Towards Data-driven Identification and Analysis of Propeller Ventilation

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***Abstract*—Propeller ventilation is one of the main reasons for the widespread mechanical failures of thrusters, with costly repairs and increased vessel down-time. In this paper, we argue that both algorithmic and dynamics/control modelling approaches should be combined and visual analytics should be adopted to gain better understanding of the complex behaviour of vessels and the ocean. We then propose ventilation detection methods which require no *a priori* information about the subject vessel or the propellers, which enables further development of automatic parameter refinement and interactive visual detection and exploration of vessel behaviour as next steps. This work is an important part of our initial efforts towards a *visual analytics* framework for maritime operations.**

***Index Terms*—Maritime operations, propeller ventilation, visual analytics.**

I. Introduction

Propeller ventilation [1], [2], [3] occurs when air from the free surface or exhaust gas being drawn into the rotating propeller blades, which will incur large loss of propeller thrust and possibly dynamic loads, noise and vibration, causing significant tear and wear of the propulsion unit. Kozlowska et al. [2] classified different types of propeller ventilation and ventilation inception mechanism. It is well accepted that propeller ventilation is one of the main reasons for the widespread mechanical failures of thrusters, with costly repairs and increased vessel down-time. Therefore, identification and analysis of ventilation events, so as to better predict and prevent the potential damage, are of great importance.

Norway is ranked as the world's second largest nation in maritime operations. In particular, the northwestern Møre region of Norway is one of the leading clusters in the global offshore support vessel (OSV) shipbuilding and shipping (ship service) market, consisting of almost 200 companies with a total turnover in excess of NOK 50 billion. As marine operations face the major challenges of increased complexity in more demanding waters, technologies are being adopted for acquiring monitoring data about how the vehicle and different components are behaving. Recently, with the intention of remote ship monitoring for better services for shipping customers, vessel builders started to adopt new sensor technology by installing different sensors for different components on board a vehicle and transmit data using satellite communications to land-based service centres, e.g., the HEalth MOnitoring System (HEMOS) by Rolls-Royce Marine AS. This development has been strengthened by the quickly increasing awareness of the new *Internet of Things* (IoT) paradigm [4]. IoT covers technologies including ubiquitous computing, pervasive computing, wired/wireless sensors, networks, and embedded systems, forming a communicating-actuating network of a large amount of *things*, In this way, physical environment and resources could have presence in the digital world.

Saveo and Steen [3] presented a fuzzy logic based analysis procedure for identifying propeller ventilation events using data from HEMOS. The main drawback in this approach is that it requires large amount of manual identification of ventilation events in the training data set. In addition, the sensitivity and accuracy of the developed approach for providing timely warnings relies on a number of threshold values which are manually chosen to detect major events and therefore the approach predictability is subjected to a significant risk of false alarms which might harmful its credibility. The developed toolbox is not capable of detecting events during *dynamic positioning* operations. As mentioned in [3], in real practice, Rolls-Royce Marine AS found that existing detecting methods are effective, but still involve a lot of manual work, therefore they are not applicable to the large amount of continuous feed of monitoring data. We also observed that many existing methods consider many vessel specific parameters, which are often *not* available in the monitoring data so estimation schemes must be used [1], [5]. This creates extra difficulties in the practice, esp. in the future when the monitoring is to be expanded to a larger number of different vessels.

Another paradigm, quickly rising together with IoT, is *Big Data Analytics* (BDA). It is highlighted in a statement from the United Nations that "the world is experiencing a data revolution" [6]. Breiman, a prominent statistician, argued in his seminal paper [7] that both stochastic data modelling and algorithmic modelling (machine learning) approaches should be explored and combined to better understand the complicated phenomena, supported by the increasingly available of data, esp. from IoT. Following the same logic, we argue that both dynamics and control modelling and algorithmic approaches should be explored and combined to better understand the complex behaviours of vessels and the ocean.

Visual Analytics combines automatic analysis techniques (the algorithmic modelling approach mentioned above) with

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interactive data visualisations. The seminal papers [8], [9] have shown that visual analytics enables a virtuous cycle of user interaction, parameter refinement for algorithmic models so as to achieve rapid correction and improvement of human's knowledge and decisions.

In the framework of our Innovation Norway project "GCE Blue Maritime Big Data" [10], we obtained the monitoring data from HEMOS by Rolls-Royce Marine AS covering three years' operation by one vessel with samples of ventilation by manual detecting methods. We also acquired a smaller data set of monitoring data from another vessel, to evaluate the level of easiness to apply our method across different vessels. This paper and papers [11], [12] represent our initial results in efficient pattern identification, data visualisation, and prediction respectively, under our framework of visual analytics for maritime operations. In this paper, we propose propeller ventilation detection methods which require no priori information about the subject vessel or the propellers. Experiments show positive results of effectiveness of our method in identifying ventilation, laying a good foundation for us to develop automatic parameter refinement and interactive visual detection and exploration of vessel behaviour as next steps.

The remainder of the paper is structured as follows: Section II reviews existing literature on propeller ventilation and big data analytics. In Section III, we briefly present our framework of visual analytics for maritime operations before we present in details our signal-based propeller detection method and a simple statistical detection method using mean value and standard deviation of the motor torque data. Section IV presents the experiment results with discussions and Section V concludes the paper and present some future directions.

