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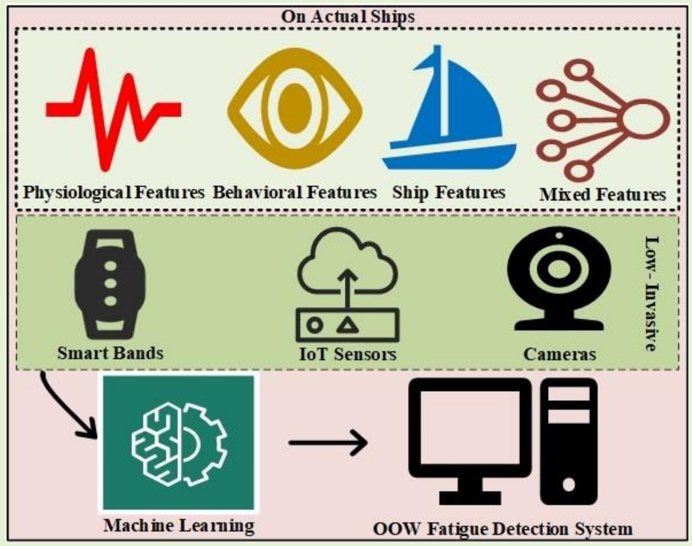
Fatigue Detection for Ship OOWs Based on Input Data Features, from The Perspective of Comparison with Vehicle Drivers：A Review

Hongguang Lyu, Jingwen Yue, Wenjun Zhang, Tao Cheng, Yong Yin, Xue Yang, Xiaowei Gao, Zengrui Hao, & Jiawei Li

***Abstract*—Ninety percent of the world's cargo is transported by sea, and the fatigue of ship officers of the watch (OOWs) contributes significantly to maritime accidents. The fatigue detection of ship OOWs is more difficult than that of vehicles drivers owing to an increase in the automation degree. In this study, research progress pertaining to fatigue detection in OOWs is comprehensively analysed based on a comparison with that in vehicle drivers. Fatigue detection techniques for OOWs are organised based on input sources, which include the physiological/behavioural features of OOWs, vehicle/ship features, and their comprehensive features. Prerequisites for detecting fatigue in OOWs are summarised. Subsequently, various input features applicable and existing applications to the fatigue detection of OOWs are proposed, and their limitations are analysed. The results show that the reliability of the acquired feature data is insufficient for detecting fatigue in OOWs, as well as a non-negligible invasive effect on OOWs. Hence, low-invasive physiological information pertaining to the OOWs, behaviour videos, and multisource feature data of ship characteristics should be used as inputs in future studies to realise quantitative, accurate, and real-time fatigue detections in OOWs on actual ships.**



***Index Terms*—Detection methods, fatigue detection, maritime safety, OOWs' fatigue.**

I. Introduction

NINETY percent of the world's cargo is transported by sea. A marine accident involving a large ship at sea is likely to result in significant casualties and property damage, and oil spills from ships are detrimental to the marine environment.

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A. Importance

Fatigue can result in reduced alertness and deteriorated work performance in ship crew, and is a primary cause of accidents, such as ship groundings, collisions, and reefing [1]. Additionally, fatigue occurs on board fishing ships and contributes significantly to human errors and accidents [2, 3].

A study conducted by the US Coast Guard Research and Development Centre showed that fatigue is the primary cause of 16% of ship casualties and 33% of board injuries [4]. One-third of ship groundings is due to fatigue in OOWs and performing night duties solitarily at the bridge, according to a study by the UK Department for Transport involving 1,647 collisions, groundings, and other accidents between 1994 and 2003 [5]. The International Maritime Organization (IMO) has prioritised the issue of crew fatigue and has thus developed "Guidance on Fatigue", which defines fatigue as "a state of physical and/or mental impairment resulting from factors such as inadequate sleep, extended wakefulness, work/rest requirements out of sync with circadian rhythms and physical, mental or emotional exertion that can impair alertness and the ability to safely operate a ship or perform safety-related duties" [6].

Low sleep quality tends to cause fatigue and reduces the driving ability of professional drivers [7]. This is more likely to occur on board a ship because ship OOWs may encounter more difficult and challenging working conditions, as follows [8]:

1) 24/7 working patterns, changing time zones, and shifts (e.g., four- and six-hour shifts [9]), which result in irregular circadian rhythms and working hours, as well as disruption to the biological clock [10, 11].
2) Severe weather, rough seas, seasickness, vibrations, noise, prolonged loneliness, tension, and stress, which result in low sleep quality [12, 13].
3) Frequent port calls and the associated cargo work, excessive workloads, and reduced sleep duration [14].

The IMO requires shipping companies to implement active measures to avoid or prevent crew fatigue and has issued clear regulations pertaining to crew rest time, shift handover requirements, and duty hours. However, monitoring whether these rules are enforced on board is an ex-post investigation mechanism that does not significantly prevent fatigue and accidents. Some crew would falsify questionnaires due to a sense of job insecurity and the principle of "ship first" adopted by them [15]. Meanwhile, monitoring fatigue symptoms during surgery has been verified as an effective method for detecting controlling the risk of fatigue [16]. Therefore, detecting fatigue at an early stage is extremely important for the implementation of proactive interventions to avoid the consequences of fatigue and improve the safety of navigation.

B. Urgency

Owing to the increase in autonomous driving technology, vehicle and ship drivers tend to use watch systems, which require vigilance and can easily cause fatigue. Körber et al. [17] performed a validation experiment in which 20 participants drove for 42.5 min using a car driving simulator via automated driving. The participants' passive fatigue was confirmed by monitoring their eye-tracking parameters and conducting a questionnaire that assessed their thoughts. The results showed that the monotonous operation of autonomous driving is more likely to cause driver fatigue. Matthews & Desmond [18] suggested that "passive fatigue" caused by a low-task demand model with more environmental monitoring and less intervention will become increasingly prevalent in intelligent vehicle-road systems as control is shifted from the driver to the vehicle. This topic is particularly pertinent to the investigation of fatigue in ship OOWs, as ships typically navigate via an autopilot in open waters and require only observation by ship OOWs. In future smart ships, the working patterns of ship OOWs or remote monitors are likely to induce fatigue [19].

