Psychophysiological Evaluation of Seafarers to Improve Training in Maritime Virtual Simulator

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A B S T R A C T

Over years, safety in maritime industries has been reinforced by many state-of-the-art technologies. However, the accident rate hasn't dropped significantly with the advanced technology onboard. The main cause of this phenomenon is human errors which drive researchers to study human factors in maritime domain. One of the key factors that contribute to human performance is their mental states such as cognitive workload and stress. In this paper, we propose and implement an Electroencephalogram (EEG)-based psychophysiological evaluation system to be used in maritime virtual simulators for monitoring, training and assessing the seafarers. The system includes an EEG processing part, visualization part, and an evaluation part. By using the processing part of the system, different brain states including cognitive workload and stress can be identified from the raw EEG data recorded during maritime exercises in the simulator. By using the visualization part, the identified brain states, raw EEG signals, and videos recorded during the maritime exercises can be synchronized and displayed together. By using the evaluation part of the system, an indicative recommendation on "pass", "retrain", or "fail" of the seafarers' performance can be obtained based on the EEG-based cognitive workload and stress recognition. Detailed analysis of the demanding events in the maritime tasks is provided by the system for each seafarer that could be used to improve their training. A case study is presented using the proposed system. EEG data from 4 pilots are recorded when they were performing maritime tasks in the simulator. The data are processed and evaluated. The results show that one pilot gets "pass" recommendation, one pilot gets "retrain" recommendation, and the other two get "fail" results regarding their performance in the simulator.

1. Introduction

Despite the effort that has been put into the maritime industry to improve the reliability and structural stability by means of technology over the past years, the rate of maritime accidents has not had a significant reduction. Early Investigation shows that an estimated of 75% to 96% of the accidents in maritime are due to human errors [1]. Even in recent years, humans are still the main cause to most of the maritime accidents [2, 3]. Though the maritime industry is moving towards autonomous ship, human still play an important role as the autonomous ships have to interact with other manned ships in the same traffic areas and it may influence on the crew of other manned ships; the autonomous ships have to interact with the remote control system in situations where the onboard decision making system cannot solve the situation for one reason or another; the autonomous ships are built by humans; the autonomous ships can also be remotely controlled [4]. In summary, human factor is crucial in maritime.

Various human factors studies are conducted in maritime domain to understand the underlying reasons and causes. It is found that there are three human factors related to safety, namely organizational, group, and individual factors. The organizational factors could impact the safety by company policies, company standards, etc.; the group factors may increase the accident rate by miscommunication between individuals and the mangers/supervisors; while the individual factors include improper competence, stress, workload, and motivation of individuals which could lead to human errors [5]. To investigate these human factors in maritime domain, the current methods usually utilize a full mission simulator with real-world scenarios. Traditional methods such as post-exercise questionnaires [6], observation from behaviors [6], case study [7], or advanced methods such as bio-signals recorded when the seafarers are performing the maritime tasks can be used to understand how human factors affect safety. Bio-signals have two unique advantages over other technologies such as continuous monitoring of the seafarers' psychophysiological states during the maritime tasks performance and high temporal resolution of the measurements. The recognized psychophysiological states can be used not only to find out the causes of human errors but also to evaluate the performance of the seafarers during their training or assessment. It could be used as an additional assessment tool in maritime simulator to evaluate and improve training of seafarers. Different bio-signals are used to detect the psychophysiological states. For example, in [8-10], Electroencephalogram (EEG)-based brain states recognition algorithms are proposed to identify human cognitive workload, emotions, and stress levels and applied in studying human factors. In [11], we proposed a novel EEG-based system to assess cadets training and performance. In this paper, we propose and implement EEG-based seafarers' evaluation algorithms using machine learning, and present a case study with 4 pilots. The revised system includes a data processing part for brain states recognition from EEG, a visualization part to show the recognized brain states in a more intuitive way, and an evaluation part based on the brain states recognized from EEG. The final output of the evaluation part gives a recommendation on "pass", "retrain", or "fail" of the seafarer with detailed analyses of which tasks need more training. Thus, it is possible to find out which operation performance is the weak point of the seafarer's training and may need the re-training.

The paper is structured as follows. Section 2 reviews on the related work such as maritime simulators, seafarers' assessment, psychophysiological states which are important in maritime human factor study, and the method to evaluate such states. Section 3 introduces the EEG-based assessment system. Section 4 presents a case study using the proposed system and Section 5 gives the conclusion.

2. Related Work

2.1. Maritime Simulators

The traditional way of studying human factors in maritime domain is through analyzing the data concerning accidents. There were no standardized accident reporting systems [12] and near misses were often not reported [13] in the past, which made it hard to explain the accidents or get a comprehensive study. In recent years, reporting systems such as the Confidential Hazardous Incident Reporting Programme (CHIRP) [14], the Mariners Alerting and Reporting Scheme (MARS) [15]. Statistical methods are applied to analyze the accident trends [16, 17]. Another way to study human factor is making use of a full mission virtual maritime simulator can be considered as it allows collecting all information about the crew during the navigation of the ship. Besides that, the environment and tasks performed in the simulator could be fully controlled. For example, the traffic density, the visibility, the length of the exercise, and the weather condition can be changed to adjust the task difficulty level and risk level according to the purposes of the exercises. Besides the application in human factor study, simulators are also used in maritime institutes for training and assessing seafarers. Though the instructional learning is still important for transferring knowledge to the learners, the simulator can enhance the learning process as it enables the learners to be fully immersed in the simulator with stressors or distractions that may happen in real situation [18]. Additionally, it is possible to do comparison among different seafarers as they could go through the same simulation settings [13].

