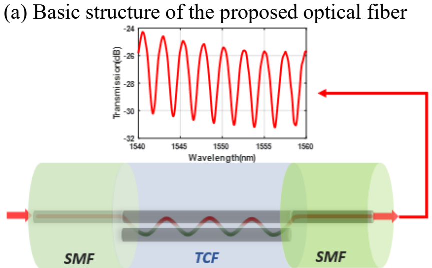
After integral operation, the output is described as

$$\sqrt{3}\varphi(t) = \sqrt{3}\phi(t) + \psi(t) \tag{6}$$

where $\psi(t)$ is regarded as a slow change quantity, which can be filtered out through a high-pass filter. I_{out} is the output signal of the 3×3 demodulation scheme, which is known as the BCG signal transmitted to the computer. Fig. 4 shows the mechanism and basic structure of the proposed vital signs signal monitoring system.



(a) Basic structure of the proposed optical fiber



(b) Mechanism of the proposed optical fiber sensor

Fig. 3. Proposed optical fiber sensor system with fiber interferometer.

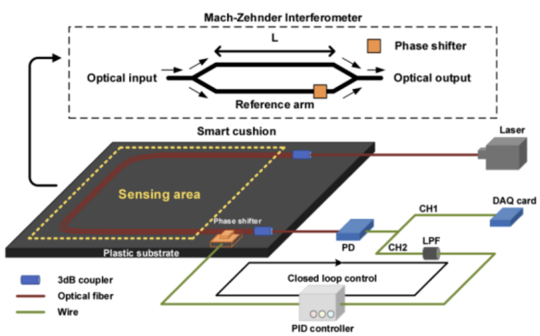


Fig. 4. Structure of the proposed vital signs signal monitoring system.

The fibrous appearance of optical fiber allows it to be used for weaving fabrics like traditional textile materials. The optical fiber itself has the advantages of flexibility, lightness, durability, low cost, and resistance to electromagnetic interference. The optical fiber fabric is easy to shape, simple to connect, and has good biocompatibility. By integrating optical fibers into appropriate textile structures, light transmission or emission can be achieved in any part of the smart fabric, and physiological parameters can be monitored by measuring mechanical variables with optical fiber sensing technology.

In this study, we use the optical fiber sensor with r=3mm, N=6, and D=15mm. There is no need to sew and fit the clothing fabrics. We design vital signs monitoring clothing samples according to the method in Fig. 5. The sensor is located just below the sternum (point A in Fig. 5). According to ergonomics, the area directly below the sternum will undergo large changes during human breathing movements, while different postures of the human body have little effect on the circumference changes of this area. The detection circuit is placed in the mezzanine on the left side of the sensor (point B in Fig. 5), it is used to output light to the optical fiber sensor and detect the light intensity output by the sensor. It calculates vital signs data through relevant algorithms and sends the obtained information to computer monitoring software. The external pigtails of the sensor are connected to the detection circuit from the upper and lower directions respectively. The detection circuitry in the garment is powered by a flexible battery located in the left pocket of the garment's waistline (point C in Fig. 5). As for the sensor integrated with smart clothing, wireless transmission is applied to transmit and process data that measured by sensors. We use two batteries of about 5 cm large and the capacity of 2000 mAh per hour for power supply and management, which can maintain the power consumption of its monitoring one day. The sensor system integrated in the clothes is about 200 g.

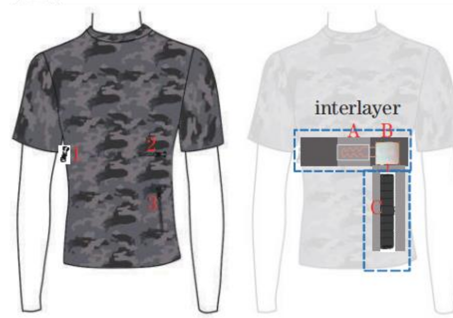


Fig. 5. The proposed clothing based on optical fiber interferometer for vital signs monitoring of construction workers.

Compared with traditional wearable devices such as smartwatches and fitness trackers, the proposed wearable smart clothing shows unique advantages in measurement of biological signals. Firstly, the clothing has excellent anti-electromagnetic interference ability, which makes them still work stably in complex electromagnetic environments, while traditional electronic sensors are easily disturbed [42]. Secondly, its comfort is better. It uses soft and breathable textile materials, which has a high degree of fit and no restraint. Wearing devices such as smartwatches and fitness trackers are limited to discomfort [43]. Its measurement range is also more comprehensive. It can integrate sensors in multiple parts of the clothing to monitor a variety of biological signals and body posture movements, while the acquired signals by smartwatches and fitness tracker are relatively limited [44]. The fabric is hidden, the appearance looks like ordinary clothing, and the user has no psychological burden [45].

The maximum error of the proposed wearable smart clothing in respiratory monitoring is less than 2bpm/min, and the average error is within 0.8 times/min. In addition, its strain coefficient can reach 71.01, the stretching rate reaches 83%, and the lagging error is less than 12%, showing the ability of unidirectional stretching perception. In terms of measurement accuracy, the smart clothing can obtain signal at a higher sampling frequency, and its sampling frequency can reach 3000Hz, while smartwatches are generally from 10Hz to 1000Hz [46]. In terms of signal stability, optical fiber sensors are extremely disturbing by external electromagnetic interference, and its signal stability index is about 30%~50% higher than that of devices such as smartwatches [47].

Overall, compared with banding loss-based optical fiber sensors, the proposed optical fiber interference-based optical fiber sensor has the characteristics of light weight, compact structure, flexible geometry, explosion-proof, and anti-electromagnetic interference. It has higher sensitivity in vital signs monitoring of construction workers.

B. Overview

Fig. 6 shows the overall architecture of the experiment setup. And as shown in Fig. 7, the proposed CWMformer framework consists four important modules, termed MDSW, EDM, MGON and TDE, respectively. It is worth noting that HRV analysis can be complex, and various mathematical and statistical techniques are employed for accurate extraction and interpretation. Software tools and dedicated HRV analysis packages are available to simplify the process and provide comprehensive HRV insights. Fig. 8 shows the mechanism and analysis of extracting HRV from the raw BCG signal with the proposed optical fiber sensor.