Marine transportation is an important mode of transportation and tends to be intelligent. However, studies regarding fatigue detection in ship OOWs are significantly fewer than those of road traffic [20]. Many well-established automobile companies such as Toyota, Volkswagen, and Nissan have developed relatively mature driver fatigue detection systems [21], which can detect driver fatigue based on vehicle handling and driving characteristics such as lane deviation, pedalling, and steering wheel actions, or on the physical characteristics of drivers such as yawning, blink frequency, blink duration, and head movement. By contrast, most methods for detecting fatigue in ship OOWs are limited to questionnaire surveys [22] [23, 24] and the analysis of fatigue causes [25] [26], which are not real-time, practical, and effective methods. Current legislations and guidance pertaining to crew fatigue have not resulted in the expected effect; thus, solutions from other transportation industries should be considered [27].

Additionally, since the Corona Virus Disease 2019 outbreak, crew fatigue has worsened owing to difficulties in shift changes, increased work duration on board, and increased mental stress [28, 29]. Pauksztat et al. [30] analysed questionnaires from 622 seafarers and showed that the epidemic had significantly increased their fatigue and mental health problems, which can severely affect ship safety.

Therefore, the detection of crew fatigue is particularly urgent, and further investigations are required.

C. Difficulty

Measuring fatigue is difficult as it involves the integration of physiological functioning, performance, and subjective perceptions [31]. In particular, fatigue detection in ship OOWs is difficult as it is determined by their professional characteristics and working environment.

Meanwhile, owing to the large bridge working space and the watchkeeping requirements imposed on OOWs, electrooculography and pupillometry [23] for measuring physiological functioning are difficult to adopt on board because they are highly invasive and likely to interfere with the OOWs' watchkeeping activities.

Additionally, long-period separation from family, loneliness at sea, nationality differences, limited recreational activities, and insufficient sleep on board contribute to an increased risk of stress among crew members [32]. Ship OOWs may indicate diverse performances and subjective perceptions under the same physiological conditions. However, these individual differences have not been investigated much [33], and experimental samples related to driving tasks are few, which increases the difficulty of fatigue detection in OOWs.

Therefore, multiple data sources should be used for fatigue detection to alleviate the consequences of these differences. According to [34], at least three sources of data, i.e. driver physical variables, driving ability variables, and information from interactive video information systems, must be combined in addition to driver physiological and behavioural features as well as vehicle features to reduce driving risks.

The multidimensional complexity of these considerations renders fatigue detection more difficult for detecting fatigue in ship OOWs. Identifying an appropriate and real-time method for detecting fatigue in ship OOWs is important yet extremely difficult. Hence, the following are provided herein:

1) Based on literature review, a comprehensive summary of the status pertaining to fatigue detection in ship OOWs is presented.
2) Fatigue detection methods are systematically organised and explained, based on various data features and their

corresponding feasibility.

3) The prerequisites for detecting fatigue in ship OOWs are discussed comprehensively based on two aspects: the detection environment and data acquisition methods.

The literature search of drivers' fatigue field studies covering the observation period from the beginning to March 2023 was conducted using the Web of Science, ScienceDirect, and PubMed, etc, database. Studies on fatigue in two types of drivers were identified the following search topics:(fatigue OR sleepiness) AND (seafarer OR sailor OR seaman), (fatigue OR sleepiness) AND (driver).

Among them, the literatures about vehicle drivers were selected with high representativeness or citations. Compared with vehicles, there are few literatures on shipboard fatigue research. Therefore, we analyzed all literatures on shipboard fatigue, including publication titles and literatures' topics association, as shown in Fig. 1, and Fig. 2, respectively, and chose to focus on fatigue detection rather than fatigue analysis as much as possible.

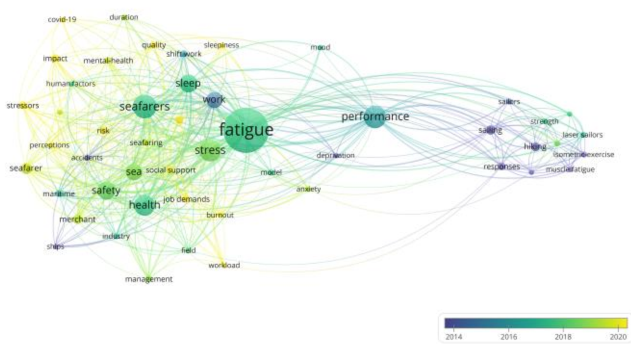

Fig. 1. According to the time, the topic words appeared in the literature were divided into five categories and the node size was determined according to the frequency of occurrence. Finally, the connection between the topic words was displayed to expand the research.

Fig. 2. Summarize the publication titles of all literatures and determine the size of publication titles according to the quantity to compare various publications. Among them, MARINE POLICY and MARITIME POLICY MANAGEMENT were the most, with 9 papers each.

The remainder of this paper is organised as follows: Section II presents the typical fatigue detection methods based on various input data features, as well as analysis of their availability for fatigue detection in ship OOWs. Section III presents the prerequisites for fatigue detection in ship OOWs. Section IV describes the features used in the fatigue detection of ship OOWs and analyzes their feasibility. Section V provides a discussion pertaining to the engineering requirements for conducting fatigue detection in ship OOWs. Section VI presents the conclusions.

II. Fatigue Detection Dethods Based on Various Input Features

Data are the basis for fatigue detection. When selecting various input data to detect fatigue, the corresponding acquisition methods, detection methods, internal mechanisms, and accuracy degree differ significantly. Fatigue detection methods are classified based on various data sources in numerous studies [35], where an understanding of their respective characteristics and application limitations can provide an important reference for fatigue detection in ship OOWs. Additionally, a comparative study with fatigue detection methods for vehicle drivers is performed in this study, where physiological, behavioural, vehicle/ship, and mixed features are investigated to detect fatigue, including the respective application contents available, as shown in Fig. 3.

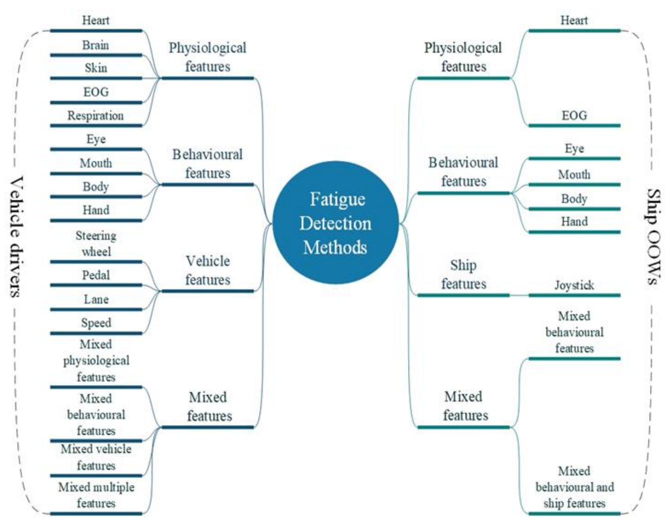

Fig. 3. Physiological, behavioural, vehicle/ship, and mixed features are investigated to detect fatigue, including the respective application contents available.