2.2. Seafarers' Assessment

The assessment of seafarers in maritime domain usually includes written examination, achievement reports [19], oral examination [20], the performance assessment of the seafarers in the simulators [21], etc.

The written exams are mostly about memorizing what was taught during the class. However, [22] pointed out that the seafarers may pass the examinations which are mostly dependent on memory but still have low ability to analyze the information by themselves in unseen situations. In such cases, memory failure could lead to human errors. The achievement report, which is provided by the instructors and is more subjective, may have problems such as unreliability, invalidity, and unfairness [19].

Another commonly used assessment tool is the maritime simulator which is employed in addition to written or oral examinations. The performance in the simulator during maritime tasks are always used as indicators of the seafarers' capability. Besides the behavioral indicators such as reaction time, actions during the task, it is also important for the seafarers to handle stress in any abnormal situation [21]. However, the current simulator-aided assessment has only limited focus on psychophysiological states such as stress, workload, etc. of the seafarers. Last but not the least, the performance of the seafarers in the simulator is evaluated by instructor, which could be affected by the subjectivity of the instructors. Researchers are working on proposing other methods or automated programs to remove this kind of subjectivity in assessing seafarers [23]. In summary, the current simulator-aided assessment is lack of monitoring the psychophysiological states and may have bias because of subjectivity from instructors. We tried to overcome these two limitations of the current seafarers' assessment method in maritime simulator and proposed an automated psychophysiological evaluation system for seafarers.

2.3. Psychophysiological States in Maritime Human Factor Study

Although in recent years, the ship losses and seafarer fatalities has decreased due to the development of new maritime technology, human factor is still the main causality of maritime accidents [24]. Psychophysiological states such as workload, stress, situation awareness, and fatigue are important individual factors as they may lead to human errors. Thus, it is important that these states could be monitored during the assessment of seafarers.

Stress has been found to affect not only the productivity but also health and wellness of people [12]. [25] pointed out that seafarers are always exposed to stressors on board for several months. In [26], it shows that the seafaring population are facing higher stress than a normalized onshore population. [27] investigated the impact of stress on the performance, and the results reveal that excessive stress could lead to increasing number of errors.

Situation awareness is defined as the ability of understanding what is going on and how the situation is in the near future [28]. It is found that over 177 maritime accident reports from 1987 to 2000, 71% of all human errors were related to situation awareness [29]. Similarly, it is also claimed in [30] that inadequate lookout is the reason of 84% of collision accidents.

Fatigue can be induced by many factors. For example, [31] claims that increasing workload of the crew could increase the fatigue that the crew faces. It also reports that fatigue has been the main contributor of 23% of 98 critical vessel and personnel injuries. [32] summarizes the accident data from 1989 to 1999 and found that fatigue related accidents mostly happened during the first week of the tour and during the first four hours of a shift in calm conditions for long sea routes. While for the short sea and coastal routes, the study found that seafarers had higher levels of fatigue, and 52.6% of the respondents believe that the levels of fatigue encountered are potentially dangerous. [33] also concludes that fatigue has a negative impact on seafarers' work and life, which may lead to accidents.

Workload is defined as the mental effort that is needed to complete certain tasks [34]. [35] shows that increased mental workload is associated with higher levels of collision threat. [36] also emphasized the importance of analyzing cognitive workload of the maritime crew. Additionally, extreme workload could also lead to increased stress, low situation awareness, and increased fatigue.

2.4. Bio-signal based Psychophysiological States Evaluation

In recent years, biosignals are used to evaluate psychophysiological states in human factor study as it can get continuous monitoring without interrupting the primary work of the subjects. Different biosignals that have been used include voice, electrocardiogram (ECG), skin conductance, Electrooculogram (EOG), Electroencephalogram (EEG), etc. [37]. For example, [38] proposed to use human voice to detect stress and workload of the subjects in aviation. ECG measures the electric potential of the skin, which reflects polarization of heartbeat. Heart rate and heart rate variability are considered as good indicators of stress and emotional states, since stress is usually associated with a high heart rate level. In a recent research, three indices extracted from ECG were used to recognize the stress state of the subject [39]. Skin conductance measures the sweat level of the skin. It can reflect levels of emotional arousal and stress of a person. For example, a deep learning network were proposed for stress recognition based on skin conductance [40]. EOG can measure eye movements by placing pairs of electrodes around the eyes. Movements of eyes lead to difference in potential between the electrodes. [41] extracted the time-frequency eye movement features from multi-channel EOG signals with short-time Fourier transform (STFT). It is found that time domain eye movement features (i.e., saccade duration, fixation duration, and pupil diameter) were useful for recognition of different emotional states.

