Nautical and Maritime Culture, from the Past to the Future

Proceedings of the 4th International Conference (CNM 2024), Venice, Italy, 28–29 November 2024

Edited by

Alberto Marino', Serena Bertagna, Vittorio Bucci and Luca Braidotti

IOS Press

Since the dawn of history, the sea has both connected and divided human societies, but it has never presented an insuperable barrier, and humans still take to the sea to discover and connect the world, developing increasingly ingenious and innovative technological solutions in order to do so.

This book presents the proceedings of CNM 2024, the 4th International Conference of Nautical and Maritime Culture, held on 28 and 29 November 2024 in Venice, Italy. Conferences in the ICNM series, organized by the Associazione Italiana di Tecnica Navale (ATENA), are important scientific events covering all aspects of maritime culture. They aim to promote a dialogue between scholars, professionals, and all those with the relevant skills, in the areas of research and development, and the enhancement of knowledge. A total of 29 submissions were received for the conference, of which 19 were accepted for presentation and publication after review, resulting in an acceptance rate of 66%. Topics covered include the refitting and conservation of nautical marine and maritime heritage; naval architecture and the evolution of marine engineering; marine archaeology and the history of ships and navigation; waterfront evolution; coastal marine environment; and ship and nautical design.

Covering a wide range of topics, the book will be invaluable to all those with an interest in nautical and maritime culture.

NAUTICAL AND MARITIME CULTURE, FROM THE PAST TO THE FUTURE

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Volume 8

Recently published in this series

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PRINTED IN THE NETHERLANDS

Preface

About ICNM

The ICNM conference, organised by the Associazione Italiana di Tecnica Navale (ATENA), is one of the major Italian scientific events on maritime and nautical culture. The conference covers all conceptual and theoretical aspects of research in the engineering, history, architecture, economic, and social-sciences fields.

Since the dawn of history, the sea has connected and divided human societies, but it has never been an insuperable barrier for man. Now, as in the past, human beings traverse the sea to discover, inhabit and connect the entire known world, developing increasingly ingenious and innovative technological solutions in order to do so. They build cities and ports on the shore, increasing productive capacity and establishing new commercial and political relations, and despite the virtual interconnection of the modern world, the essence of human evolution is still expressed and sublimated at sea in a constant tension towards the unknown and the attempt to go beyond the limits of knowledge. This is a path marked by the discoveries, failures and transitions which are the milestones of the secular, human-sea relationship.

The ICNM conference aims to promote a dialogue between scholars, professionals, and all those with particular skills in research into, and development and enhancement of, maritime culture.

About ATENA

ATENA (Associazione Italiana di Tecnica Navale) was established in Genoa in 1947 on the initiative of a group of Italian naval architects and marine engineers. Its principal aim was to extend the initiatives of the Collegio degli Ingegneri Navali e Meccanici in such a way as to incentivise the discussion of ship design and maritime industry between the Italian specialists in this sector.

The first Technical National Conference was held in February 1948, attracting contributions from the most representative personalities of the national maritime sector, including professional naval architects and marine engineers, professors, researchers, ship owners and insurers.

Since the foundation of ATENA, its members have been providing high-level contributions to research, ship design & construction, and the shipping industry. A primary focus is also given to other relevant topics such as maritime safety and environmental issues.

Because the maritime industry acts in a global market, ATENA also spreads this vision worldwide by opening its conferences and events to international professionals.

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About the Conference

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Topics

- Refitting and conservation of nautical marine and maritime heritage
- Naval architecture and marine engineering evolution
- Marine archeology
- Seafaring costumes and traditions
- History of ships and navigation
- Maritime museums and libraries
- Waterfront evolution
- Coastal marine environment
- Shipowners and shipyards
- Ship and nautical design

Peer Review Statement

Number of submitted papers: 29
Number of accepted papers:19
Acceptance rate: 66%

Proceedings of the 4ᵗʰ International Conference on Nautical and Maritime Culture

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Contents

Predicting Sailing Yacht Hull Resistance Using Gaussian Process Regression

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Abstract. Hull resistance is a critical factor in determining a vessel's performance, fuel consumption, and overall efficiency. Traditional methods for evaluating hull resistance involve time-consuming and expensive experiments or computational fluid dynamics (CFD) simulations.

Machine learning (ML) offers a promising alternative for predicting ship resistance, leveraging data-driven models to establish relationships between hull characteristics and resistance values. This study investigates the application of machine learning to evaluate a sailing yacht bare hull resistance using a machine learning Gaussian Process Regression model trained with the Delft systematic hull series. A dataset comprising 50 sailing yacht hull forms and corresponding resistance values evaluated for Froude numbers between 0.1 and 0.6 is used to train and validate various ML models. The models are evaluated based on RMSE, R-Squared and MSE values. The results demonstrate the effectiveness of ML Gaussian Process Regression models in predicting ship resistance and the can be integrated into the early stages of ship design, facilitating the optimization of hull forms for improved hydrodynamic performance.

In conclusion, this research establishes machine learning as a powerful tool for evaluating sailing yacht resistance, offering generalizable predictions that significantly contribute to more efficient, cost-effective yacht and ship design optimization.