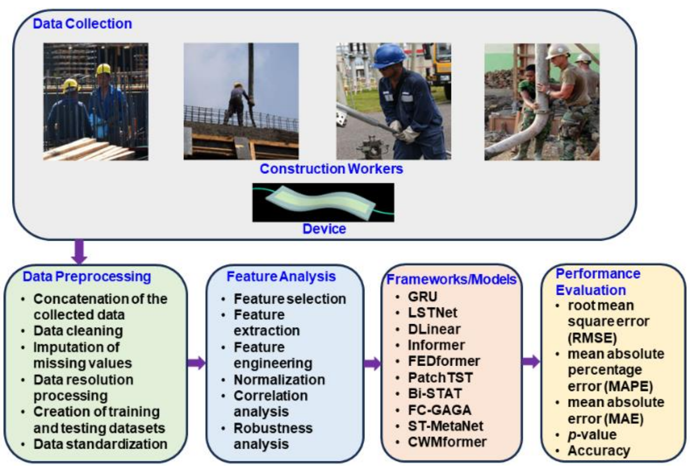


Fig. 6. Overall architecture of the experiment setup.

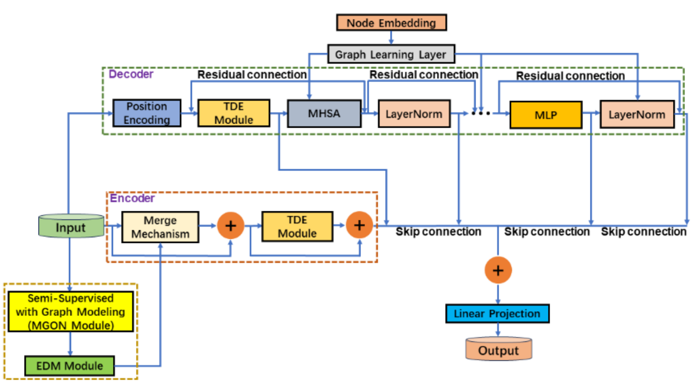


Fig. 7. Whole structure of the proposed CWMformer framework.

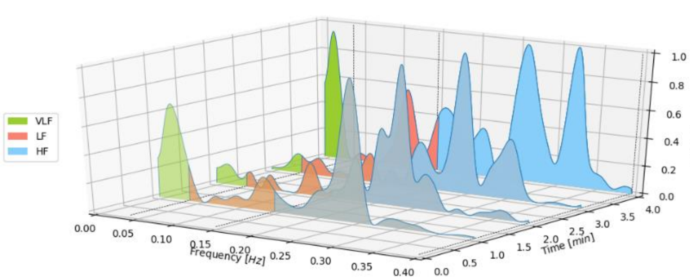


Fig. 8. Frequency domain analysis with the acquired HRV data of construction workers (VLF: very low frequency; LF: low frequency; HF: high frequency).

Detail information of the proposed MDSW, TDE, EDM and MGON modules in CWMformer framework can be found at Supplemental Material.

III. EXPERIMENTS AND RESULTS

A. Implementation Details

The optimizer is ADAM, the batch size is 60, the learning rate is set as 0.0005, the lookback window is set as 5, and the activation function is ReLu. All the experiments are carried out based on a computer equipped with graphics processing unit (GPU) and NVIDIA GeForce RTX4060 graphics card. We implement the framework under the TensorFlow framework with Python language. We conduct whole experiment based on 10-fold cross-validation mechanism to verify the robust of the proposed framework and avoid the potential overfitting problem.

In this study, to investigate the effect of hyperparameter adjustment on accuracy, we use different batch size, learning rate and lookback window values, to obtain the best parameter value that suitable for our proposed framework. The average experimental results are shown in Table I, Table II and Table III, respectively.

TABLE I
AVERAGE EXPERIMENTAL RESULTS BASED ON DIFFERENT BATCH SIZE.

Batch Size	Male	Female
20	0.92	0.91
40	0.92	0.93
60	**0.93**	0.93
80	0.92	0.90
100	0.92	0.89

TABLE II
AVERAGE EXPERIMENTAL RESULTS BASED ON DIFFERENT LEARNING RATE.

Learning Rate	Male	Female
0.0003	0.91	0.90
0.0004	0.92	0.91
0.0005	**0.93**	0.92
0.0006	0.92	0.92
0.0008	0.92	0.92

TABLE III
AVERAGE EXPERIMENTAL RESULTS BASED ON DIFFERENT LOOKBACK WINDOW.

Window	Male	Female
1	0.91	0.91
2	0.93	0.93
3	0.92	0.93
4	0.93	0.92
5	**0.93**	**0.93**

In this study, four evaluation metrics are adopted, which including Accuracy, root mean square error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE) and *p*-value. When the three metrics are lower, the model performance is better. Relative to other methods, the proposed model produces better performance. Several evaluation metrics are defined below

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right|$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where $\hat{y}_i$ represents the value achieved through processing, and y_i refers to the observed value; *TN* stands for true negative, *FN* refers to false negative, *TP* refers to true positive, and *FP* stands for false positive. In the experiment, gated recurrent unit (GRU) [48], long- and short-term time-series network (LSTNet) [49], DLinear [50], Informer [51], frequency enhanced decomposed Transformer (FEDformer) [52], patch time series Transformer (PatchTST) [53], Bi-STAT [54], FC-GAGA [55] and ST-MetaNet [56] are set as baseline models.

B. Data Acquisition and Preprocessing

Due to the physiological differences between male and female, the HRV of male and female is also different. In general, the HRV of male is relatively smaller than that of female. Women are more obviously affected by their physiological cycle and emotional changes on HRV. Women are often more susceptible to stress and emotional factors, resulting in larger fluctuations in HRV. Men may have relatively slow changes in HRV when facing stress. In addition, aging also has different effects on the HRV of male and female. Women may have more obvious changes in HRV after menopause, while men may have relatively smaller changes. Therefore, it is necessary to divide them according to the actual situation to make the results more meaningful.