Another technology gaining attention is EEG-based brain state recognition, which reflects neurophysiological activities happening in the brain by the electrical voltage generated from neurons. In comparison to other methods, EEG signal is preferred as it is accurate, has high temporal resolution, and has been successfully used for recognition of various psychophysiological states including emotion, workload, and stress. For example, an EEG-based emotion recognition algorithm was proposed and validated in [9]. After being filtered by a 2-42 bandpass filter, statistical features and fractal dimension features were extracted from the EEG data. Support Vector Machine (SVM) was chosen to be the classifier. An accuracy of 69.53% is reported for 8 emotions recognition. With fewer types of emotions to be recognized, the accuracy is increasing. For seafarers' assessment, negative, neutral, and positive emotions are targeted to be identified and the best accuracy for 3 emotions is 72.22%.

Another brain state which is very important especially in human factor study is mental workload. The definition of workload varies and in this paper we define the mental workload as the mental effort required to complete the task [42]. In [8], the same bandpass filter and features (statistical and fractal dimension features) were applied while different classifiers such as k-Nearest Neighbors and SVM were compared. SVM outperformed the other with the best accuracy of 80.09% for 4 workload levels.

To achieve a better accuracy, both EEG-based emotion and workload recognition algorithms are subject-dependent, which means for each user, the classifier has to be trained by carrying out a calibration. Audio stimuli from IADS database [43] are employed in the calibration for emotion recognition. The stimuli to invoke certain emotions could be visual such as IAPS database [44] as well, however, our previous work [45] shows there is no significant difference on the classification accuracy using visual and audio stimuli. The EEG data are recorded while the subjects are listening to the sound clips and are used as training data with different emotional labels. To collect EEG data for workload calibration, Stroop color test is used to evoke four levels of workload. The recorded EEG data together with different workload labels are used to train the SVM classifier. In both algorithms, a 4-second sliding window with 3 second overlapping was the used to extract the corresponding features from EEG data. The features are then input to the SVM classifier for training. The trained SVM models are then used to identify the subjects' emotions and workload levels during the maritime exercises.

Once the emotions and workload are identified from EEG, by using the algorithm proposed in [10] where stress is recognized as the combination of emotional and workload states, 8 levels of stress can be recognized.

3. System Design

3.1. Overview of the EEG-based Evaluation System for Seafarers

As mentioned in Section 2.4, it is possible to use biosignals such as EEG to identify different mental states. In this paper, we propose and implement an evaluation system of seafarers to assist the training in maritime virtual simulator. With this system, the maritime instructors are able to monitor how the brain states such as emotion, workload, and stress change over time, what the seafarers' mental states are during demanding events, which maritime operation induces higher workload/stress for the seafarers, what the correlation is between the seafares' brain states and their performance, etc. The proposed system consists of three parts – a processing program, a visualization program, and an evaluation program as shown in Fig. 1.

To achieve a higher recognition accuracy, the EEG-based brain state recognition algorithms are subject-dependent [8-10]. A calibration session is needed before the classifier can be applied to identify the brain states during the maritime exercise. Thus, in the processing program, feature extraction is done for both EEG data collected during the calibration session and maritime exercise. Then, a SVM classifier is trained using the features from the calibration data and then applied to classify the EEG data from the maritime exercise. The recognized brain states such as workload, emotion, and stress are the input to 1) the visualization program, which can synchronize and display the raw EEG signal, recognized brain states, and videos recorded during the simulator-aided tasks, and 2) the evaluation program. With the machine learning algorithms implemented in the evaluation program, a final decision about "pass", "fail", or "retrain" is given. The details of the EEG processing part, visualization part, and evaluation part of the system are given in the following sections.

