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Mental Fatigue Assessment in Demanding Marine Operations

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Preface

The maritime operation is very demanding. These operations can be especially complex and dangerous when effective coordination between different maritime vessels and several maritime operators is required naturally and necessarily. Although the safety and efficiency of maritime operations have been improved significantly due to the unitizing of modern technology, human operators are still an indispensable factor of maritime operations and have direct impacts on the quality and safety of such complex operations. With the development of ship intelligence, human operators start to be transferred from vessels to onshore control centers slowly. However, the impact of human operators in maritime operations will still be significant. It is not likely that humans are completely removed from the maritime operational loop.

A poor performance in a critical moment can lead to disastrous results, including near misses, economic and environmental losses, and fatalities. Several human factors can lead to poor performance, including incorrect, incomplete, or nonexistent following of procedures; lack of situational awareness; and physical or mental fatigue. Among these issues, mental fatigue is responsible for reducing cognitive capabilities, situational awareness, and decision-making skills. Early detection and assessment of mental fatigue (MF) can be used to reduce the number of causalities, to benefit crew members, ship owners, and the maritime environment. How to assess MF objectively in real-time maritime operations is still a challenging and unanswered question. As a conclusion, it is important to develop and implement methods to monitor the decrement of performance from operators, aiming to increase safety in demanding maritime scenarios.

This book will try to investigate how MF can be objectively measured during demanding maritime operations so as to improve the operation safety. Based on the physiological characterization of MF, the best approach to quantify this phenomenon is through the use of physiological sensors. Different sensors such as ECG, EMG, EEG, temperature sensor, and eye tracker can be applied, individually or in conjunction, in order to collect relevant data that can be mapped to an MF scale. More than simpler sensor fusion, this book will bridge the gap between relevant sensor data and a quantifiable MF level using both data-driven and model-based approaches. Data-driven part investigates the use of different Neural Networks (NNs) combined for the

MF assessment (MFA) task. Among the different architectures tested, Convolutional Neural Networks (CNN) showed the best performance when dealing with multiple physiological data channels. Optimization was used to improve the performance of CNN in the cross-subject MFA task. Testing different combinations of physiological sensors indicated a setup consisting of EEG sensor only was the best option, due to the trade-off between assessment precision and sensor framework complexity. These two factors are of great importance when considering an MFA system that could be implemented in real-life scenarios. The model-based discussion applies the current knowledge about the use of EEG data to characterize MF to develop an MF approach to quantify the progression of MF in maritime operators.

More importantly, for all research results presented in this book, realistic vessel simulators were used as a platform for experimenting with different operational scenarios and sensors' setups.

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Acronyms

BO	Bayesian optimization
BOGP	Bayesian optimization with Gaussian process
CNN	Convolutional neural network
DBN	Deep belief neural network
DT	Decision tree
DWT	Discrete wavelet transform
ECG	Electrocardiogram
EEG	Electroencephalogram
EI	Expected improvement
EMG	Electromyogram
EOG	Electrooculogram
FFT	Fast Fourier Transform
FNN	Feed-forward neural network
FPCA	Functional principal component analysis
FRE	Fatigue-related errors
FRI	Fatigue-related incident
FRMS	Fatigue Risk Management System
FRT	Fatigue-risk trajectory
HF	Human factors
HFACS	Human Factors Analysis and Classification System
ICA	Independent Component Analysis
IMO	International Maritime Organization
KSS	Karolinska sleepiness scale
LSTM	Long short-term memory neural network
MF	Mental fatigue
MFA	Mental fatigue assessment
MFP	Mental fatigue prediction
MLP	Multilayer perceptron
NN	Neural network
NTNU	Norwegian University of Science and Technology
PCA	Principal Component Analysis

POI	Probability of improvement
PSD	Power spectral density
PSV	Platform supply vessel
PVT	Psychomotor vigilance test
RBM	Restricted Boltzmann machine
SA	Situational awareness
SLP	Single layer perceptron
SMBO	Sequential model-based optimization
SVM	Support Vector Machine
UCB	Upper confidence bound

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