In this work, 350 healthy construction workers who do not suffer from any disease, comprising 180 males and 170 females, were recruited to monitor vital signs signals from January 20th to July 27th, 2024. Among all these subjects, 100 workers were tested twice. The ages of subjects are ranged from 30 to 60 years, and the study period extended over more than six months. The raw vital signs data of every construction worker is collected from 9:00 to 18:00 in construction sites. During the period, it also includes a brief rest time at noon. Every subject's HRV data has over 3000 data points. Among them, 60% of the data is used to train models, 20% of them is applied to test, and the rest is used for validation. And in statistical analysis of dataset, the *p*-value by the T-test is generally $p<0.05$ as significant, which means that the probability of the difference between samples caused by sampling error is less than 0.05 [57]. Detailed information is presented in Table IV. All procedures conducted in this study adhered to ethical standards for human experimentation, including the 1964 Helsinki Declaration and its subsequent amendments. The study received approval from the Ethics Committee of the Hong Kong Polytechnic University (Reference Number: HSEARS20230522004). All subjects voluntarily participated in the experiment after being informed of the relevant details.

TABLE IV
THE NUMBER OF SUBJECTS ON DIFFERENT AGES AND GENDERS.

Age/year	Male	Female
30~35	19	22
35~40	31	28
40~45	40	27
45~50	35	25
50~55	25	35
55~60	30	33

As shown in Fig. 9, in this study, combining the proposed optical fiber sensor with smart clothing to measure vital signs relies mainly on the high sensitivity and stability of optical fiber sensor, as well as the comfortable fit of clothing. In order to acquire the raw vital sign signal accurately and effectively, we integrate the proposed optical fiber sensor into clothing, and the design needs to ensure that the sensor and clothing are seamlessly integrated without affecting the daily activities of construction workers. We use soft optical fiber and elastic materials that allow the sensor to deform with clothing and body movement. When the construction worker moves or changes, the optical fiber sensor captures the corresponding changes in light signals. These changes are transmitted to the data processing unit via fiber optics. Meanwhile, when designing smart clothing, there is a need to balance sensor performance and wearer comfort. Clothing materials should be breathable, soft, and skin-friendly, while ensuring that the sensor is fixed in a way that does not cause irritation or discomfort to the skin.

Fig. 9. Raw vital signs acquisition from construction workers. The red rectangles around the construction workers represent the area of smart clothing that integrated with the proposed optical fiber sensor system.

In some cases, such as equipment failure, signal interference, and data transmission failure, the HRV data collected in the process of collecting HRV data fluctuates and deviates from the true value. When the sample data is abnormal, it should be corrected in time, otherwise it will affect the training and learning of the model, such that it will not be possible to obtain a more accurate HRV data change law and reduce the processing accuracy. Abnormal data that are common in research, for example, extreme values and glitches. To be specific, the extreme value is divided into maximal value and minimal value, the maximal value means that the sample value at the non-peak time exceeds the sample value at the peak time; and the minimal value means that the sample value at the non-trough time is smaller than the current value. Furthermore, a glitch suggests that the sample value at a certain time point is notably larger or much smaller than the sample value at its adjacent time point. In general, the data is processed in accordance with the characteristics of abnormal data.

The HRV value in a short time range slightly varies, and little difference is identified in the HRV value at adjacent moments. If the absolute value of adjacent HRV values exceeds the allowable error threshold, the HRV value at this point turns out to be abnormal. The equation for judging abnormal data is expressed as

$$\max[|X_{t+1}-X_t|,|X_t-X_{t-1}|]>\varepsilon(t) \tag{7}$$

where X_t denotes the abnormal HRV value at the t time, $\varepsilon(t)$ represents the error threshold, X_{t-1} refers to the HRV value at the t-1 time, and X_{t+1} denotes the HRV value at the t+1 time.

When the abnormal data is detected, the value should be corrected and divided into the following four steps:

(1) The HRV values at two moments before and after the time corresponding to the abnormal HRV value are selected, with the aim of ensuring a slight change before and after the adjacent values of HRV values, such that the equation of the average HRV value at five adjacent moments of X_t is written as

$$G_1=\frac{I_{t+2}+I_{t+1}+I_t+I_{t-1}+I_{t-2}}{5} \tag{8}$$

where G_1 is the mean value of HRV.

(2) Determine the HRV mean value of the three adjacent moments of X_t, the equation is written as

$$G_2=\frac{I_{t+1}+I_t+I_{t-1}}{3} \tag{9}$$

where G_2 is the mean value of HRV.

(3) Determine the HRV mean value of two adjacent moments of X_t, the equation is expressed as

$$G_3=\frac{I_{t+1}+I_{t-1}}{2} \tag{10}$$

where G_3 is the mean value of HRV.

(4) Determine the corrected HRV value, the equation is presented as

$$H_t=w_1G_1+w_2G_2+w_3G_3 \tag{11}$$

where w_1, w_2 and w_3 are corrected weights, and H_t is the corrected HRV value.

Moreover, since sample data are insufficient under the effect of some other factors, the HRV numerical processing can be conducted to fill in the missing data periodically because of its timeliness, with the aim of increasing the processing accuracy. Although the time is different, the HRV values at the identical time are similar. The HRV data at the previous adjacent time point where the missing data is located is averaged as the data that should be filled. Likewise, the HRV values at the adjacent and preceding moments at different time points are similar, such that the average value of the HRV data at the adjacent previous time point where the missing data is located can be taken as the data that should be filled.

The goal of data normalization is to scale the sample data to a fixed range. After normalization, the sample data are capable of avoiding the large deviation due to different dimensions and attributes. Moreover, the algorithm iteration convergence speed can be increased, thus expediting the improvement of HRV processing accuracy. The min-max method is adopted for normalization, which uses the maximal value for calculation processing, and fixes the sample data between the [0, 1] range through a linear map. The min-max normalization is defined as follow

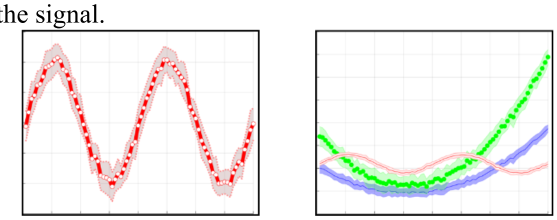
$$P=\frac{I-I_{\min}}{I_{\max}-I_{\min}} \tag{12}$$

where I_{max} denotes the maximal value in the sample, P and I represent the value after normalization and original value, respectively, and I_{min} is the minimal value in the sample.