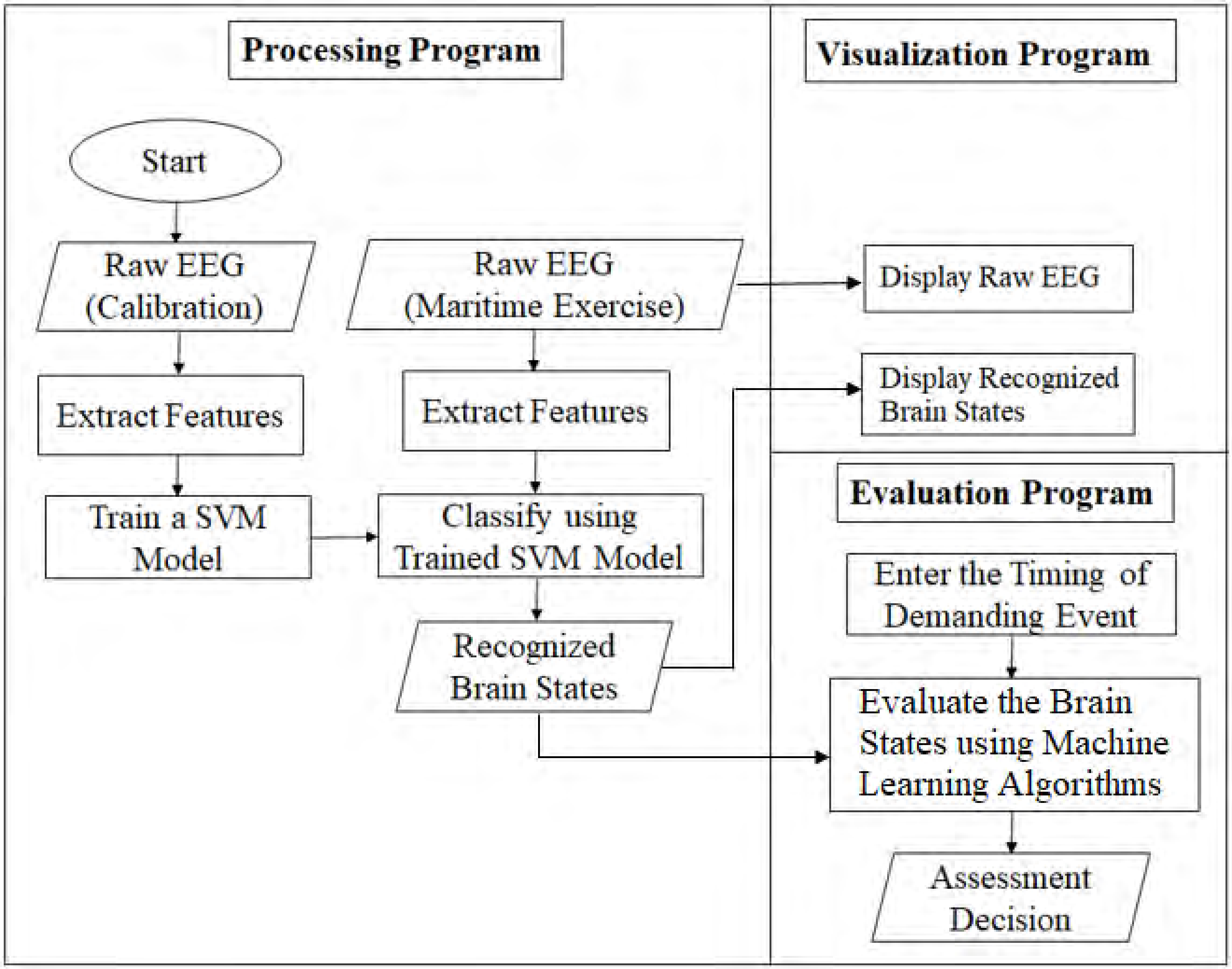

Fig. 1 - Diagram of EEG-based evaluation system for seafarers.

3.2. EEG Processing Program and Visualization Program

The input of the EEG Processing Program is the raw EEG data, and an output of the program is the recognized brain states such as workload, emotion, and stress experienced by the seafarers during simulator-aided maritime tasks. The EEG data recorded from the workload and emotion calibration are used as the training data to train the SVM classifier. The state-of-the-art algorithms described in Section 2.4 are used in the system. The program is implemented in C++ on Visual Studio 2017.

The identified brain states can then be visualized in the Visualization Program together with the displaying of the videos taken during the maritime tasks and the raw EEG as shown in Fig. 2. The instructors can playback and monitor how the brain states are changing over time, especially when there are certain demanding events.

Fig. 2 - Screenshot of the Visualization Program.

3.3. EEG-based Machine Learning Evaluation Algorithm

We set the evaluation standard by using an existing database which consists of 18 maritime trainees. The average age of them was 27 while the average total sea time was 28.6 months. All of them attended five maritime exercises, and each exercise was with different difficulty level assigned by instructors. The EEG data were collected by Emotiv [46] device with 14 electrodes when the maritime trainees were performing the exercise. Videos were recorded as well. By observing the videos and getting comments from the instructors, each exercise performed by maritime trainee was labeled with one of three evaluation decisions, namely pass, fail, or retrain. These labels are considered as the ground truth of the assessment decision. The emotion, workload, and stress states of these trainees are identified from EEG.

Then we extract the features to train the classifier. The probability mass function $P(wl)$ of workload level wl across the entire exercise is calculated for each subject as shown in equation (1). Here, wl is the workload level recognized from EEG using the EEG processing program introduced in Section 3.2, $wl \in \{1, 2, 3, 4\}$,

$$P(wl) = \frac{c(wl)}{\sum_{wl=1}^{4} c(wl)} \tag{1}$$

where *c(wl)* is the count of occurrence of workload *wl*.

For example, workload level 1 takes 90%, workload level 2 takes 3.7%, workload level 3 takes 4%, and workload level 4 takes 2.3% for subject 1 in the exercise 1. The difficulty level of that exercise and the percentage of different workload levels are used as features, while the evaluation decision (fail, pass, or retrain) of that subject in the exercise is used as labels. A logistic regression classifier is trained to identify the evaluation decision (pass, fail, or retrain) with leave-one subject-out cross validation. The classification accuracy obtained from leave-one subject-out cross validation is 88.89%.