Keywords. Gaussian Process Regression (GPR), Bare Hull Resistance Prediction, Hydrodynamic Performance Optimization

1. Introduction

The prediction of ship resistance has traditionally relied on empirical methods and physical testing. Early methods, such as towing tank experiments and the use of empirical regression models, provided accurate but time-consuming results. Gerritsma et al. (1981) [1] pioneered the use of systematic hull series, including the Delft Systematic Yacht Hull Series (DSYHS), to predict ship resistance, offering valuable insights into hull form performance. While effective, these traditional approaches require significant resources and are limited in their ability to generalize to new hull forms without substantial testing.

In recent years, machine learning (ML) has emerged as a powerful tool for predicting ship resistance, offering data-driven models that capture the complex relationships between hull geometry and resistance. Early applications of ML in ship resistance

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prediction involved techniques such as linear regression and decision trees. For example, Li et al. [2] explored the application of decision trees and support vector machines (SVM) in predicting ship resistance, achieving promising results compared to traditional methods.

More advanced ML models, such as neural networks and Gaussian Process Regression (GPR), have shown even greater potential. Sun et al. [3] applied GPR in industrial prediction tasks, demonstrating its ability to handle non-linear relationships and achieve high accuracy. In the context of ship design, GPR offers a flexible approach that can incorporate various design parameters—including length, beam, and displacement—to predict resistance with greater precision than traditional models. These advancements underscore the value of ML models, particularly GPR, in modern naval architecture.

Hull resistance is a pivotal factor influencing a vessel's performance, fuel consumption, and overall efficiency. Traditionally, evaluating hull resistance has relied on labour-intensive and costly methods, such as physical experiments in towing tanks or computational fluid dynamics (CFD) simulations. While accurate, these methods come at the cost of significant time and resources. CFD simulations, for example, provide detailed insights but require substantial computational power and expertise.

To streamline the design process in the early stages, empirical formulas based on statistical data are often used for quick resistance estimates. These are supplemented by data from systematic hull series, such as the Delft Yacht Series, which provides standardized resistance values for various hull forms.

This study explores the use of Gaussian Process Regression (GPR), a machine learning approach, to predict the resistance of a sailing yacht's bare hull. By training the model with the Delft Systematic Yacht Hull Series, which includes more than 50 sailing yacht hull forms and their corresponding resistance values for Froude numbers between 0.1 and 0.6, this research aims to validate the efficacy of GPR models. The models' performance is assessed using Root Mean Square Error (RMSE), R-Squared (R^2), and Mean Squared Error (MSE) metrics.

The findings highlight the potential of GPR models to provide accurate, efficient, and generalizable predictions of ship resistance, demonstrating their applicability in the early stages of ship design for optimizing hull forms and enhancing hydrodynamic performance. This approach is particularly useful in the preliminary phase of design projects, where quick and reliable predictions can significantly streamline the process.

In this context, we apply GPR to the DSYHS dataset to assess its performance and compare various kernels for predicting hull resistance, aiming to validate its use in early-stage yacht design optimization.

2. Materials and methods

The foundation for this study's machine learning model is the Delft Systematic Sailing Yacht Series (DSYHS), which provides a comprehensive dataset of sailing yacht hull forms and their corresponding resistance values. Using this dataset, we calculate the total resistance for each yacht across a range of Froude numbers up to 0.6, employing established regression formulas specific to the series. The calculated resistance values serve as the target variable for our machine learning models.

To train and validate the models, we split the dataset, reserving 10% of the data for testing purposes and using the remaining 90% for training. This approach ensures that

the model's performance is evaluated on an independent subset of data, offering a robust assessment of predictive accuracy.

While traditional methods like towing tank experiments provide accurate results, their high cost and time-consuming nature limit their use in the preliminary design phases. In contrast, machine learning (ML) methods, such as Gaussian Process Regression (GPR), allow for rapid, data-driven predictions, leveraging the DSYHS dataset for accurate and efficient resistance estimation.

2.1. The Delft Systematic Yacht Hull Series

The Delft Systematic Yacht Hull Series (DSYHS) is a well-established collection of empirical data and regression models developed by the Ship Hydromechanics Laboratory at Delft University of Technology [1]. Primarily used for predicting the resistance and powering of sailing yachts, it offers a systematic and reliable approach to yacht performance analysis.

The development of the Delft Yacht Series involved extensive towing tank tests on a variety of yacht hull forms, gathering detailed resistance data across configurations that vary in length, beam, draft, displacement, and hull shape. By systematically altering these parameters, researchers were able to understand their individual and combined effects on yacht resistance.

A key contribution of the Delft Yacht Series is its provision of regression formulas and empirical data for predicting the total resistance of yacht hulls in calm water. This includes:

- Viscous resistance, related to friction between the hull and water.
- Wave-making resistance, caused by the energy required to create waves as the yacht moves.

Accurate prediction of these resistance components is critical for designing efficient and competitive sailing yachts.

The DSYHS is widely used by naval architects and yacht designers, particularly during the preliminary design stages. It allows designers to optimize hull shapes to achieve minimal resistance, improving overall efficiency. By leveraging the data and formulas provided by the Delft Series, designers can make informed decisions without the need for costly model testing for every new design.

One of the major advantages of the DSYHS is the reliability of its predictions, stemming from the comprehensive nature of the data collected and the robust regression models developed. This reliability reduces uncertainty in performance predictions, offering a solid foundation for design decisions.

In modern yacht design, the Delft Series data is often integrated into design software, enabling designers to quickly assess the resistance and performance characteristics of their designs. This integration streamlines the design process, making it easier to evaluate different hull configurations and optimize them for specific performance goals.