After obtaining the predicted results, it is necessary to use the denormalization method should be employed for recovering the results. The denormalization is written as follow

$$Q_{de}=P\times(I_{\max}-I_{\min})+I_{\min} \tag{13}$$

As shown in Fig. 10, we perform abnormal data processing on the raw signal and extracted its changing trend. The processed abnormal data and extracted trends with spatial-temporal modeling make the source signal more visual and help to intuitively understand the structure and changes of the signal.



(a) (b)

Fig. 10. (a): A case of abnormal data (white node) processing; (b): Trend extraction from the raw signal with spatial-temporal modeling.

C. Experimental Results and Analysis

The obtained HRV measures can be interpreted for clarifying autonomic function, stress levels, and overall cardiovascular health. A higher standard deviation of the IBIs (SDNN) and root mean square of successive differences (RMSSD) in time domain analysis, and higher power in the HF band of the frequency domain analysis, generally indicate better cardiovascular health.

Table V and Table VI show the experimental results based on different methods, respectively.

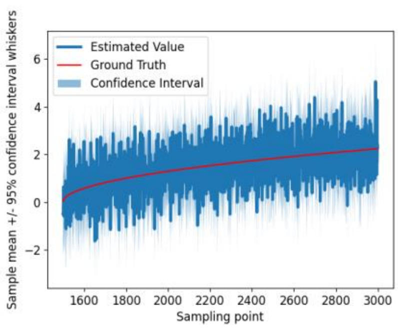
TABLE V
AVERAGE EXPERIMENTAL RESULTS OF MALE SUBJECTS.

Methods	Accuracy	MAE	RMSE	MAPE	*p*-value
GRU	0.81	11.213	11.402	17.531	0.0473
LSTNet	0.82	10.985	10.007	13.046	0.0421
DLinear	0.90	3.541	4.316	5.462	0.0359
Informer	0.88	4.454	4.977	6.812	0.0364
FEDformer	0.88	4.571	5.111	5.892	0.0371
PatchTST	0.86	6.745	5.124	6.174	0.0387
Bi-STAT	0.90	3.221	3.501	4.924	0.0319
FC-GAGA	0.92	2.745	3.448	4.514	0.0311
ST-MetaNet	0.93	2.332	2.852	3.641	0.0284
CWMformer	0.93	**2.272**	**2.518**	**2.885**	**0.0267**

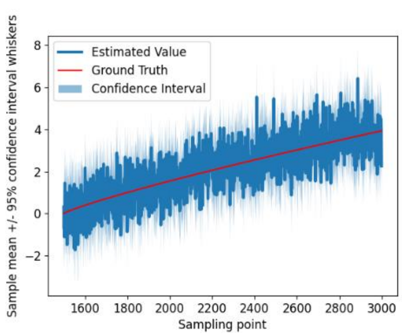
TABLE VI
AVERAGE EXPERIMENTAL RESULTS OF FEMALE SUBJECTS.

Methods	Accuracy	MAE	RMSE	MAPE	*p*-value
GRU	0.80	14.536	14.601	22.665	0.0489
LSTNet	0.81	11.477	11.995	20.290	0.0455
DLinear	0.87	4.514	3.735	4.789	0.0421
Informer	0.86	4.941	4.225	6.984	0.0501
FEDformer	0.86	5.401	5.524	7.454	0.0568
PatchTST	0.85	5.482	5.687	7.889	0.0595
Bi-STAT	0.90	3.701	4.205	6.665	0.0485
FC-GAGA	0.92	3.653	4.152	6.552	0.0452
ST-MetaNet	0.91	3.601	3.789	5.583	0.0366
CWMformer	**0.93**	**2.859**	**2.998**	**4.496**	**0.0295**

In this study, we also conduct the statistical analysis on the relationship between the sampling points of the average HRV data and fatigue conditions of construction workers of different genders. The p-value represents the probability of observing the current data or more extreme cases if the null hypothesis is true. The confidence interval is an estimate range of the overall parameter, giving a possible value range with a certain confidence level. p-value mainly provides evidence from the perspective of hypothesis testing, while confidence interval gives a specific range of parameter estimates. A smaller p-value means stronger evidence to reject the null hypothesis, which also corresponds to a narrower confidence interval width. If the p-value is small, it indicates that the result is statistically significant, which means that the estimate of the population parameter is more accurate, making the width of the confidence interval relatively narrow. On the contrary, if the p-value is large, the result is not significant, the uncertainty in the estimate of the population parameter increases, and the width of the confidence interval tends to be wider. Fig. 11 shows the changes between the p-value, estimated value, ground truth, and the widths of different confidence intervals.



(a)



(b)

Fig. 11. Visualization of changes between the p-value, estimated value, ground truth, and the width of different confidence intervals. (a): Male construction workers; (b): Female construction workers.

According to the experimental results shown in Table II and Table III, the following points and analysis can be drawn:

(1) The p-value is a statistical concept that measures the strength of evidence in support of a null hypothesis in statistical analysis. It represents the probability that the results of designed test occurred randomly if the null hypothesis is true. If the p-value is less than or equal to a predetermined significance level, the null hypothesis is rejected in favor of the alternative hypothesis. The lower p-value indicates that the results have strong statistical significance [57]. Compared with all baseline methods, the CWMformer framework achieves the best accuracy at all output time point lengths. In addition, the experimental results of the CWMformer framework rise steadily and slowly with the increasing output time point length, which shows that the CWMformer framework has more prominent output capabilities in long-sequence data processing tasks. This is all due to the role of the sequence embedding layer of the EDM module, MGON module and TDE module.