A. Fatigue Detection Based on Physiological Features

Physiological trait-based detection methods can be used to prevent accidents via early or real-time detections of fatigue, including, but not limited, to signals from breathing as well as from the heart, brain, eyes, and skin.

1) *Fatigue Detection Based on Heart Signals*

Electrocardiography (ECG) and photoelectric volumetric pulse tracing (PPG) can be regarded as suitable methods for detecting fatigue accurately. Cherian et al. [36] proposed a real-time fatigue-detection approach based on heart rate variability (HRV) obtained from ECG preprocessing. They developed a deep-learning network model comprising an autoencoder network based on unsupervised learning to classify HRV features (frequency and time domains). The accuracy of the model was 85% but can be improved via unorthodox approaches, such as by increasing the training datasets and including people with various physiques. Compared with obtaining ECG data, obtaining PPG data is more convenient for actual driving situations as it can be performed by attaching smart bands to the body; however, PPG data contain more noise. Therefore, Lee et al. [37] proposed a noise replacement method that enables improved correlations to be obtained in terms of the power spectral density between ECG and PPG data to extract the HRV features of PPG data for detecting driver fatigue; this method is superior to the noise filtering method. Meanwhile, owing to the development of smart bracelets in recent years, heart rate (HR) [38] and HRV [39] have become feasible feature detection signals. Wearable smart ECG devices have been used to detect mental fatigue via a K-Nearest Neighbour [40]. The use of cardiac signals for crew fatigue detection has only been investigated briefly in a study by Jaipurkar et al. [41] that investigates the effect of sleep duration on crew performance on board naval ships. In that study, HR and blood pressure were measured and compared between underway and non-underway cases. The results showed that both the HR and blood pressure (2 mmHg increase in blood pressure and 3 beats per minute increase in HR) increased significantly during underway. However, this may not be clinically relevant as it does not offer clinical significance.

2) *Fatigue Detection Based on Brain Signals*

Electroencephalogram (EEG) is the preferred method for measuring brain activity and is an excellent indicator of fatigue as well as the transition from wakefulness to sleep. Several entropies can be used to enhance the features of EEG signals for fatigue detection [42, 43]. Zhang et al. [44] used the deviations of EEG indicators between vigilant and fatigue states in the time and frequency domains. A clustering algorithm was used to extract spatial nodes with distinct connectivity attributes; the temporal features of the wavelet entropy were transformed to spatio–temporal images, and pulse-coupled neural networks were used to distinguish different stages of fatigue. The results showed that fatigue was detected in 21 among 29 accidents in a simulated driving task, which proved the effectiveness of the method.

3) *Fatigue Detection Based on Skin Signals*

Driver fatigue detection based on skin signals primarily utilises electromyographic signals and electrodermal activity (EDA). Electromyography (EMG) is used to record muscle bioelectrical signals, where features extracted from time- and frequency-domain signals can be used to predict muscle fatigue. Katsis et al. [45] evaluated three EMG metrics, i.e., the mean frequency (MNF), median frequency (MDF), and signal RMS amplitude. After performing a statistical analysis and two statistical tests (T and F), they discovered that the MDF and MNF decreased and the RMS increased, which indicates their reliability as fatigue indicators. However, the applicability of EMG is limited because of the considerable intrusion associated with EMG acquisition. The EDA [46] was utilised to extract the mean and standard deviation of the EDA signal in stress, fatigue, sleepiness, and normal states with a 10 s window interval; however, the EDA signal acquisition was limited by the ambient temperature and acquisition site.

4) *Fatigue Detection Based on Electrooculographic Signals of The Eye*

Electrooculography (EOG) measures the difference in corneal retinal potential between the front and back of the eye via electrodes connected to the left and right sides of the eye. Alpha wave changes in EOG signals are related to wakefulness, fatigue, and sleepiness. To monitor the changes in alpha waves, Jiao et al. [47] adopted a continuous wavelet transform to extract features in both time and frequency domains and used a long short-term memory network to accommodate temporal information; meanwhile, they augmented the training dataset using a generative adversarial network (GAN) and improved the classifier performance using the conditional Wasserstein GAN. The accuracy yielded using for detecting changes in alpha waves was approximately 95%. Although EOG is invasive and limits the operation of the operator, it has been used to reflect crew fatigue and sleepiness laterally on-board ships. Lützhöft et al. [48] investigated the effects of the shift system on crew fatigue and sleep; they acquired EOG data, which were automatically scored in 10 min intervals using a MATLAB program to obtain the sleepiness level of the crew at different times to analyse crew fatigue and its effect on sleep. However, the result was merely a reflection of fatigue, i.e., the method does not detect fatigue.

5) *Fatigue Detection Based on Respiratory Signals*

Respiratory signals are often associated with fatigue and sleepiness, and the respiratory rate is a typical feature of respiratory signals. Solaz et al. [49] used the respiratory rate to detect the fatigue and sleepiness of drivers. The authors proposed a non-invasive method for detecting the driver's chest using image enhancement, filters, and short-time Fourier transform, which achieved an accuracy exceeding 97% in the forward and lateral directions and offered high brightness. This method requires a camera positioned near the driver as well as a highly illuminated environment. The activity area of the ship OOWs is large, and the camera cannot capture the chest and abdomen movements sufficiently close to obtain the respiration rate.

Fatigue detection methods based on physiological features are summarised in Table I.

B. *Fatigue Detection Based on Behavioural Features*

The drivers' behaviour is the most direct feature that reflects their fatigue state and includes the blinking frequency, time elapsed with eyes closed, percentage of time elapsed with eyes closed (PERCLOS), body and head postures, gaze position, and head-nodding frequency. Fatigue detection based on the features of the eye, mouth, and head is typically used.