2.2. Machine Learning Model Training

The machine learning model training process for this study is based on the comprehensive dataset derived from the Delft Systematic Yacht Hull Series (DSYHS). The steps involved are outlined below:

First, the resistance for each yacht in the series is calculated across a range of Froude numbers from 0.1 to 0.6. The Froude number is a dimensionless parameter crucial in naval architecture, as it relates the yacht's speed to its length and influences both hydrodynamic performance and resistance characteristics.

For these calculations, regression formulas derived from the empirical DSYHS data are applied, using coefficients specific to each yacht's parameters—such as length, beam, draft, and displacement. Once the total resistance values are calculated for this range of Froude numbers, a comprehensive dataset is compiled. The dataset includes input features like hull dimensions, geometric coefficients, and corresponding resistance values.

To train the machine learning models, the dataset is divided into training and testing subsets, with 90% of the data used for training and 10% reserved for testing. This split ensures the model's performance can be evaluated on unseen data, offering an unbiased assessment.

Several machine learning algorithms are tested to identify the most effective model for predicting yacht resistance, including linear regression, decision trees, random forests, and support vector machines (SVM). Each model is trained on the 90% training dataset, learning the complex relationships between the yacht's design parameters and resistance characteristics. Gaussian Process Regression (GPR) is selected as the focus due to its flexibility in handling non-linear relationships.

During the training phase, cross-validation techniques are used to optimize the model's hyperparameters and avoid overfitting. Cross-validation involves dividing the training data into multiple folds, training the model on different subsets, and ensuring generalization to unseen data.

After training, the models are evaluated using the 10% testing dataset. Performance metrics, such as mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2), are calculated to assess each model's accuracy and reliability. These metrics help assess how well the models predict resistance based on the input features.

Finally, the best-performing model is selected based on these evaluation metrics [Table 1]. The chosen model is then fine-tuned and validated to ensure its robustness and accuracy for predicting yacht resistance across different design configurations.

In summary, this approach involves calculating resistance values for yachts using Delft Series regression formulas, creating a comprehensive dataset, training multiple machine learning models, and evaluating their performance. The systematic process ensures that the resulting machine learning model is reliable and effective for use in yacht design and optimization.
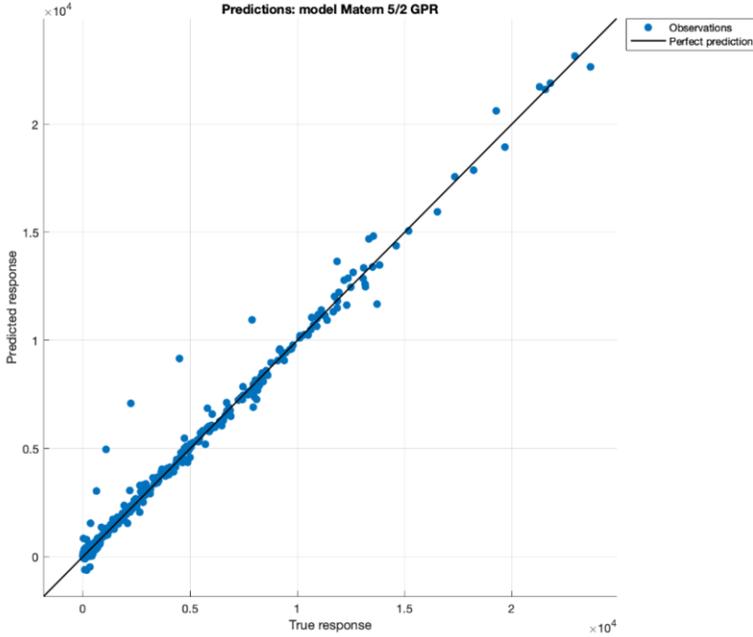
Figure 1. Model Matern 5/2 GPR results

Table 1. Models training

Model trained	RMSE (Validation)	R-Squared (Validation)	MSE (Validation)
Matern 5/2 GPR	429.33	0.99	1.8432e+05
Rational Quadratic GPR	434.94	0.99	1.8918e+05
Squared Exponential GPR	509.64	0.98	2.5973e+05
Exponential GPR	718.94	0.97	5.1688e+05

3. Results

The evaluation of various Gaussian Process Regression (GPR) models was conducted to assess their performance in predicting yacht hull resistance using the Delft Systematic Yacht Hull Series (DSYHS) dataset. The models were evaluated using three key metrics: Mean Squared Error (MSE), R-squared (R^2), and Log-Marginal Likelihood (LML). These metrics offer insights into the accuracy of the predictions, the proportion of variance explained by the model, and the model's fit to the observed data. The following GPR models were analysed: Matern 5/2, Rational Quadratic, Squared Exponential, and Exponential GPR models [Table 1].

3.1. Matern 5/2 GPR

The Matern 5/2 GPR model demonstrated the best performance, with an MSE of 429.33 and an R^2 value of 0.99, indicating a high level of accuracy in its predictions.

Additionally, the LML for this model was 1.8432e+05, reflecting a strong fit to the observed data.

The Matern 5/2 kernel is well-suited for datasets that require a balance between flexibility and smoothness, which likely explains its success in predicting yacht hull resistance. Its ability to model smooth, moderately complex functions is particularly effective for the DSYHS dataset, which includes variations in hull geometry and performance characteristics.

3.2. Rational Quadratic GPR

The Rational Quadratic GPR model exhibited slightly higher MSE at 434.94, but maintained an R^2 value of 0.99, suggesting a similar level of predictive accuracy to the Matern 5/2 GPR.