(2) The CWMformer framework and the method based on the multi-head attention mechanism, that is to say, compared with Informer, DLinear, FEDformer and PatchTST, the CWMformer framework can achieve an accuracy improvement of up to 7.00%, 6.00%, 7.00% and 8.00%, respectively. The reason of the CWMformer framework can achieve higher accuracy than the baseline method based on the multi-head attention mechanism is that the CWMformer framework captures neighbor dependencies through the embedding mechanism and cross-dimensional attention module based on the embedding of the EDM module. Furthermore, the proposed loss function based on long sequences can help model convergence, thereby improving the accuracy of the output.

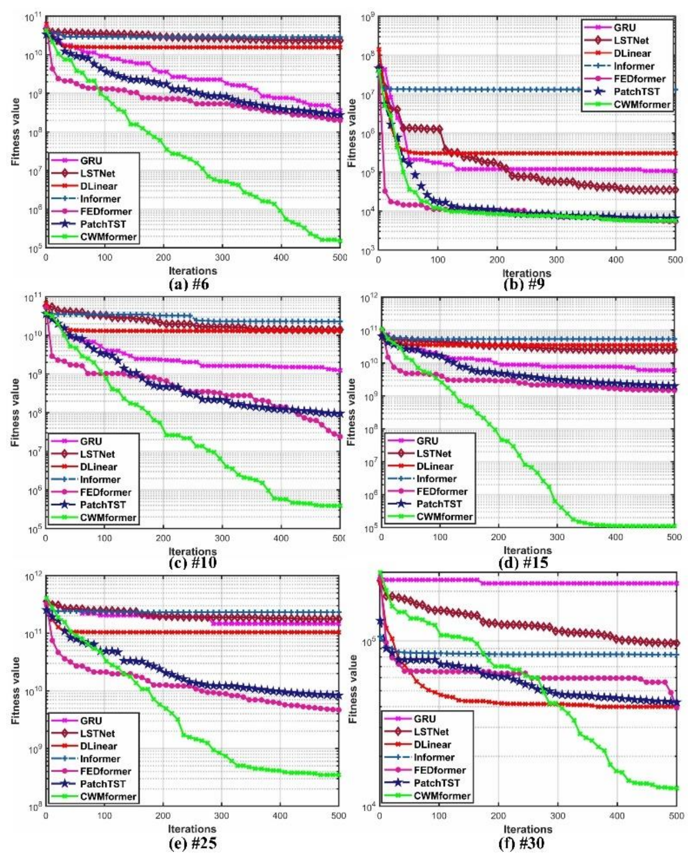


Fig. 12. Change of fitness values during different iterations with six subjects. (a), (b), (c): Male construction workers, aged 30, 40 and 50 years old, respectively; (d), (e), (f): Female construction workers, aged 35, 47 and 54 years old, respectively.

(3) As the CWMformer framework, compared with the LSTNet model based on convolutional neural network (CNN) and recurrent neural network (RNN), the CWMformer framework greatly improves the output performance. This also shows that not using cross-dimensional attention mechanisms to extract long-term dependencies in sequence data will have a negative impact on the output results.

Moreover, the structure of the LSTNet model is relatively complex and requires more computing resources, including memory and processor power, which may limit its application in resource-constrained environments. And the LSTNet model is more sensitive to the quality and characteristics of the input data, such as the noise level of the data, the processing of missing values, etc. These factors may affect the performance of the model. Compared with the CWMformer framework, as the output length increases, the performance improvement of the CWMformer framework is more obvious than that of the LSTNet model. The reason is that the CWMformer framework can extract long-term dependencies through the multi-head attention mechanism and can better extract dynamic changes between dimensions.

(4) The baseline methods based on the multi-head attention mechanism, namely Informer, DLinear, FEDformer and PatchTST, all perform better than the LSTNet model based on CNN and RNN. This is because the long-sequence data processing task places high demands on the ability of neural network to extract long-term dependencies. The LSTNet model is mainly composed of CNN and RNN, resulting in insufficient ability to extract long-term dependencies.

In the proposed MGON module, the fitness value is applied to evaluate the quality or fitness of a method. The algorithm tries to either maximize or minimize this value, depending on the problem at hand. The fitness value is applied to evaluate the fitness of a method, which is used to guide the search process towards the optimal method. As shown in Fig. 12, when the fitness value curve converges, it usually means that the model has found the optimal solution to the problem. Fast convergence means that the algorithm can reach a stable fitness value in a relatively short time or a small number of iterations, indicating that the model has high efficiency and optimization capabilities.

t-distributed Stochastic Neighbor Embedding (t-SNE) is an algorithm for high-dimensional data visualization [58]. It can map data points in high-dimensional space into two-dimensional or three-dimensional space so that we can intuitively observe the structure and distribution of data. t-SNE maintains the local structure by simulating the similarity between data points, so that data points that are similar in the high-dimensional space remain as close as possible in the mapped low-dimensional space. In semi-supervised learning, t-SNE can be used as a method to understand the structure of data, especially when dealing with large-scale unlabeled datasets. As shown in Fig. 13, we used t-SNE to visualize the original representation and the representation learned through CWMformer in a three-dimensional feature space. It can be concluded that CWMformer has learned discriminative representations of the data. To be specific, t-SNE compresses the features of the fatigue conditions with construction workers into three-dimensional space, making similar features closer in space. When the data shows obvious clustering or dispersion, it can reveal potential category divisions or anomalies of fatigue conditions.

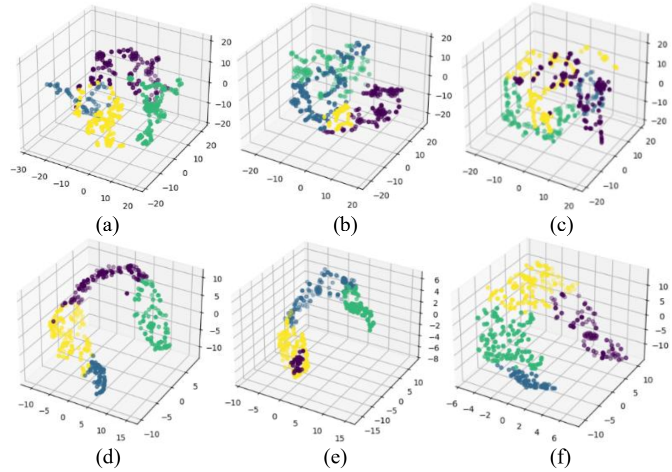


Fig. 13. The t-SNE plots on data processing of different construction workers aged 35, 45 and 55 years old, respectively. (a), (b), (c): The original sample representations; (d), (e), (f): The computed sample representations by CWMformer framework.