1) *Fatigue Detection Based on Eye Features*

Blink frequency, eyelid distance, and PERCLOS have been used extensively to detect fatigue in drivers. Savaş and Yaşar [50] used OpenCV and Dlib libraries to detect the facial expressions of drivers. Subsequently, they used an SVM to train facial expressions and showed that the maximum accuracy of fatigue detection was 97.93% based on tests performed using live videos. In another study, eye status was used to detect fatigue in crew members [51]. Zhang [52] proposed a modified PERCLOS criterion for monitoring the fatigue state by detecting the face-eye state of watchmen on

TABLE I
FATIGUE DETECTION IN SHIP OOWS BASED ON PHYSIOLOGICAL FEATURES.

Physiological signals	Ref	Features	Parameters	Methods	Results	Limitations	Availability to OOWs	Ref	OOWs Applications
Heart signals	2021[36]	ECG	HRV	Deep neural networks, autoencoder network	Acc=85% but can be improved in various ways	Intrusiveness and data reliability	Medium	2019[41]	Heart rate and blood pressure
	2017[37]	PPG	HRV	Noise handling, noise filtering	Obtain the improved correlation in PSD between ECG and PPG	Intrusiveness and data reliability	Medium		
Brain signals	2020[44]	EEG	Time and frequency domains	Clustering algorithm, pulse-coupled neural networks	21 of 29 accidents detected fatigue in laboratory	Intrusiveness and laboratory environment	Low		
Skin signals	2018[46]	EDA	Mean and standard deviation	Analysis of variance	Identify stress, fatigue, sleepiness, and normalcy	Intrusiveness and varies from person to person	Low		
	2004[45]	EMG	Three metrics (MDF, MNF, RMS) of EMG	Statistical analysis and tests	MDF increase, MNF increase, RMS decrease	Intrusiveness and varies from person to persondata reliability	Low		
Electrooculographic signals	2020[47]	EOG	The start and end points of alpha waves	Continuous wavelets transform, LSTM, GAN, CWGAN	Acc=95% in detecting the changes of alpha waves	Intrusiveness and data reliability	Low	2010[48]	EOG
Respiratory signals	2016[49]	Breathing rate	Chest and abdominal exercises	Image enhancement, the Filters, Short Time Fourier Transform	Acc=97% in the frontal position in laboratory with high brightness	Camera position and ambient light.	Low		

board ships. The driver's eye fixation location can also be used for driver status analysis [53]. Oldenburg & Jensen [54] conducted pupillary measurements 396 times on all crew members to investigate the general sleepiness of day labourers and watchmen on board. The results showed that those who were watchkeeping slept less and experienced lower sleep quality than those working during the day. Additionally, sleepiness was prevalent among those on duty.

2) *Fatigue Detection Based on Mouth Features*

Among the mouth features, yawning and mouth opening have been shown to be good indicators of fatigue detection [55]. Knapik & Cyganek [56] performed thermal imaging to detect fatigue based on yawning. Eye-corner detection was performed to align the face, whereas the yawning thermal model was used to detect yawns. Experiments were performed under both laboratory and actual car conditions, and the F-values obtained were 0.71 and 0.87 for cold and hot voxels, respectively. Mouth features were utilised for fatigue detection in ship OOWs, and the PERCLOS criterion was used to determine their fatigue state [57].

3) *Fatigue Detection Based on Body Features*

Ansari et al. [58] developed a semi-supervised approach to identify cognitive fatigue patterns based on driver posture. Unsupervised clustering based on a Gaussian mixture model was applied to display the driver's head, neck, and sternum, and a labelling algorithm was developed to automatically mark normal and fatigued postures to establish a dataset for the body posture. Gaussian support vector machines and bootstrap aggregating-based ensemble classifiers were trained on the dataset for real-time driver fatigue detection. The accuracies obtained were 93% and 90% for two test subjects in various driving postures. Yang [59] performed skin colour modelling and used OpenCV to detect facial features dynamically, followed by the Haar feature classifier to accurately and dynamically identify faces to determine whether a ship's bridge watchman is unmanned or in an unsatisfactory watchkeeping condition because of fatigue caused by the state of his head. The system demonstrated excellent real-time performance. Unlike the vehicle driver, the ship OOWs has a larger activity area, and the full-body features of the ship OOWs, including his body pose and gait features, can be captured using a camera. Therefore, the body pose was applied to the fatigue status of the ship OOWs, which yielded excellent real-time performances, based on video sequences [60].

4) *Fatigue Detection Based on Hand Features*

Hand movement features can be used to analyse fatigue. Wristbands are typically used to measure the driver's hand activity and are equipped with accelerometers to measure the three-axis acceleration information of the wrist. Choi et al. [46] proposed using a wristband-based system to detect driver stress, fatigue, and sleepiness via the ANOVA, followed by using sequential floating forward selection algorithms to obtain the best feature set data, and then classifying the driver's state using an SVM. Youn & Lee [61] used wristbands to investigate the effects of ocean voyages on the typical physical activities and sleep patterns of crew members. Three scenarios (berthing and sailing, sailing and non-sailing, and day and night sailing) were examined for various exercise and sleep indicators; the results showed low levels of physical activity and short sleep times of the crew members.

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TABLE II
FATIGUE DETECTION IN SHIP OOWS BASED ON BEHAVIOURAL FEATURES

Behavioral features	Ref	Parameters	Methods	Results	Limitations	Availability to OOWs	Ref	OOWs Applications
Eye features	2018[50]	PERCLOS	OpenCV, Dlib and SVM	Acc=97.93% from live videos	The environment and specific training dataset	High	2019[52]	PERCLOS
							2019[54]	Pupil measurements
Mouth features	2019[56]	Yawning detection	Thermal imaging, face, and eye corners detection, yawning thermal model	F=0.71 and 0.87 for cold voxels and hot voxels	The environment and specific training dataset	High	2022[57]	Mouth
Body features	2022[58]	Head, neck, and sternum offset	GMM clustering, Gaussian Support Vector Machines, Bootstrap-Aggregating based Ensemble Classifiers	Acc=93% and 90% for two various driving postures	Driver's driving habits and the environment.	High	2017[60]	Postural features
							2010[59]	Facial features
Hand features	2018[46]	Tri-axial acceleration	Analysis of variance, the sequential floating forward, selection algorithms, the SVM	Acc=98.43% for five-fold cross-validation of data	Each person's hand habits and laboratory environment	Medium	2020[61]	Hand movements

Fatigue detection methods based on behavioural features are summarised in Table II.