The LML for this model was 1.8918e+05. The Rational Quadratic kernel is known for handling data with varying degrees of smoothness, which likely contributed to its strong performance. While this model is slightly less flexible than the Matern 5/2, it still provided reliable predictions, making it a viable alternative in scenarios where different smoothness levels are present in the dataset.

3.3. Squared Exponential GPR

The Squared Exponential GPR model performed adequately, with an MSE of 509.64 and an R^2 value of 0.98, though it did not match the accuracy of the Matern 5/2 or Rational Quadratic models. The LML for this model was 2.5973e+05.

The Squared Exponential kernel, which assumes smooth and continuous functions, may have been less effective due to potential overfitting or insufficient flexibility to model the complexities of the dataset. While this kernel is widely used for its simplicity, it appears less suited for the intricate relationships between hull parameters and resistance values in the DSYHS dataset.

3.4. Exponential GPR

The Exponential GPR model recorded the highest MSE of 718.94 and the lowest R^2 value of 0.97, indicating the least accurate predictions among the models tested. The LML for this model was 5.1688e+05.

The Exponential kernel is typically used for modelling fewer smooth functions. Its simplicity, however, may have limited its ability to capture the complexities of the data in this study. As a result, this model was less effective in predicting yacht resistance, suggesting that it is not ideal for datasets that require more flexible and smooth functions.

3.5. Summary of Results

In summary, the Matern 5/2 GPR model provided the best balance of low prediction error and high model accuracy, closely followed by the Rational Quadratic GPR model. The Squared Exponential and Exponential GPR models, while still providing reasonable predictions, exhibited lower precision, and fit compared to the Matern 5/2 and Rational Quadratic models.

These results highlight the importance of selecting an appropriate kernel function in Gaussian Process Regression to match the characteristics of the data being modelled. In the context of yacht hull resistance prediction, the Matern 5/2 and Rational Quadratic kernels appear particularly well-suited for capturing the nuanced relationships between hull geometry and resistance, offering valuable tools for early-stage yacht design optimization.

4. Conclusions

This study demonstrates that Gaussian Process Regression (GPR) is a reliable and effective method for predicting sailing yacht hull resistance. Among the models tested, the Matern 5/2 kernel achieved the highest accuracy, with an MSE of 429.33 and R² value of 0.99, highlighting its suitability for modelling the complex, non-linear relationships between hull geometry and resistance. The results show that GPR models can provide highly accurate predictions, making them valuable tools for early-stage yacht design.

These findings have significant implications for both academic research and practical yacht design. The ability to generate accurate, real-time predictions of hull resistance can streamline the design process, reducing the reliance on expensive and time-consuming methods such as towing tank experiments and computational fluid dynamics (CFD) simulations. By integrating GPR models into design workflows, naval architects can optimize hull forms more efficiently, leading to improved hydrodynamic performance and fuel efficiency.

In addition, this study underscores the importance of selecting appropriate kernel functions in GPR to match the complexity of the data being modelled. The Matern 5/2 and Rational Quadratic kernels have proven effective in capturing the nuanced relationships between design parameters and resistance, offering valuable insights for yacht optimization.

Future research could explore the use of more advanced machine learning algorithms, such as deep neural networks or ensemble methods, to further improve prediction accuracy and generalization across a broader range of vessel types.

Additionally, expanding the dataset to include more diverse hull forms and operational conditions could provide a more comprehensive model, further enhancing the predictive power of machine learning in naval architecture. Investigating hybrid approaches that combine GPR with other machine learning techniques may also unlock new levels of accuracy and efficiency in hull resistance prediction.

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Enhancing Leisure Sailing Experience Through Technology and Artificial Intelligence

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Abstract. This paper explores the potential of technology and artificial intelligence (AI) to revolutionize leisure sailing experiences by dynamically tailoring onboard environments to individuals' emotions and preferences. Traditionally, leisure activities have been somewhat static, offering limited scope for personalization. However, advancements in sensor technology and AI systems have opened new possibilities for enhancing well-being and enjoyment during leisure activities. Using leisure sailing as a case study, this paper demonstrates how onboard sensors and AI systems can respond in real-time to participants' emotions, adjusting various environmental factors such as lighting, music, ventilation, colours, and furniture layout to optimize comfort and enjoyment. By harnessing the power of technology and AI, leisure sailing experiences can be personalized and enriched, leading to enhanced relaxation and joy for participants. Furthermore, this paper encourages discussions on the broader potential of technology and AI to elevate leisure experiences across different domains. By focusing on advancements, applications, and ethical considerations, it aims to deepen our understanding of personalized and engaging leisure experiences. By fostering collaborations between technology developers, leisure industry professionals, and researchers, this paper seeks to inspire the creation of innovative solutions that reshape the future of leisure. In summary, this paper envisions a future where leisure sailing experiences are enhanced through seamless integration of technology and AI. By dynamically adapting to individuals' emotions and preferences, the onboard environment can be optimized to maximize comfort and happiness, providing a truly personalized and engaging leisure experience.

Keywords. Personalized Leisure Experiences, AI-Driven Sailing, Emotion-Responsive Environments

1. Introduction

This paper explores how technology and artificial intelligence (AI) can revolutionize leisure activities by dynamically tailoring experiences to individuals' emotions and preferences. Using leisure yachting as an example, it showcases how onboard sensors, AI systems, smart fabrics, and dynamic furniture can respond to participants' emotions, adjusting lighting, music, ventilation, colours, and furniture to enhance well-being. The paper encourages discussions on the potential of technology and AI to elevate leisure, focusing on advancements, applications, and ethical considerations.