Feature visualization of neural networks is of great significance. It can help us intuitively understand how neural networks capture spatial and temporal feature when processing data. Through visualization, the key areas and nodes of the model's attention to provide a basis for the improvement of the model can be found. Meanwhile, it helps to analyze the decision-making process of the model and improve the interpretability of the model. Fig. 14 shows the visualization of spatial-temporal features extraction and representation within average experimental results generated by the proposed CWMformer framework, where darker colors indicate stronger extracted spatial-temporal features between different nodes.

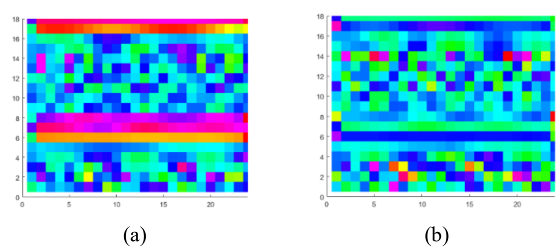


Fig. 14. Visualization of spatial-temporal features extraction and representation within average experimental results generated by THCADP framework. (a): Male construction workers; (b): Female construction workers.

Meanwhile, if the volume of data is too large, the training time will be too long. It may even trigger poor convergence. Besides paying attention to the size of the data, when collecting sample data, it is also necessary to consider data loss and data abnormalities arising from equipment failure or other factors. However, the issue data cannot be directly used for HRV data processing, otherwise it will lead to a large deviation in the processing results, such that the issue data should be filled or corrected. In order to further study the relationship between HRV and fatigue conditions, make the experimental results and conclusions more convincing and representative, we calculated the average value of the experimental results of all subjects. Fig. 15 shows the average experimental results of all subjects with six different classical baseline methods and different HRV data volumes.

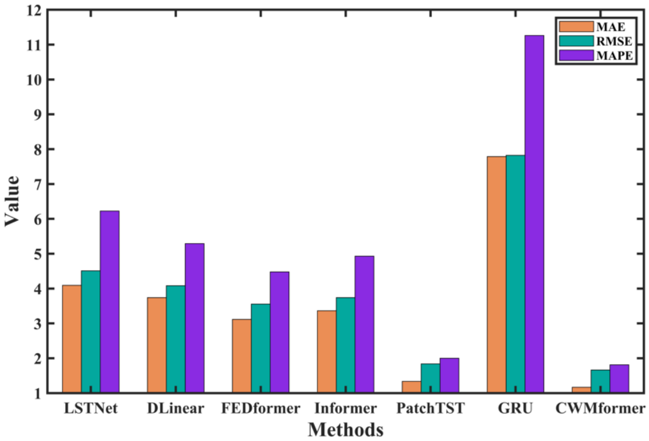


Fig. 15. Average experimental results of comparison with different methods.

Ultimately, computational complexity refers to the amount of computing resources, such as time and space, required by an algorithm to solve a problem. It is used to analyze and compare the efficiency of different algorithms. The two main types of computational complexity are time complexity, which is how the running time increases of algorithm with input size, and space complexity, that is to say, the memory usage of algorithm increases with input size. Table VII shows the average time complexity of the proposed CWMformer method is compared to that of other methods. The reason of the CWMformer framework occupies less GPU memory than the LSTNet model is because the LSTNet model has deeper neural network layers, which causes it to occupy a higher GPU memory. However, due to the various parameters of the proposed CWMformer framework, it also leads to a relatively long simulation and simulation time. Long simulation time will reduce work efficiency, especially in scenarios that need to be responded quickly. In the proposed MGON module, the high model complexity is mainly due to the complexity of the structure itself. The module contains more nodes and edges, which increases the amount of calculation and the module needs to be considered. The transmission of information in the module is also complicated. The aggregation and update operation of information transmission between nodes may involve complex mathematical operations. It is difficult to deal with the diagram standard and depth increase. In addition, semi-supervised learning will increase the complexity, because the labeled data is not used. It is difficult to explore the information without labeled data. It needs to propose complex strategies. It is likely to use a format model or the consistency of the graph-based hypothesis to label the unlabeled data. In addition, the learning with labels and unlabeled data should be balanced during training, and the weight of the loss function is required. Because the unlabeled data is uncertain, the model must try multiple assumptions and parameters to adapt to different distribution.

Therefore, in the future work, to reduce the complexity of the graph modeling, the module can be sampled, such as random sampling or feature sampling, reduce the nodes and edges participating in calculation, and use the rough technology to merge similar nodes. In the framework architecture, the layered neural network structure can be adopted, and different particle size information is treated at different levels. Meanwhile, the node represents the update method, and the simple and efficient polymerization function can be used. For the complexity caused by semi-supervised learning, multi-view learning will be used to represent data from different angles, and use the consistency of unlabeled data to simplify learning at different views. And we may apply the pre-training technology to first have unsupervised pre-training on unlabeled data, and then use the labeled data to fine-tune the framework.

TABLE VII
COMPARISON OF AVERAGE TIME COMPLEXITY WITH DIFFERENT METHODS.

Methods	GPU	Parameter	Time (s)
GRU	7648MB	**1906**	**402**
LSTNet	6534MB	3951	588
DLinear	6213MB	4811	575
Informer	6110MB	5033	570
FEDformer	3175MB	7659	545
PatchTST	3721MB	10099	540
Bi-STAT	5133MB	19885	570
FC-GAGA	3059MB	25632	535
ST-MetaNet	2950MB	41383	522
CWMformer	**2485MB**	36781	520

Moreover, vital signs monitoring of drivers has been a popular research topic. Fatigue of driver can easily lead to some traffic accidents, endangering the lives of drivers and passengers. Therefore, fatigue condition detection helps assess the driver's health and prevent accidents. Among them, HRV monitoring is particularly important because cardiovascular diseases (CVDs) have become the leading cause of death among various fatal diseases in the world. As shown in Fig. 16, we also focus on phase-sensitive fiber interferometer solutions, and also achieve the better performance of driver's fatigue condition detection in practical.