C. Fatigue Detection Based on Vehicle and Ship Features

Fatigue reduces a driver's ability to perform. Deviations from normal values in features such as the state of driving in a lane and the steering wheel angle are important indicators of the deterioration in the driving ability of a driver. Additionally, abnormalities in the pressure changes on the brakes and throttle, load distribution on the driver's seat, and vehicle speed highly suggest driver fatigue. Vehicle features can be categorised into the steering wheel angle, lane deviation variousial, speed variation, and pedal features. The fine adjustment frequency of the steering wheel is reduced during driver fatigue [62].

Therefore, the steering wheel features can be used to detect driver fatigue in vehicles. The steering wheel angle (SWA) [63] and steering wheel movement [64] are the most typically used steering wheel features. Compared with the PERCLOS, the SWA combined with the random forest is a more accurate method for detecting driver fatigue and can predict fatigue 6 s earlier.

The lane, speed, and pedal features can be correlated with driver fatigue. Yang et al. [65] designed a testbed using a driving simulator and performed an experiment using sleep differences as the only independent variable. The response time of subjects with less sleep deteriorated significantly, as reflected by the mean and standard deviation of lane bias. Campagne et al. [66] investigated driving operation errors caused by the fatigue in drivers of various ages based on the vehicle speed. Sahayadhas et al. [67] reviewed the sensors used to detect driver sleepiness, including pedal features obtained using pressure sensors. Results of highway driving tests indicated that changes in the pedal pressure typically showed minor high-frequency corrections related to driver alertness. In addition, the Bayesian network and SVM were combined with other features to achieve the state classification of vehicle drivers [68].

However, it was demonstrated that vehicle features alone are not a reliable indicator of driver fatigue. Krajewski et al. [69] reviewed the significant inter- and intra-individual variations in fatigued driving and discovered the unreliability of using vehicle features alone to detect driver fatigue.

Various ships may exhibit similar features, such as deviations from their course or track, abnormal rudder schemes, and irregular speeds. However, these features are determined by personal driving habits and do not necessarily reflect crew fatigue [51]. Hence, these features should only be used to facilitate fatigue detection. Liu et al. [70] investigated the relationship between crew visual features and fatigue driving behaviour by establishing a function between the amplitude of rudder shift and a set of variables. They concluded that the gaze time ratio exerted the most prominent effect on fatigue driving behaviour. Ships are generally steered according to a set course at a constant speed in open waters; hence, no explicit relationship related to fatigue driving can be established based on the ship speed. When manoeuvring in restricted waters or operating in port areasor channels, the OOWs must perform frequent speed adjustments. In this regard, the OOWs' reaction speed and the adjustment pattern to the ship's speed may reflect their fatigue in the manoeuvring process.

Fatigue detection methods based on vehicle and ship features are summarised in Table III.

D. Fatigue Detection Based on Mixed Data

In fatigue detection based on mixed data, the latter can be a mixed signal with a single feature or a mixture of unique features.

1) Fatigue Detection Based on A Single Feature Mixed With Multiple Signals

Fatigue detection based on a single feature mixed with multiple physiological features is a typical detection method

TABLE III
FATIGUE DETECTION IN SHIP OOWS BASED ON SHIP FEATURES

Vehicle features	Ref	Parameters	Methods	Results	Limitations	Availability to OOWs	Ref	OOWs Applications
Steering wheel features	2019[64]	SWM	Random Forest	Acc=94.6% for five-fold cross-validation	Driving habits and increased automation	Medium	2013[70]	Joystick Features
	2014[63]	SWA	Random Forest	More correct than PERCLOS and 6 seconds earlier to predict fatigue				
Pedal features	2004[68]	Pressure changes	Bayesian networks, SVM	Typical small high-frequency corrections related to alertness in practical road tests	Driving habits and the real-time lag	Low		Engine Telegraph
Driveway features	2009[65]	Standard deviation and mean values of lane deviations	Bayesian network paradigm, stimulus-response task	Significantly less resistant to interference when fatigued	Critical situation when driving behavioral errors occur	Low		Course and track features
Speed features	2004[66]	Over speed, slow speed	Electroencephalographic analysis	Older drivers' decline in driving performance associated with the evolution of low-frequency waking EEG	Critical situation when driving behavioral errors occur	Low		Speed features

[71]. Sun & Yu [72] acquired EEG, ECG, and EOGinformation and used the Wierwille and Ellsworth criteria (fatigue-based visual cues) as a baseline for fatigue assessment to detect fatigued driving. Their results showed that the transient time and frequency increased with fatigue; the alpha and beta wave power densities decreased with fatigue; the low-/high-frequency of the SDNN decreased with fatigue, while the RMSSD increased with fatigue.

The accuracy of fatigue detection can be improved effectively by mixing behavioural features [73]. Xing et al. [74] obtained the three-dimensional head rotation angle and joint positions of the upper human body using feedforward neural networks. The results showed that the fatigue detection accuracy yielded by mixed features was much higher than that yielded by single features. Owing to the differences between the driving environments of ships and other vehicles, utilising the mixed behavioural features of ships is preferable. In studies of ship bridge watchkeeping using mixing multiple behavioural features, Wang et al. [57] combined eye and mouth features to detect fatigue in OOWs. Whereas Zhao [60] proposed a vector angle-based human pose recognition algorithm to detect body pose features. Meanwhile, an improved DTW (dynamic time warping) algorithm to identify gait features while performing fatigue detection in ship OOWs.

Wakita et al. [75] used the vehicle speed, brake pedal, accelerator pedal, and distance to the front vehicle as inputs to the Gaussian mixture and Helly models. After performing comparative tests, they discovered that the Gaussian mixture model was more effective than the Helly model, and that the fatigue detection accuracy based on a simulator was 81%. Meanwhile, the accuracy of fatigue detection based on an actual vehicle driving environment was 73%.

2) *Fatigue Detection Based on Multifeature Mixing*

A combination of multiple features was used in recent studies to detect fatigue. Behavioural/vehicle [76], behavioural/physiological [77], and physiological/vehicle features [78] have been used for fatigue detection. Compared with single or similar fatigue feature detection schemes, a combination system offers higher detection efficiency and anti-interference ability. Samiee et al. [79] combined behavioural, vehicle, and physiological features to detect fatigue and used a decision module to combine the decisions of three neural networks. Various features were used in each to detect fatigue, including the eye state, lateral position, SWA, as well as ECG, EEG, and sEMG signals. Additionally, the KSS (karolinska sleepiness scale), whose accuracy was 94.63%, was used as a benchmark. Meanwhile, anthropometry, muscular performance, subjective wellness, and salivary cortisol in professional sailors were to analyze fatigue [80]. Ship and behavioural features were used to detect fatigue in ship OOWs [70].