This article is deeply inspired by my PhD research [2][5], which was developed through a collaboration between the University of Genoa, and the Genoa Merchant Marine Academy. Thanks to this partnership, it was possible to conduct extensive experiments and gather the necessary data for analysis. The research (Fig.1) focuses on multimodal emotion recognition systems to enhance safety and well-being in maritime environments. Through the integration of Facial Emotion Recognition (FER) and Speech Emotion Recognition (SER), we demonstrated AI's ability to detect and respond to emotional states, which has promising applications for dynamically adapting environments to improve both safety and comfort aboard ships.

Building on this foundation, this paper extends those findings to the realm of leisure activities, envisioning how AI-enhanced environments can not only improve operational safety but also significantly elevate passenger experiences by personalising onboard settings in response to emotional cues. The goal is to deepen our understanding of personalized and engaging leisure experiences, inspiring collaborations to reshape relaxation and joy. The envisioned future promises customized comfort and happiness in leisure through seamless technology and AI integration.

1.1. Our methodology
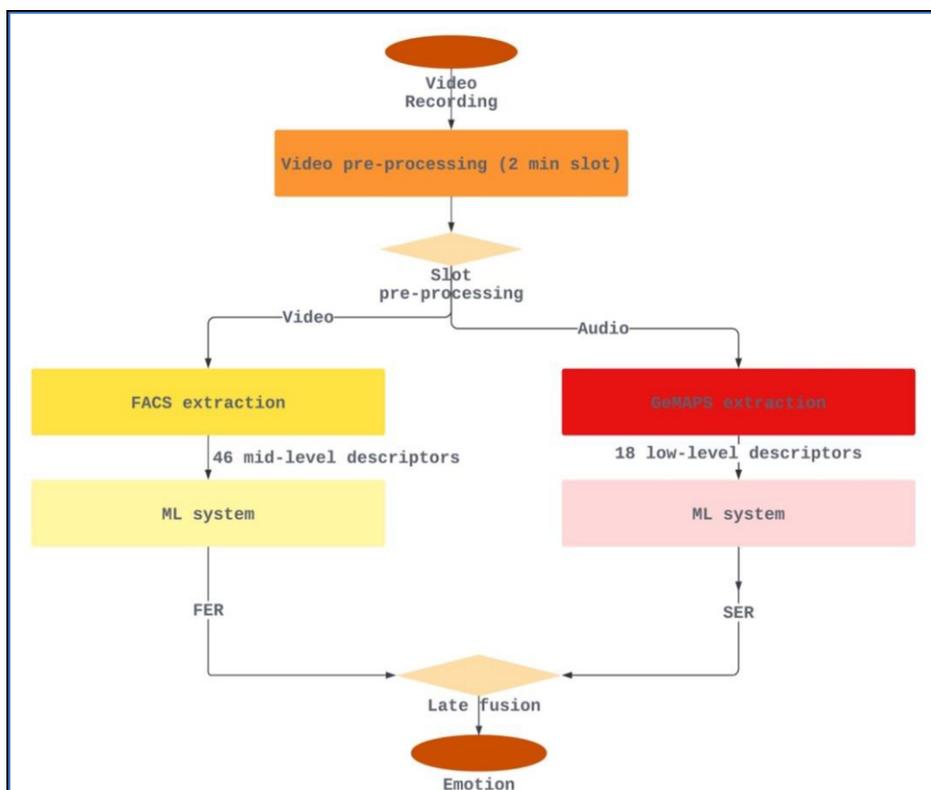
Figure 1. Our methodology

The methodology employed in this research involved a multimodal approach to emotion recognition, integrating facial expression analysis and speech emotion recognition.

The following steps outline the core components of our experimental design and data analysis process (Fig.1).

1.1.1. Participant Selection and Setup

A cohort of 12 participants was selected for the study, comprising maritime professionals and trainees from the Genoa Merchant Marine Academy. The participants were exposed to controlled maritime scenarios that were designed to elicit a range of emotional responses, including stress, relaxation, and excitement. These scenarios included simulated high-pressure situations, such as emergency drills, and calmer environments, such as routine operations or leisure settings on board.

The data analyzed in this study were derived from facial expression analysis using the Facial Action Coding System (FACS) and from speech analysis using the Geneva Minimalistic Acoustic Parameter Set (GeMAPS). These methods allowed for the detailed assessment of participants' emotional states based on their facial movements and vocal characteristics.

In future phases of the research, we plan to expand the methodology by incorporating biometric sensors, including Electrodermal Activity (EDA) sensors for skin conductance, heart rate variability (HRV) monitors, and Electroencephalogram (EEG) equipment, to track physiological changes associated with emotional states. This will enable a more comprehensive, multimodal understanding of emotional responses [3].

1.1.2. Data Collection

Data collection consisted of recording the following visual and auditory information from participants after exposing them to a series of scenarios. The video input was analyzed using FACS for facial micro-expressions, while audio input was processed with GeMAPS to indicate emotional changes in voice intonation and speech rhythm. This allowed a multimodal data integration of data streams, from facial expressions and voice patterns, into comprehensive analysis.