3.4. Evaluation Program

With the evaluation algorithm introduced in section 3.3, the evaluation program is implemented using HTML and JavaScript. In this system, first, the maritime instructor/examiner needs to input information such as the seafarer's name and age. The user also has to input the timing, the corresponding difficulty levels, and importance of the demanding events as shown in Fig. 3. The next step is specifying the directory where the workload and stress recognition results are stored. After inputting all necessary information, the program 1) retrieves the EEG-based brain states recognition results corresponding to the demanding events, 2) calculates the probability mass function $P(wl)$ of workload level $wl \in \{1, 2, 3, 4\}$ across each events, 3) feeds these probability and difficulty level of each event into the pre-trained logistic regression classifier. Instead of showing the decision label directly, the probability of "passed", "fail" and "retrain" decision p_{ij} output by the logistic regression classifier are displayed for the demanding events as shown in Fig. 4, here , $\mathrm{i} \in \{\text{pass, fail, or retrain}\}$ which represents different decisions, $\mathrm{j} \in \{1, \ldots, \mathrm{n}\}$ which denotes all n demanding events. A score P_i of decision i, i∈{pass, fail, or retrain} is then calculated based on p_{ij} using weighted sum model as shown in equation (2). This score is used to make a final decision about the seafarer's performance.

$$P_i = \sum_{j=1}^{n} w_j p_{ij}\,, \mathrm{i} \in \{\text{pass, fail, or retrain}\} \tag{2}$$

where w_j the importance level inputted by the user for each event j and p_{ij} is the probability of decision i in each event j. Finally, the decision with the highest probability is considered as the final assessment conclusion.

$$\text{Decision} = \max(P_i),\ i \in \{\text{pass, fail, or retrain}\} \tag{3}$$

A pseudocode is given as Algorithm 1 to further explain the algorithm of evaluation program. As shown in Fig. 4, both detailed analysis of the demanding events and a final decision such as pass, fail or retrain are given, together with a pie chart that illustrates the proportion of fail, retrain, and pass. If the maritime instructor/examiner is interested to monitor how the workload/stress of the seafarer change over time in particular events, the system provides such details in a bar chart as shown in Fig. 5 where the time resolution is 1 second. The same procedure can be used to assess the stress states of the seafarers during the exercise when EEG-based stress results are retrieved. Additionally, full result and summary descriptions are given to let the maritime instructors get an insight of the seafarers' psychophysiological states during the whole exercise. Fig 6, 7, and 8 give examples of full result and summary result descriptions for the overall pass, fail, and retrain decision respectively.

Algorithms 1 Evaluation algorithm

```
{Input includes the timestamps, the difficulty level, the
importance level of the demanding events}
Input: eventInfo
{retrieve the number of the demanding events}
n ← size(eventInfo, 1)
for all j such that 1≤ j ≤ n do
    {Retrieve the timestamps of a demanding event}
    timePoints ← size(eventInfo_j, 1)
    {Retrieve the difficulty level of the demanding event}
    difficultyLvl ← eventInfo_j
    {Retrieve the importance level of the demanding event}
    importanceLvl ← eventInfo_j
    {Retrieve recognized brain state of the demanding event}
    brainState ← getEEG(timePoints)
    {Calculate probability mass function }
    P(wl) = ComputePMF(brainState)
    {Input probability mass function together with
    difficulty level to logistic regression classifier}
    p_ij = LR(P(wl), difficultyLvl)
end for
{make final decision based on weighted sum model and
 importance level}
P_i = ComputeWSM(p_ij, importanceLvl)
D = max(P_i)
```

4. Case Study on Workload Assessment

A case study to analyze performance of 4 maritime pilots using the implemented EEG-based assessment system is done and presented in this Section.

4.1. Data Collection

Four pilots whose average age was 30 while the average total sea time 34 months participated in the experiment. Each pilot attended one simulation exercise in the simulator, and the exercise took about 60 minutes. The simulator provides a 360-degree field of view and provides the state-of-the-art equipment such as Automatic Radar Plotting Aid (ARPA), True Motion radar, navigational aids displays and controls.

Consent form and briefing were done for each pilot before the experiment. After that, calibration of EEG-based emotion and workload recognition was done in the simulator, followed by the maritime exercise. In the exercise, the pilot was the authority onboard the vessel. The captain and the helmsman assisted to the pilot in bringing the vessel safely to the port with the help of the vessel traffic officer on the walkie-talkie. EEG data were recorded during the exercise as shown in Fig. 9 using Emotiv [46] device with 14 electrodes. Videos were taken during the experiment to label the demanding events during the exercise and monitor the behavior of the pilots.

4.2. Results

The EEG data were processed by the processing program and then fed into the evaluation program to get the assessment recommendation on the performance. Based on the videos, all events for each pilot are labeled with the corresponding time. The name of the events, the corresponding time, the difficulty level of the events, and the importance of the events were input into the evaluation program. After that, each event is assessed with the pass, retrain, and fail probability. The results are presented in Table 1. There are mainly two events in common in this exercise, which are passing vessels and controlled turn. Thus, the pilots may encounter slightly different events according to the speed and route of their cruise. Recommendation on each event based on the probability and the final recommendation are also tabulated in Table 1. For example, it can be seen that Pilot 4 performed the best among all the pilots, while Pilot 1, 2, and 3 may need more training as Pilot 4 got a pass recommendation, Pilot 2 got a retrain recommendation, and Pilot 1 and 3 got fail recommendation when considering the overall performance. Fine details are also provided, for example, Pilot 3 was likely to manage controlled turn but didn't do well in passing vessels and berthing. A maritime expert, who has 7-year experience as a captain and 26.5-year experiment as lecturer and manager in maritime institute, was interviewed to assess the performance of the pilots and the decisions from the expert is consistent with the output of the system.