Detection methods based on mixed data are summarised in Table IV.

These findings show that fatigue detection based on mixed data has been performed and will be further developed in the future for detecting fatigue in ship OOWs. However, the highly invasive nature of the mixed data method limit fatigue detection in ship OOWs. Wearable devices may overcome this limitation. Additionally, mixed behavioural features for detecting fatigue in ship OOWs require a combination of the ship-specific environment and OOWs' navigation condition to accurately identify the behavioural features of ship OOWs. Currently, methods based on mixed ship features are not applicable to highly automated ships.

III. PREREQUISITES FOR FATIGUE DETECTION

Fatigue detection in OOWs is a systematic and complex problem. Some prerequisites are important, including, but not limited to, establishing the detecting environment, and determining the data acquisition method.

A. *Fatigue Detection Environment*

The fatigue detection environment significantly affects the results of fatigue detection, and its applications vary. The more realistic the fatigue detection environment, the higher is the fatigue detection accuracy, and the better is the application in maritime practice. Currently, laboratory- and simulator-based fatigue detection environments exist, in addition to realistic environments. Driver fatigue detection studies have primarily been conducted in laboratories. However, Chowdhury et al. [33] discovered that drivers in a laboratory

TABLE IV
FATIGUE DETECTION IN SHIP OOWS BASED ON MIXED DATA

Mixed data		Ref	Parameters	Methods	Results	Limitations	Availability to OOWs	Ref	OOWs Applications
Mixed multiple signals with a single feature	Mixed behavioral features	2018[74]	Head angle, upper limb joint position	Feed-forward neural networks	Acc=80% in the laboratory	environment's background complexity, brightness, etc.	High	2022[57]	Eye and mouth features
								2017[60]	Human posture and gait features
	Mixed physiological features	2014[72]	HR, HRV, alpha, and beta waves	Digital Signal Processing	Transient time and frequency increase, alpha and beta wave power density decrease with, LF/HF and SDNN decrease, while RMSSD, LF, and HF increase	Highly intrusive data acquisition and driver specificity.	Low		
	Mixed vehicle features	2006[75]	Speed, pedal pressure, distance from the vehicle in front	Gaussian mixture model	ACC=81% on the simulator and 73% in a real car driving environment	Critical situation when driving behavioral errors occur but not to predict fatigue.	Low		
Mixed multi-features		2014[79]	Eye status, laterality, SWA, ECG, EEG, and sEMG	Data fusion, Artificial Neural Networks	Acc=94.63% in the laboratory and robustness to the absence of input features	Requires the cooperation of multiple feature systems and the processing of individual applications.	High	2013[70]	Rudder features and eye features

environment were significantly less concerned with driving safety and were more relaxed. Thus, the features acquired in laboratory and realistic environments are various.

Simulators used in a laboratory are typically set up in the same manner as an actual vehicle, including various ancillary facilities, and typically use multi-angle screens to display driving scenes [49]. However, the development of technology has resulted in the use of head-mounted VR devices for displaying driving scenes [81]. The equipment to be used must be selected based on the features acquired for fatigue detection or must not interfere with the acquisition of feature information. Meanwhile, some driving tasks use simpler driving simulation software [46], although it is used less frequently in detecting driver fatigue via simulators. However, for detecting fatigue in ship OOWs, the application of ship driving simulation software is necessary as ship simulators are not universally equipped. Researchers have attempted to detect fatigue in drivers on duty using ship simulators or the corresponding videos of activities on the bridge to establish important datasets. Previous vehicle-driver fatigue detection experiments involved driving in an actual environment as well as data testing.

Nadai et al. [82] evaluated drivers who drove 30 km per day along a single route in an actual open urban road environment. And they conducted a driving test for 10 d to detect the drivers' ECG signal and investigate the relationship between the drivers' ECG features and fatigue. In those 10 d of actual driving, any circumstances that would affect the normal driving of the driver were avoided. Vehicle control data and eye movement data are used for driver fatigue detection and can be used to distinguish drivers in various scenarios [83, 84]. Similarly, in detecting fatigue in ship OOWs, ship driving tasks have been conducted on actual ships, and data pertaining to the features of fatigue in OOWs have been acquired. Liu et al. [70] performed an experiment based on a straight line between two piers under good weather conditions; the ship traversed naturally, and the observation conditions facilitated the acquisition of the visual response data and fatigue driving behaviour data of the ship OOWs at various times. However, the experimental conditions of the ship were limited significantly, and the effects of the external environment and other factors on the acquisition of feature data should be avoided.

B. Data Acquisition Methods

A significant amount of correct and targeted data is required for fatigue detection; therefore, an appropriate data acquisition method must be used.

Data acquisition methods differ depending on the feature data required for fatigue detection. Currently, many methods are available for acquiring the features of vehicle drivers as well as advanced acquisition methods. They integrate the data of many features simultaneously, such as ECG and respiration signal measurements integrated into clothing [82]. However, these methods are still being investigated in the laboratory, and further research is required to determine whether they are applicable to driver fatigue detection. In conclusion, new data acquisition methods are being developed to allow the simultaneous, efficient, non-intrusive, and optimal acquisition of data. Currently, the camera is the primary method for acquiring ship data to detect fatigue in OOWs [49], whereas the wristband bracelet is primarily used for detecting fatigue in vehicle drivers [46]. Meanwhile, extensions of the available smart band/watch [85], which offers low invasiveness, can be used to acquire the physiological/behavioural feature data of OOWs. Additionally, based on the results of vehicle driver fatigue detection, combining both physiological and behavioural features results in favourable driver fatigue

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TABLE V
DATA ACQUISITION METHODS FOR DETECTING FATIGUE IN SHIP OOWS

Equipments	Ref	Collection features	Placement	Invasive	Placement on the ship	Availability to OOWs
Camera (Kinect)	2016[49]	Behavioral features	In front of the vehicle's driver's seat	None	Ship bridge's top In front of the ship bridge	High
Smart bracelet/watch, Wristbands	2021[85] 2018[46]	Behavioral features/ Physiological features	Vehicle driver's wrist	Low	Ship OOWs' wrist	Medium
Specialized instruments (Biopac MP00 ECG)	2009[86]	Physiological features	Vehicle driver's head, hands, etc.	High	Head, eye, and upper arm muscles of ship OOWs	Low
Sensors (pedal pressure values, GPS, etc.)	2006[75]	Vehicle and ship features	Pedals, steering wheel	None	Steering wheel	Low

detection. Other customised measuring instruments [86] are not suitable for detecting fatigue in ship OOWs because of their price and high invasiveness. Owing to the current high level of automation in ship driving, the use of various sensors to capture vehicle features for detecting driver fatigue [75] cannot be migrated easily to the detection of driver fatigue on ships. Besides, the detection of driver fatigue using sensors placed at other locations, such as the steering wheel, is not applicable. Data acquisition methods for detecting fatigue are summarised in Table V.