1.1.3. Emotion Recognition Systems

To analyze and interpret the data collected, we employed a range of AI-powered emotion recognition systems, including Morphcast, HumeAI, and OpenFace, and compared the results with the performance of an algorithm developed in-house (Fig. 2). These systems employed various advanced machine learning and deep learning techniques to detect and classify emotional states from the input data represented through facial expressions, voice, and physiological signals.

All systems were calibrated to identify the key emotional states, namely stress, happiness, sadness, and relaxation, and to check coherence among the emotional signals captured from different modalities (visual and audio). This was achieved with the multimodal approach that provided results cross-validated across different channels, hence increasing the accuracy and reliability of identified emotions.

1.1.4. Validation and Triangulation

To ensure the validity of the detected emotional states, we incorporated multiple levels of validation:

- *Self-reports:* At the end of each scenario, participants had to fill in a structured questionnaire based on which their self-perceived emotional states were assessed. We used the Self-Assessment Manikin (SAM) elaborated by Bradley and Lang in 1994 [1] that is well-known to be one of the most accepted tools from psychological studies to other fields like marketing and advertising. SAM is a non-verbal scale designed to quantify three basic dimensions of emotion-pleasure, arousal, and dominance-referred to as PAD. We did not use dominance.It consists of a set of abstract graphical figures placed horizontally along a 9-point continuum. Fig.3.
- *Expert Analysis:* An independent expert in cognitive anthropology, to add a further level of emotional interpretation, reviewed video recordings of the participants' facial expressions. This will then be compared with the AI-driven results to further ensure accuracy.
- *Triangulation:* The last step was triangulation of the results identified from the AI emotion recognition systems, self-reports, and expert ratings. In this regard, inconsistencies among these sources were outlined and were helpful in enhancing the AI algorithms to realize improved accuracy concerning the detection of emotions.
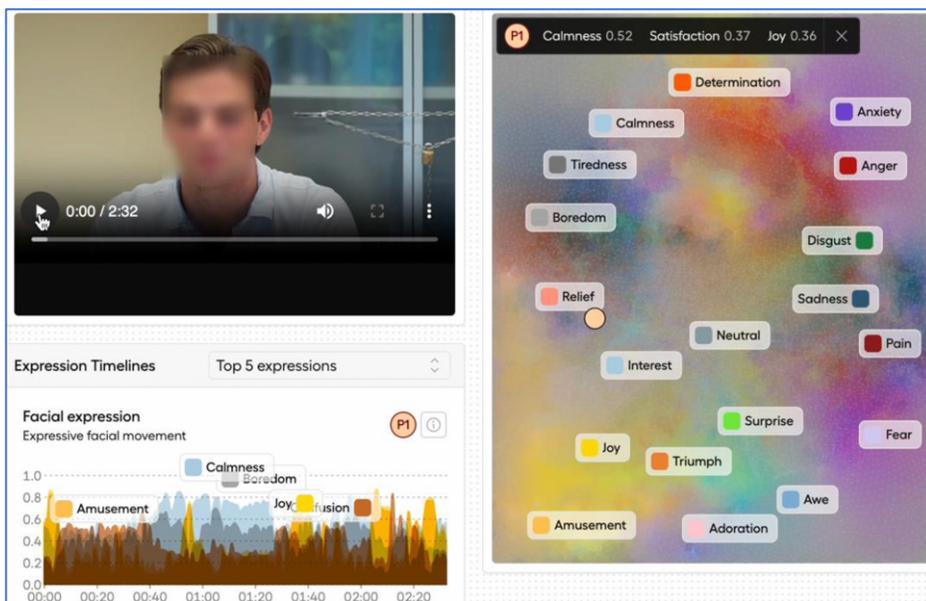

**Figure 2.** Example of emotion recognition from FACS

1.1.5. Data Analysis

The collected data was processed and analyzed using both quantitative and qualitative methods. Quantitative analysis involved calculating the correlation between the emotional states detected by the different systems (FACS, GeMAPS), while qualitative analysis focused on exploring the nuances of emotional responses, such as unconscious emotional cues that participants may not have been aware of but were detected by the AI.

The level of valence
(Tell us which number of pictures best describes
the level of happiness you feel right now)

unpleasant　　　　　　　　　　　　　　　　　　　pleasant
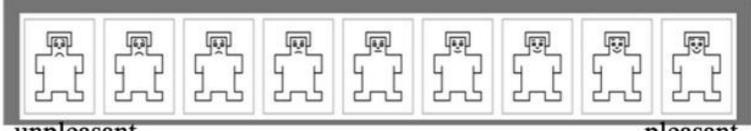
1　　2　　3　　4　　5　　6　　7　　8　　9

The level of arousal
(Tell us which number of pictures best describes the level of arousal you feel right now)

calm　　　　　　　　　　　　　　　　　　　　excited
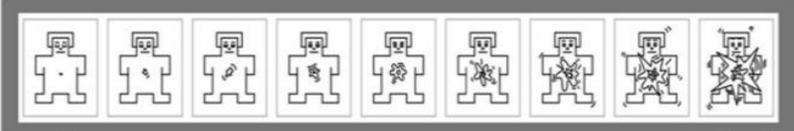
1　　2　　3　　4　　5　　6　　7　　8　　9

Figure 3. Part of the self-report questionnaire - Self-Assessment Manikin (SAM) [1]

The experimental procedure gave some critical results that showed the efficiency of a multimodal emotion recognition system in detecting and analysis of emotional conditions. The key findings are:

- The use of FACS for analyzing facial expressions, supported by GeMAPS for vocalizations analysis, allowed for a high level of accuracy in recognizing emotions such as stress, happiness, and relaxation. The system amply detected subtle changes in the emotional conditions of the participants in both highly charged and serene conditions.
- Results proved that there was a moderate to high correlation between the emotional states identified from facial expressions and those identified from speech. This indicates that the system identified coherent emotional signals across different data channels, hence giving a comprehensive assessment of the emotional responses from the participants.
- Differences in the self-reported emotions and AI-detected ones were the divergence between the emotional states by participants who experienced lower stress levels than what was assessed by the system from facial expressions and vocal patterns. This would go to show that the system picked up unconscious emotional responses, which means revealing hidden emotions that participants either did not recognize well or even shy away from showing.
- The system demonstrated the potential for real-time emotional feedback, which could be used to dynamically adapt environments based on detected emotional states. This is particularly valuable in maritime safety and leisure contexts, where the emotional well-being of individuals can significantly impact performance and overall experience.
- The system's ability to detect stress and fatigue in high-pressure scenarios, such as simulated emergency drills, was particularly promising. It suggests that

future applications could involve monitoring the well-being of professionals in demanding environments, enabling timely interventions to prevent errors or accidents.

In summary, the results of the experimentation validate the effectiveness of using multimodal systems for emotion recognition, providing a strong foundation for future applications in both safety-critical and leisure settings. Further research will incorporate additional biometric sensors to enhance the system's accuracy and comprehensiveness.

2. The Evolution of Leisure on Luxury Yachts: Harnessing Research Outcomes for the Future

Based on the results obtained from our research on multimodal emotion recognition systems, we can envision how this technology could be effectively applied to create a next-generation luxury yacht that not only enhances the onboard experience for passengers, but also significantly improves the working environment for the crew.

By using advanced AI systems, onboard sensors, and real-time emotional feedback, the luxury yachts of the future could adapt dynamically to the needs and emotional states of individuals. These adaptations would have profound implications for both leisure experiences and safety management during critical situations.

Let's imagine together a series of future scenarios in which technology enhances every aspect of the onboard experience.

2.1. Creating Personalised and Emotionally Attuned Spaces

One of the most exciting applications of this research is the creation of emotionally responsive environments on luxury yachts. By integrating FER and SER, the onboard environment can be dynamically adjusted to match the emotional and psychological state of each passenger. This is made possible through a combination of strategically placed sensors and cameras throughout the yacht, as well as smart watches or bracelets that passengers can wear comfortably to monitor their vital signs (Fig.4).

These smart watches can track a range of parameters, including heart rate, body temperature, and skin conductance.

When a guest boards the yacht, the AI system gathers baseline data from these indicators to create a personalised well-being profile. As the journey progresses, the sensors and bracelets continuously monitor the guest's vital signs, and the AI interprets this data to assess their emotional state.

Once the system detects a change in the guest's emotional state, it takes action to enhance their well-being. For example, if the guest's heart rate increases and their skin conductance suggests stress, the system can make subtle adjustments to the environment, such as lowering the temperature to increase comfort and create a more calming atmosphere. Alternatively, if the sensors or smart bracelets pick up signs that a guest is feeling cold or emotionally down, the system can raise the temperature and adjust the lighting to a warmer, more inviting tone (Fig.4).

This ability to respond immediately to emotional cues demonstrates the sophistication of the AI and sensor technologies used on future luxury yachts.

Figure 4. Lights colours and temperature changes.

2.2. Personal Well-being Robots

Based on the findings of our research, we can envision a future where empathetic robots aboard yachts will serve as perfect companions for passengers, offering both emotional support and engaging interactions. These robots, equipped with advanced AI and machine learning algorithms, will be able to connect deeply with guests, adapting to their needs and preferences to create a fully personalised experience. They will not only engage in meaningful conversations on a wide variety of topics, but will also share experiences with passengers, such as joining them for meals, dances, and suggesting onboard activities to enhance their journey.

Thanks to their ability to connect to the guest's smartwatch in real time, these robots will be able to continuously monitor both emotional states and vital signs. By analysing key indicators such as heart rate, body temperature, and other physiological data, they will be able to detect if a guest is feeling stressed, relaxed, or in need of company. With this information, the robots can adapt their behaviour, offering soothing activities, like relaxing music or guided meditations for a stressed guest, or engaging in more lively discussions and social activities when a passenger is feeling energetic.

In addition to emotional support, the robot will also monitor the passenger's physical well-being. If it detects signs that the guest might require medication or medical

assistance, the robot will promptly notify onboard healthcare professionals to ensure immediate attention. This proactive role in health monitoring adds an extra layer of safety and well-being for every passenger.

The luxury yacht of the future will prioritise comprehensive telehealth services, providing guests with access to a global network of healthcare professionals, including doctors, nurses, and specialists, via telehealth platforms. This ensures that guests can receive medical assistance, even in remote locations, through video consultations. AI integration enhances these services by offering immediate responses, in-depth analysis, and assisting healthcare providers with real-time data and diagnosis suggestions. AI also proactively monitors guests' health, providing early warnings for potential issues, allowing preventive measures to be taken.

Additionally, robotic surgery systems on board provide precise, minimally invasive procedures with remote assistance from surgeons worldwide. These systems, equipped with AI algorithms and haptic feedback, ensure real-time guidance and immediate response in case of complications. Overall, these innovations guarantee world-class medical care, ensuring guests' safety and well-being throughout their journey.