Fig. 16. Application of the proposed optical fiber sensor for HRV monitoring and fatigue condition detection in vehicle driving.

D. Ablation Study

The ablation study is a useful tool for comprehending the significance of various components within a model and their impact on its overall performance. This method involves the systematic removal or alteration of model parts, such as layers, connections, or specific modules, and monitoring the subsequent effect on the performance of model.

Through the execution of an ablation study, it is possible to identify which parts of the model are vital for its performance and which are less significant. This knowledge can guide the creation of more streamlined models, as superfluous components can be eliminated without drastically impacting performance. Moreover, ablation studies can assist in evaluating the interaction between different components of a model. This could potentially lead to the development of new, more efficient architectures or training strategies.

In experiments, to validate the importance of mode decomposition and semi-supervised learning mechanism in the proposed model, we replaced the EDM module (w/o EDM), MGON module (w/o MGON), and replaced the TDE module (w/o TDE). By comparing the Accuracy, MAE, RMSE, MAPE and *p*-value, CWMformer framework exhibits the best performance compared to another three variant models. As shown in Table VIII and Table IX, experimental results effectively verify the importance and necessity of cross dependency extraction, graph modeling and semi-supervised learning mechanism.

TABLE VIII
AVERAGE EXPERIMENTAL RESULTS OF VARIANT MODELS (MALE SUBJECTS).

Model	Accuracy	MAE	RMSE	MAPE	*p*-value
w/o EDM	0.88	3.531	3.629	3.552	0.0385
w/o MGON	0.90	3.349	3.532	3.352	0.0325
w/o TDE	0.90	2.437	2.524	2.817	0.0253
CWMformer	**0.94**	**1.642**	**2.223**	**1.928**	**0.0226**

TABLE IX
AVERAGE EXPERIMENTAL RESULTS OF VARIANT MODELS (FEMALE SUBJECTS).

Model	Accuracy	MAE	RMSE	MAPE	*p*-value
w/o EDM	0.84	3.331	3.259	3.338	0.0487
w/o MGON	0.86	3.198	3.157	3.165	0.0344
w/o TDE	0.89	3.146	3.475	3.617	0.0312
CWMformer	**0.91**	**2.151**	**2.784**	**2.216**	**0.0235**

IV. DISCUSSION

According to the proposed framework and related experimental results, it should be noted that the proposed MGON module is a graph modeling-based semi-supervised learning method used for classification and label propagation tasks. MGON leverages the structure of the data in the form of a graph, where nodes represent data points, and edges represent relationships or similarities between the data points. The algorithm aims to exploit both local and global consistency in the data to improve the quality of the classification results. The MGON module combines information from nearby data points (local) and distant data points (global). It achieves this by formulating a graph Laplacian that reflects the relationships between data points. Local information helps in smooth label propagation within clusters, while global information aids in capturing the broader structure of the data. MGON module can work with partially labeled datasets, making it useful in scenarios where only a small fraction of the data has ground truth labels. It utilizes the labeled data to propagate labels to unlabeled data points, effectively utilizing the available supervision. MGON module is relatively robust to noisy or outlier data points because it considers the global structure of the data. Outliers or erroneous labels are less likely to influence the final classification results significantly. MGON allows for flexibility in how the graph is constructed. Depending on the specific application, we can define the similarity or affinity measure between data points to create the graph. This adaptability makes it suitable for various types of data, such as text, images, and sensor data. In regions of the data space with sparse data points, MGON module can effectively propagate labels from more densely populated regions, aiding in the classification of data in areas with limited information. MGON module is conceptually simple and easy to understand, which can be advantageous when explaining and justifying the results of algorithm to stakeholders or in educational settings. MGON module has shown its competitive or state-of-the-art performance in various classification and label propagation tasks, especially when the underlying structure of data can be well represented by the graph structure.

Transformer is becoming more and more widely used in the field of signal processing, mainly due to its powerful sequence data processing capabilities. Transformer models are becoming more and more widely used in the field of signal processing, mainly due to their powerful sequence data processing capabilities. The deep learning model based on Transformer uses the self-attention mechanism to capture the relationship between any two elements in the sequence. And it can realize end-to-end learning, directly from the original input to the final output, reducing the dependence on complex feature engineering. It does not rely on the cyclic or convolutional structure of the sequence, so it can be flexibly applied to a variety of tasks and data types. The improved Transformer model can reduce computational complexity through the cross-stage attention mechanism, making the model more suitable for processing long sequence data. As for vital signs monitoring of construction workers, Transformer-based models can be used to extract meaningful features from raw vital signs data. These features can then be analyzed to detect anomalies, trends, or patterns indicative of specific health conditions. For example, a Transformer-based model could learn to identify patterns in HRV sequences that are associated with fatigue conditions. Given the sequential nature of vital signs data, the Transformer-based models are well-suited for forecasting future measurements based on past data. This capability can be particularly useful in predicting acute events, allowing it for timely interventions. The Transformer-based models can also be trained to classify segments of vital signs data into different categories, such as normal and abnormal heart rhythms (arrhythmias) or different conditions of fatigue based on HR and RR patterns. This classification can aid in the diagnosis and monitoring of various health conditions. Meanwhile, the Transformer-based models, with their ability to handle sequences and their variations, can integrate and analyze multimodal data to provide a more holistic view of construction workers' health conditions. The application of Transformer-based models in processing vital signs signals of construction workers is a promising area of research that could lead to significant advancements in healthcare. By leveraging the ability of Transformer to handle sequential data, we can develop models that improve the monitoring, diagnosis, and treatment of various health conditions of construction workers. However, while Transformer models can achieve high accuracy, their complex architectures make them relatively opaque, posing challenges for interpretability. This is a significant concern in healthcare, where understanding the rationale behind the performance of model is also important.