IV. APPLICATIONS

Various subjective questionnaires, reports, objective survey reports, and general models are the quickest and most direct way to analyze and detect ship OOWs' fatigue. Meanwhile, they obtain a more correct picture of ship OOWs' fatigue status or other fatigue-related manifestations at a fraction of the cost. But the inability to detect ship OOWs' fatigue in real-time is its big-gest drawback [87].

At present, the subjective reports commonly used in the fatigue detection of ship OOWs include KSS [88], ESS (epworth sleepiness scale) [89] and many other detection scales [54, 90-92]. Commonly used objective reports include the RTT (reaction time tests) [48] and the PVT (psychomotor vigilance task) [41]. And biomathematic models are often used to study ship OOWs' fatigue [93].

From the above subjective and objective reports, the detection of fatigue, drowsiness, and sleep behavior of crew and ship OOWs is still qualitative or simply quantitative. There isn't a real-time detection method, so the current requirements for real-time detection and prevention of ship OOWs' fatigue are far from being met.

Additionally, physiological features have been used in fatigue detection of ship OOWs but few [41, 48]. Certain parameters and fatigue detection methods can be used to detect fatigue in ship OOWs; however, the current data acquisition methods are unsuitable, which necessitates the use of less invasive data acquisition methods. Smart wristband is a low invasive means of physiological data collection. By letting OOWs wear a smart wristband and collecting the wristband data through a Bluetooth router, not only the sleep condition of OOWs can be monitored for a long time, but also the triaxial acceleration of their hand features can be monitored in real time to judge the real-time status of OOWs. This method has high feasibility in OOWs fatigue detection.

The video-based fatigue detection method is also a low invasive method, which is the primary method for detecting OOWs' fatigue on board ships [54, 57, 61]. However, the camera shooting distance, face shooting angle, ambient brightness, complex shooting background, and OOWs' movement in the bridge all affect the video-based fatigue detection.

Ship features have also been applied, but the application analysis of vehicle features in vehicle driver fatigue detection shows that driving errors caused by fatigue are not suitable for real-time fatigue detection [70]. Compared with vehicles, large ships have the characteristics of large mass, large inertia, and large steering radius. When the ship turns, the change range of Joystick is generally small (the maximum is about 35°), and there is a certain delay from the operation of joystick to the obvious change of the ship's actual heading. This is very different from vehicle steering, which is based on a large rotation of the steering wheel and the vehicle's faster response to action. Therefore, it is difficult to identify fatigue through the behavior of OOWs operation joystick. It may be a feasible method to identify the reaction speed and operational rhythm of OOWs operating the vessel in restricted waters, where OOWs will frequently use rudder and propeller.

The current methods for detecting fatigue of ship OOWs rely on a combination of multiple features [57, 70, 80]. While the acquisition of physiological signals presents limitations in detecting OOWs fatigue at sea, it is preferred to utilize physiological features. Valuable research will focus on integrating multiple features for more effective detection of OOW fatigue onboard. A typical framework showing steps of a typical research work in this area is shown in Fig. 4. The appropriate data acquisition methods, such as camera, smart bracelet, etc. were selected to collect data according to the onboard environment, and the dataset including heart rate, sleep, triaxial acceleration, yawning, eye closing, etc. was established based on the fatigue judgment benchmark. Public datasets related to ship OOWs fatigue detection are scarce. Dataset based on ship simulation bridge [57] may be requested

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from the authors. More datasets can be migrated and used according to vehicle drivers fatigue detection [96], including physiological data and video data, etc. Real-time fatigue detection was achieved through machine learning techniques and multi-source data features, with final deployment and early warning taking place on an actual ship rather than being limited to laboratory settings.

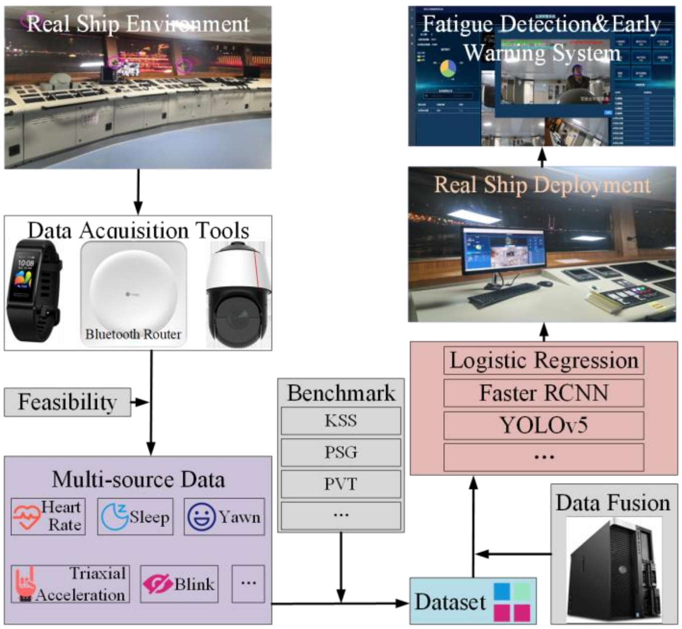

Fig. 4. According to the actual ship environment, the multi-source data of ship OOWs are collected with the help of appropriate data acquisition equipment, and the dataset is established based on the fatigue judgment benchmark and the machine learning methods are used to realize real-time fatigue detection. Finally, the system is deployed on the real ships and early waring.