Table 1. Assessment results of four pilot.

Subject	Event	Probability			Final Recommendation on each event	Overall Recommendation
		pass	retrain	fail		
Pilot 1	Passing vessels	0.00%	8.82%	91.18%	Fail	Fail
	Steering failure	0.00%	7.66%	92.34%	Fail	
	Controlled turn	0.00%	9.62%	90.38%	Fail	
	Parallel indexing	0.00%	27.04%	72.96%	Fail	
Pilot 2	Passing vessels	0.00%	23.19%	76.81%	Fail	Retrain
	Maneuvering in restricted waters	3.06%	96.94%	0.00%	Retrain	
	Controlled turn	0.32%	99.68%	0.00%	Retrain	
Pilot 3	Passing vessels	0.00%	24.25%	75.75%	Fail	Fail
	Controlled turn	88.15%	11.85%	0.00%	Pass	
	Berthing	0.00%	16.50%	83.50%	Fail	
Pilot 4	Passing vessels	89.54%	10.46%	0.00%	Pass	
	Maneuvering in restricted waters	90.21%	9.79%	0.00%	Pass	Pass
	Controlled turn	90.18%	9.82%	0.00%	Pass	

5. Conclusion

In this paper, a novel EEG-based system for psychophysiological evaluation of seafarers is presented. It enables the current simulator-aided assessment with additional evaluation by psychophysiological states of the seafarers, which can provide the maritime instructors/examiners with the more comprehensive view of the seafarers' performance. It not only enables an automatic evaluation of the seafarers which ease the burden of the instructors/examiners, but also avoid performance evaluation bias if any. EEG-based seafarers' evaluation algorithms using machine learning techniques were proposed and implemented. The proposed system can output an indicative recommendation such as "pass", "retrain" or "fail" based on the objective EEG-based measurements of mental workload and stress experienced by the seafarers during the exercises.

A case study to assess 4 pilots using the proposed system is presented. The results show that two of the pilots get "fail" results, one gets "retrain" result, and one gets "pass" results. The output of the system is consistent with the decision made by the maritime expert towards the pilots' performance, which confirms the reliability of the proposed system. In addition, the system also provides the detailed evaluation results for each demanding event. The instructors can use such details to decide which operation still lacks skills and require retraining for a particular seafarer. In the next step, the system will be tested with more seafarers and we are also working on improving the accuracy of the EEG-based brain state recognition algorithms. Subject-independent algorithms using deep learning techniques are being proposed and will be validated in future as it can ease the burden of the calibration when the system is used.

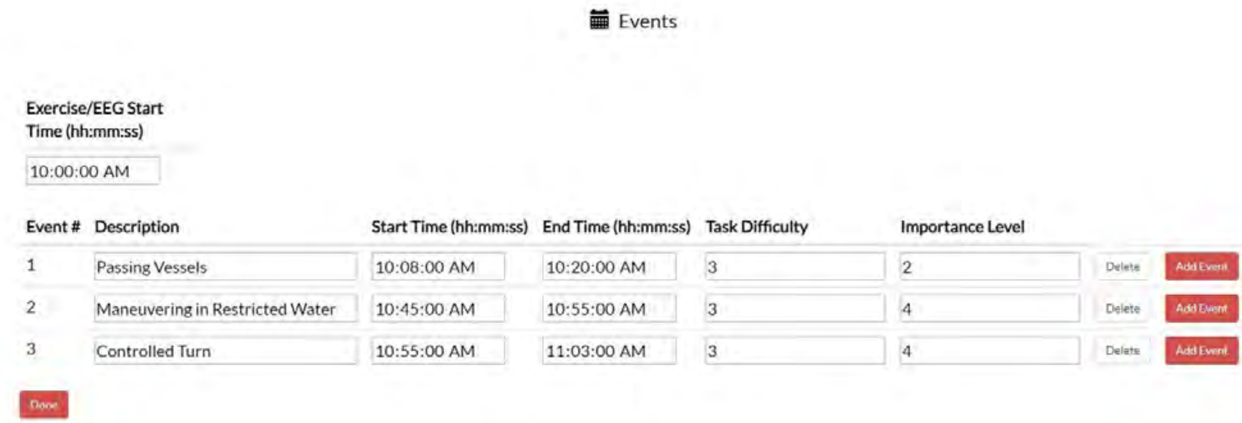

Fig. 3 - Screenshot of inputting the demanding events in evaluation program.