2.3. Enhancing Safety and Managing Emergency Situations

Another critical application of the research lies in its potential to enhance safety and manage emergency situations on board luxury yachts. The same AI systems that respond to emotions in leisure settings could be invaluable during high-stress or dangerous scenarios. Potential applications include:

- *Emergency Detection and Response*: By using biometric sensors to monitor real-time data such as heart rate variability (HRV), skin conductance (EDA), and facial micro-expressions, the system can detect when crew members or passengers are experiencing high levels of stress, which could indicate an emergency or dangerous situation. In these cases, the AI system could immediately alert the onboard crew or even trigger safety protocols automatically. For example, during an emergency, it could activate emergency lighting, alert all crew members, and guide passengers to safety zones based on their location and condition.
- *Stress Monitoring During Critical Tasks*: For crew members engaged in high-stakes activities, such as navigating through rough weather or responding to an onboard fire, the system could monitor their stress levels and provide real-time feedback to ensure they remain calm and focused. If the system detects that a crew member is becoming overwhelmed, it could automatically deploy additional safety measures, such as rerouting responsibilities or calling for backup, thus helping to prevent errors due to emotional strain.
- *Safety Drills and Preparedness:* During safety drills, the technology could be used to assess the emotional and physiological state of participants, ensuring that crew members are not only performing the required tasks but are also mentally prepared to handle real emergencies. Over time, this data could help refine the effectiveness of training protocols by identifying specific emotional triggers that need to be addressed to improve performance under pressure.

2.4. Advanced Virtual Reality Exploration

The next-generation luxury yacht provides guests with the unique opportunity to embark on immersive underwater adventures through advanced virtual reality (VR) experiences. With cutting-edge VR technology on board, guests can explore the ocean's depths without ever leaving the comfort of the yacht.

By donning a lightweight, high-resolution VR headset, guests are instantly transported to a vivid undersea world. They can swim alongside dolphins, explore vibrant coral reefs, and observe rare marine species up close. These VR experiences are far from passive; they are fully interactive, allowing guests to engage with marine life, solve puzzles related to marine conservation, and even participate in virtual dives with expert guides.

Beyond recreational activities, the yacht also offers educational VR content. Guests can attend virtual lectures and workshops on topics such as marine biology, conservation, and sustainability. Renowned experts from around the globe lead these sessions remotely, sharing their knowledge and insights with the guests.

These educational VR experiences empower guests with knowledge and raise awareness about the importance of marine conservation and a sense of responsibility towards the planet.

3. The Ethical Dimension of AI-Enhanced Well-being

The integration of advanced AI systems into luxury yachts introduces essential ethical considerations, especially regarding *privacy*, *data security*, and *human autonomy*. These elements are critical in ensuring that while AI enhances well-being, it does so responsibly and with full respect for individual rights and dignity.

3.1. Privacy and Data Security

AI-driven well-being systems rely heavily on the collection and analysis of biometric data, including emotional states, physiological metrics, and personal well-being profiles.

Given the sensitivity of this data, maintaining the highest standards of privacy and security is paramount. All collected data must be anonymised, encrypted, and stored in compliance with international privacy regulations, such as the GDPR and other relevant frameworks like the AI Act [4].

Strict access controls must also be in place, ensuring that only authorised personnel can handle sensitive information. Additionally, the yacht's AI systems should operate on a need-to-know basis, using only relevant data to enhance the guest's well-being while ensuring transparency about how data is collected and used.

Guests should always have full control over their personal data, with the ability to review, modify, or delete it at any time, helping to build trust in the system.

3.2. Human Autonomy and AI Interventions

While AI can significantly enhance guest well-being through personalised recommendations and dynamic environmental adjustments, it is essential that the system does not infringe on individual autonomy.

AI should serve as a *supportive* tool that optimises experiences based on preferences and emotional cues but should never replace human decision-making.

Guests must retain the final say in decisions that affect their well-being and journey. The ethical balance between AI-driven enhancements and preserving autonomy ensures that AI enhances comfort and safety without taking control or overriding personal choice.

This approach safeguards the guest's agency, making the AI a tool for empowerment rather than one of control.

3.3. Inclusivity and Accessibility

The use of AI on luxury yachts must also address the need for inclusivity and accessibility. The well-being enhancements provided by AI should be accessible to all guests, regardless of physical abilities, language, or cultural background. The interfaces and technologies onboard should accommodate guests with disabilities by offering features such as voice commands, Braille displays, and other accessibility tools.

Moreover, ethical AI usage must extend to cultural sensitivity. The AI systems should be programmed to respect cultural norms, beliefs, and practices, ensuring that well-being enhancements are inclusive and culturally relevant. Multilingual support should also be available to cater to guests from diverse linguistic backgrounds, promoting inclusivity and fostering a positive experience for everyone on board.

3.4. Continuous Improvement and Collaboration

To remain at the forefront of well-being innovation, a continuous improvement is essential. Yachts should engage in collaborative research, collecting feedback from guests on the effectiveness of AI-driven well-being enhancements and telehealth services. This data can be systematically analysed to make informed improvements, ensuring that the technology evolves with guest needs and industry advancements.

Additionally, collaborations with academic institutions and research organisations can deepen the understanding of AI's impact on human well-being, contributing to the broader field of well-being science. This ongoing research fosters ethical and innovative improvements that align with the guests' evolving desires.

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