V. Discussion

Based on a comprehensive analysis, classification, and comparison of studies pertaining to fatigue detection in vehicle drivers and ship OOWs, we discuss the key similarities and differences between the two as well as future research directions for detecting fatigue in ship OOWs. In addition, the data acquisition methods and experimental environment for driver fatigue detection are discussed to provide a foundation for investigating fatigue detection in ship OOWs. Finally, the advantages and disadvantages of the current methods used for detecting fatigue in OOWs are discussed, and issues that must be urgently addressed are highlighted.

A. Similarities and Differences in Fatigue Detection for Ship OOWs and Vehicle Drivers

The development of fatigue detection technology for ships OOWs is lagging that for vehicle drivers. The present study focuses on the method to use the existing practices and apply them to the unique operating environment of ship OOWs.

Most studies pertaining to fatigue detection in ship OOWs are conducted in a laboratory, and the participant being tested is aware that his/her level of fatigue is being evaluated. Therefore, the results can differ significantly from those obtained from an actual environment [23]. This is because OOWs lives and works on board a ship, which differs the life of a person being tested in a laboratory [94]. However, for the OOWs, there is an advantage, i.e., because the ship OOWs must live on board for a long time, the sensor data can be obtained continuously, which may be more effectively than the data of a vehicle driver.

The current data acquisition methods for detecting fatigue in vehicle drivers might not be optimal in some cases. For example, EEG, EOG, and other physiological information acquisition methods are invasive; although they can be applied (theoretically) to detect fatigue in vehicle drivers in a laboratory environment, their feasibility in a practical driving environment is yet to be verified [44]. Similar data acquisition methods are less suitable for ship OOWs. Because of the high activity level of ship OOWs, a more invasive data acquisition method will affect their ability to work and drive [48]. Therefore, selecting suitable data features as inputs for fatigue detection is more difficult for ship OOWs than for vehicle drivers.

B. Low-intrusive, Multisource Approach to Data Acquisition

Multiple data features and low-intrusive data acquisition methods are the typical methods for detecting fatigue in vehicle drivers, particularly for fatigue detection in ship OOWs. The unique operating environment of ship OOWs necessitates the use of multiple features and low-intrusive data acquisition methods to achieve fatigue detection systems of high reliability and stability [54]. Currently, fatigue in ship OOWs is primarily detected using a camera that captures the facial and posture features of the ship OOWs [57, 61], and the wristband is used to obtain the features of the ship OOWs [95]. In addition, when using the corresponding feature information acquired using a smart bracelet for fatigue detection, the information pertaining to physiological and behavioural features such as the HR and tri-axial acceleration, respectively, as well as the sleep duration and sleep quality can be used for data fusion, thus avoiding the low accuracy of single-feature fatigue detection. Owing to the emphasis on non-invasive fatigue detection methods, the smart bracelet can only be worn with the consent of the ship OOWs; otherwise, relevant feature information cannot be acquired. However, the quality and usefulness of the feature information must be further confirmed based on the driving environment of the ship OOWs.

C. Detection Environment Must Be Shifted from The Laboratory to The Actual Environment

Shifting from the laboratory to the actual environment is necessitated for driver fatigue detection, particularly for ship OOWs on duty in certain environments because of the special effects on sleep [94].

Owing to technological developments, machine learning-based data analysis and classification methods are being used increasingly. The selection of suitable models for deep learning and their continuous optimisation is a stepwise process. To improve the algorithm model, the actual efficiency of fatigue detection should be determined after validating the algorithm model based on an actual operating ship scenario and not based solely on the laboratory environment [96]. This is because the non-existence of a complex dataset in an actual driving environment renders it difficult to obtain the complex variability of the driver's features and does not provide sufficient information regarding the physiological and behavioural processes of the ship OOWs during actual driving [13]. Hence, the accuracy of fatigue detection in ship OOWs in actual driving environments is low.

D. Detection and Early Warning

The purpose of fatigue detection should be to remind the driver in time to realize early warning and avoid the danger caused by fatigue [36, 42]. For ship OOWs, fatigue detection and timely warning are the current and future research focus. Simply analyzing the fatigue problem can not meet the needs of the current marine departments. Therefore, referring to the research on vehicle drivers fatigue detection, it is equally important to select the real-time fatigue detection method and the timely warning, and select the appropriate features. When the driving errors result caused by fatigue is taken as the features, they cannot be used for real-time fatigue detection [65, 70]. Due to the huge difference between vehicles and ships, such features are not suitable for real-time detection and early warning of ship OOWs' fatigue.

The direction of ship OOWs fatigue detection is to combine the special working environment of ship and ship OOWs and select the methods and features that can be detected in real time. When the ship OOWs are in or about to be in fatigue state, timely warning is issued to remind the ship OOWs to pay attention to the state, so as to avoid danger.

VI. Conclusion

Currently, shipping companies, owners, the IMO, and other maritime organisations are focusing primarily on crew fatigue problems, particularly fatigue in ship OOWs. Crew fatigue affects the safety of ships and lives at sea, as well as the cleanliness of the ocean. In this study, the importance, urgency, and difficulty in detecting fatigue in ship OOWs were comprehensively analysed. Subsequently, based on vehicle driver fatigue detection, the progress, limitations, and universality of fatigue detection in ship OOWs based on various features were analysed. Consequently, the prerequisites for fatigue detection in ship OOWs were determined.

Owing to the limitations of onboard conditions, few features can be acquired for detecting fatigue in ship OOWs. Based on existing studies pertaining to vehicle driver fatigue detection, the technology based on vehicle and ship features is the least invasive in terms of product invasiveness, detection accuracy, and practical application. Video-based detection technology is superior in terms of user acceptability and usability. Fatigue detection based on physiological signals offered the highest accuracy [97]. The fatigue detection of ship OOWs lags that of vehicle drivers. The ship environment significantly affects the acquisition of various data features of ship OOWs. For example, the background of the environment is complex, which complicates the acquisition of the facial and physical features of a ship OOW. The distance of the camera from the target and the number of detected personnel affects the accuracy of the data features captured by the camera. Meanwhile, the physiological features obtained using the wristband and other devices result in errors owing to the wide range of activities or high workload of ship OOWs. Other sophisticated feature acquisition devices (e.g., electroencephalographs) are more unsuitable for ship OOWs because of their high intrusiveness, which restricts operation. Therefore, based on the characteristics of ships and OOWs, combining multiple features with physiological and behavioural features is the current direction for detecting fatigue in ship OOWs. Additionally, multisource data fusion processing is a key issue in the construction of robust and stable fatigue detection systems.

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