Overall, the application of the Transformer-based technique combined with optical fiber sensors in vital sign signal processing of construction workers demonstrates its great potential and value in the field of medical health monitoring. This combination may play an even more important role in future smart healthcare monitoring with construction workers effectively.

V. CONCLUSION

In this paper, in fatigue conditions measurement and prediction of construction workers, measurement and monitoring the HRV of construction workers plays a key role. It enables remote construction workers monitoring, chronic disease management, and wellness tracking. HRV assessment and monitoring supports product development, enhances clinical trials, and ensures data security. In the preventive health, it helps identify construction workers at risk, reducing healthcare industry costs. Moreover, it facilitates telehealth services and healthcare monitoring analytics, improving construction workers' healthcare and advancing healthcare innovation in real world. In this study, following the fiber interferometer, a novel wearable optical fiber sensor system is proposed. It is capable of acquiring the raw vital signs signals of construction workers accurately and effectively. Furthermore, we introduce an architectural framework, termed CWMformer. This framework is designed for enhanced processing of long-term HRV data of construction workers with knowledge discovery, data engineering and graph modeling for high quality fatigue conditions monitoring and prediction of construction workers when combined with the proposed wearable optical fiber sensor system, then provides real-time warning of possible risks. Therefore, using physiological signal technology to effectively monitor the cognitive state of construction workers during working to improve working safety is also a very interesting and promising area. In the future, devices and models can be upgraded to increase the number of network layers, the number of neurons, the time step, and so on. This enhances the training effect of the network model and improves the performance, and may make the whole system more robust. This study has full potential in healthcare monitoring, real-time and long-term fatigue monitoring of construction workers, and other engineering applications.

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Qing Wang received the Master degree in the College of Photonic and Electronic Engineering from Fujian Normal University, Fuzhou, China, in 2022. He is currently pursuing the Ph.D. degree in the Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong. His research interests include optical fiber sensor, smart healthcare, deep learning, and artificial intelligence. He has published more than 30 SCI/EI indexed papers in famous journals and conferences in the field of artificial intelligence and optical fiber sensing (including 14 journal papers as the first author/corresponding author, with more than 100 citations per paper). He served as a Reviewer for many prestigious international journals. He has applied for/approved two invention patents, and was invited to give talks at the 2022 IEEE/OSA ACP Student Workshop and ACM SEAI, and won the 2023 IEEE/OSA/SPIE OFS Best Poster Award (Track: Fiber Optic Signal Processing and Artificial Intelligence) and the 2024 IEEE ICOCN Best Paper Award (Track: Fiber Optic Sensing and Artificial Intelligence). He has participated in the National Natural Science Foundation of China Project "Intelligent Diagnosis and Prognosis Evaluation of Breast Cancer Based on Multiphoton Microscopy Imaging Technology and Artificial Intelligence" (NSFC 81741008), Mainland-Hong Kong Joint National Key R&D Project "Artificial Intelligence-Assisted Non-Invasive Hemodynamic Monitoring Technology Based on Fiber Interferometric Sensing" (MHP/237/23) and Hong Kong Research Grants Council-funded Project "Non-Invasive Sleep Monitoring Based on Interferometric Optical Fiber Sensor and Artificial Intelligence" (HK RGC 1-WZ01).

Ke Li is currently pursuing the Ph.D. degree in the School of Fashion and Textile, The Hong Kong Polytechnic University, Hong Kong. Her research interests include soft robotics, deep learning and artificial intelligence.

Xiuyuan Wang is currently pursuing the Ph.D. degree in the Department of Electrical and Electronic Engineering, The Hong Kong Polytechnic University, Hong Kong. Her research interests include optical fiber sensing, signal processing and machine learning.

Xiang Wang received the Ph.D. degree in Faculty of Aerospace Engineering, Delft University of Technology, Delft, The Netherlands, in 2023. He is currently working as a Marie Skłodowska-Curie Fellow in the Department of Engineering, University of Cambridge, United Kingdom. His research interests include optical fiber sensor system and optical fiber sensing.

Jing Qin received the Ph.D. degree in computer science and engineering from The Chinese University of Hong Kong, Hong Kong, in 2009. He is currently an Associate Professor with the School of Nursing, The Hong Kong Polytechnic University, Hong Kong, where he is also a Key Member with the Centre for Smart Health. His current research interests include virtual/augmented reality (VR/AR) for healthcare and medicine training, medical image processing, deep learning, visualization and human–computer interaction, and health informatics. He won the Hong Kong Medical and Health Device Industries Association Student Research Award for his Ph.D. study on VR-based simulation systems for surgical training and planning. He won three Best Paper Awards for his research on AI-driven medical image analysis and computer-assisted surgery, including one of the most prestigious awards in this field: MIA-MICCAI best paper award in 2017. He served as a local organization chair for MICCAI 2019, technical program committee (TPC) members for many academic conferences, speakers for many invited talks, and referees for many prestigious journals in relevant fields.

Changyuan Yu received his Ph.D. in Electrical Engineering from the University of Southern California, USA in 2005. He was a visiting researcher at NEC Labs America in Princeton, USA in 2005. He then joined National University of Singapore (NUS) in 12/2005, where he served as the founding leader of Photonic System Research Group in Department of Electrical and Computer Engineering till 12/2015. He was also a joint senior scientist with A*STAR Institute for Infocomm Research (I2R) in this period. And he was a visiting professor with University of Melbourne, Australia in 2007. In 12/2015, he joined The Hong Kong Polytechnic University, where he is now a full professor in Department of Electrical and Electronic Engineering, while he also continues as an adjunct faculty member of NUS. His research focuses on photonic devices, optical fiber communication and sensor systems, and biomedical instruments. He has been the PI/co-PI/co-I of 50+ research projects with 10 million+ US dollars fund, and supervised 20+ postdocs and 40+ PhD students. He has authored/co-authored 6 book chapters and 600+ journal/conference papers (100+ keynote/invited, including OFC in USA). He served in organizing or technical program committees for 100+ international conferences, and Telecommunications Standards Advisory Committee for Singapore government. His group won 10 best paper awards in conferences and National Championship in China Innovation and Entrepreneurship Competition in 2014. He is an Optica/OSA fellow.