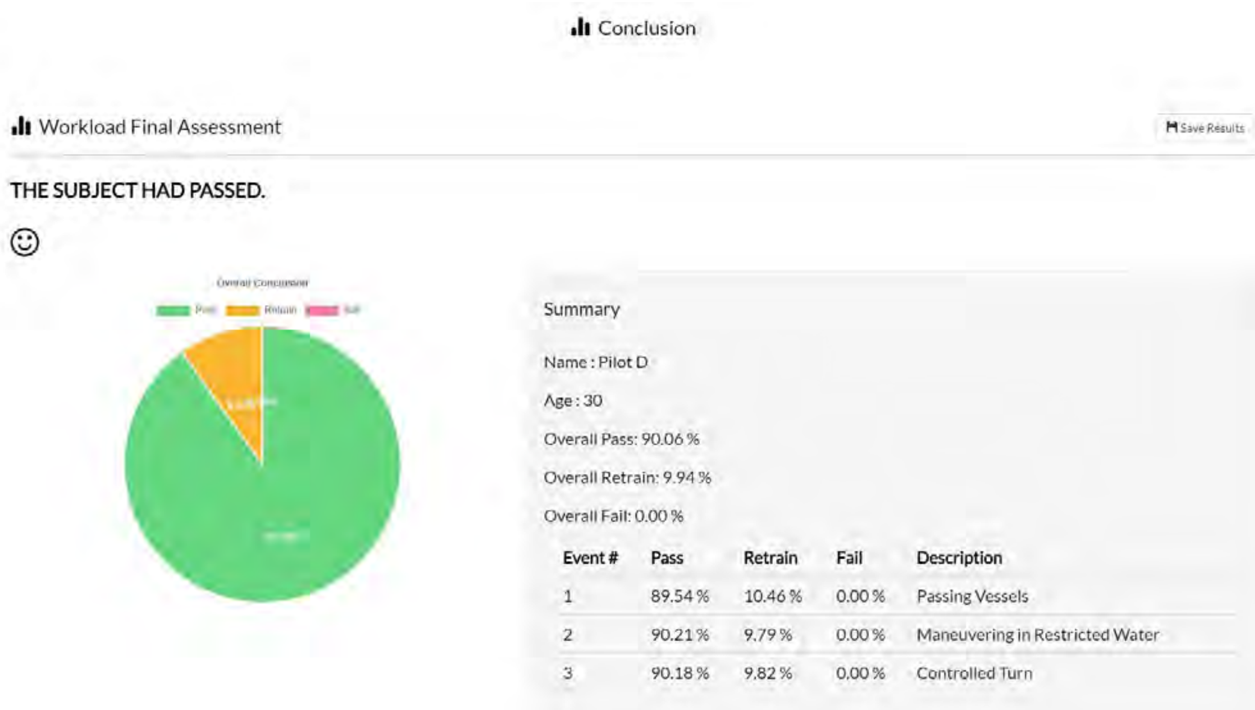

Fig. 4 - Final recommendation by the evaluation program.

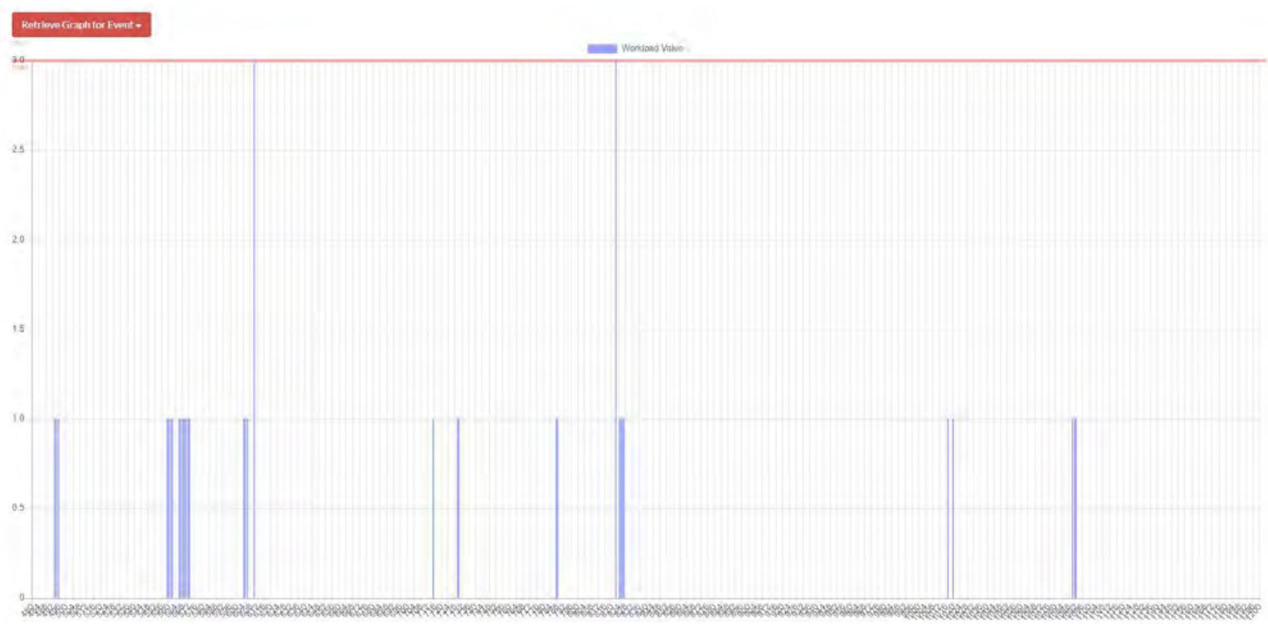

Fig. 5 - Detailed changes of workload over time in the evaluation program.

Pilot D's Full Result Description

Pilot D's performance on this maritime exercise results a pass conclusion. In the assessed exercise, the trainee encountered 3 events. The trainee tends to manage event 2, which is Maneuvering in Restricted Water with difficulty level 3. The trainee experienced low workload and low stress in this event. The trainee is less likely to be comfortable with event 1, which is Passing Vessels with difficulty level 3. The trainee experienced low workload and low stress in this event.

Pilot D's overall performance suggests a high level of ability to performance the maritime exercise.

Pilot D's Summary Result Description

- The trainee obtains a pass of the maritime exercise
- The trainee is likely to manage event 2, which is Maneuvering in Restricted Water with difficulty level 3. The trainee experienced low workload and low stress in this event.
- The trainee is less comfortable to perform well in event 1, which is Passing Vessels with difficulty level 3. The trainee experienced low workload and low stress in this event.
- The trainee shows a high level of ability to performance the maritime exercise.

Fig. 6 - Full result and summary resutls description for “Pass” recommendation.

Pilot B's Full Result Description

Pilot B's performance on this maritime exercise results a retrain conclusion. In the assessed exercise, the trainee encountered 3 events. It is suggested to retrain on the events listed below.

Event 1, Passing Vessels
Event 2, Maneuvering in Restricted Water
Event 3, Controlled Turn

Pilot B's overall performance suggests a low level of ability to performance the maritime exercise.

Pilot B's Summary Result Description

- The trainee obtains a retrain of the maritime exercise.
- The trainee is not likely to perform well in event 1, which is Passing Vessels with difficulty level 3. The trainee experienced median workload and median stress in this event.
- The trainee shows a low level of ability to performance the maritime exercise.
- It is recommended that the trainee should put more effort on Passing Vessels, Maneuvering in Restricted Water, Controlled Turn.

Fig. 7 - Full result and summary resutls description for "Retrain" recommendation.

Pilot A's Full Result Description

Pilot A's performance on this maritime exercise results a fail conclusion. In the assessed exercise, the trainee encountered 4 events. It is suggested to retrain on the events listed below.

Event 1, Passing Vessels
Event 2, Steering Failure
Event 3, Controlled Turn
Event 4, Parallel Indexing

Pilot A's overall performance suggests a low level of ability to performance the maritime exercise.

Pilot A's Summary Result Description

- The trainee obtains a fail of the maritime exercise.
- The trainee is not likely to perform well in event 4, which is Parallel Indexing with difficulty level 3. The trainee experienced median workload and median stress in this event.
- The trainee shows a low level of ability to performance the maritime exercise.
- It is recommended that the trainee should put more effort on Passing Vessels, Steering Failure, Controlled Turn, Parallel Indexing.

Fig. 8 - Full result and summary resutls description for "Fail" recommendation.

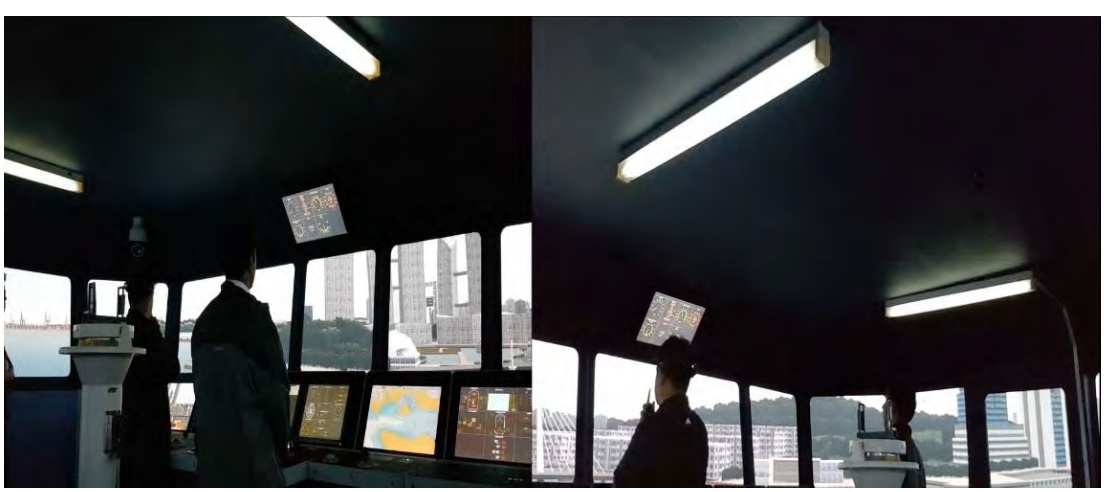

Fig. 9 - Maritime pilot with EEG device performing tasks in the simulator.

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