II. Background

A. Propeller Ventilation

Propeller ventilation has been historically related to surface-piercing, partially submerged propellers, which were first employed on shallow draught ships, and in a second stage for high-speed craft, with super-cavitating type profile [13]. It is well accepted that propeller ventilation is one of the main reasons for the widespread mechanical failures of thrusters, with costly repairs and increased vessel downtime recently. Therefore, identification and analysis of ventilation events, so as to better predict and prevent the potential damage, are of great importance.

The ventilation phenomena can be separated in three different fundamental regimes: start up, intermittent and full ventilation and this was observed by Reynolds [14] who is the first known study on the effect of air drawing. Kempf [15] was one of the earliest researcher who studied the propeller ventilation effects in 1934. There are a number of parameters affecting the propeller ventilation. Shiba [16] conducted the experiment and studied ventilation effect on thrust and torque. He analyzed the various parameters, for example, skewback, effect of rudder, expanded area ratio, contour of blade, radial variation of pitch, effect of rudder and scale effects on ventilation. When propulsion in a seaway in 1970s, Gutsche [17] studied the average loss of thrust and efficiency. In order to understand ventilation, he modelled the time averaged reduced thrust $\beta = KT/KT_0$ as a function of the submergence-to-radius ratio h/R, by means of the loss of disc area and further including the losses due to the Wagner effect [18], [19]. Where KT is the thrust coefficient, KT_0 is the nominal thrust coefficient when there is no ventilation.

More recently, Koushan [20] performed experiments and extensive model tests and showed the effect of partial submergence on the average thrust and torque of propellers at different advance coefficients. Later, Koushan [21] presented the dynamics of propeller blade thrust of the open propeller on pulling thrust at bollard condition and he found out measured fluctuations made great impact. He also discussed the effects of ventilation on the dynamics of thrust and torque of a single blade of the propeller when a pushing ducted thruster running at constant revolutions under various constant immersion conditions [22]. In his model experiments tests, the propeller rate of revolution, azimuth angle, propeller immersion ratio, carriage speed, period of heave oscillations, oscillations amplitude were varied. Kozlowska et al. [2] analysed different types of propeller ventilation and ventilation inception mechanisms. They presented that advanced ratios, propeller revolutions, submergences and time have influence on ventilation inception and thrust drop due to ventilation [2]. Califano and Steen [13] presented the amount and type of ventilation depended on propeller submergence, propeller loading and advance ratio. They pointed out the combination of these parameters determines the nature of the ventilation mechanism, (i) at deeper submergences through a free-surface vortex and (ii) at moderate submergences through the tip vortex and ultimately the blade itself piercing the free surface and identified three different ventilation regimes [13]. Savio and Steen [3] introduced usual torque KQ and J coefficients to make the analysis simpler. As it is not possible from the data available to calculate the propeller submergence exactly, they introduced a fuzzy logic approach to roughly calculate the static submergence. The vessel speeds, ship pitch, roll angles, rpm, and azimuth angle are the parameters that they used to feedback the propeller ventilation. The weather observation was added during their analysis, in which wave statistics are collected. Their experimental results showed the only parameter changing in the encounter angle calculation is the ship heading. As marine operations face the major challenge of increased complexity in more demanding waters, the previous tests carrying out with the propeller alone in calm water and in regular waves at different submergences are not enough. Therefore, Savio et al. [23] run tests in the more realistic scenario of a propeller working behind a ship and this more realistic scenario have been performed in the MARINTEK ocean basin using a free running ship model. Their tests included both calm water runs and irregular seas at different wave encounter angles and they presented the results that blade forces can undergo very large fluctuation due to the large in plane flow a propeller operating on an azimuthing thruster unit experiences during ship manoeuvring.

Propeller ventilation has been addressed in detail by [1], [5]. In this work a nonlinear state estimator was used to estimate the propeller load Q_p and then use this signal to detect

ventilation. Propeller ventilation is observed as a sudden drop in propeller load and a threshold value can be used to detect if the propeller ventilates or not. In order to estimate Q_p the shaft dynamics is modelled as:

$$J_m\dot{\omega} = Q_m - Q_p - Q_f(\omega) \tag{1}$$

where J_m is the total moment of inertia including the shaft, the gear box and the propeller, Q_m is the measured motor torque and $Q_f(\omega)$ is the friction torque, which in general is unknown. The propeller shaft speed is denoted ω and this signal is measured.

The corresponding state estimator [5] is given by:

$$J_m\dot{\hat{\omega}} = Q_m - \hat{Q}_p - Q_f(\omega) + K_1(\omega - \hat{\omega}) \tag{2}$$

$$\dot{\hat{Q}}_p = -\frac{1}{T}\hat{Q}_p + K_2(\omega - \hat{\omega}) \tag{3}$$

where T is a tunable time constant. This is a model-based state estimator, which needs information about the moment of inertia J_m and the nonlinear friction $Q_f(\omega)$, which in practice are hard to obtain with sufficient accuracy for a full-scale ship. This usually require extensive testing and curve fitting of experimental data e.g. by using system identification [5]. The observer gains K_1 and K_2 can be computed using nonlinear observer theory or the extended Kalman filter algorithm.

B. Big Data Analytics

McKinsey Global Institute [24] has the following definition:

> "Big Data" refers to datasets whose size is beyond the ability of typical database software tools to capture, store, manage, and analyze.

However, there has always been "too much" data to analyse, why only in very recent years people claim that we are now in the "new era of big data"? Dean [25] gives a good observation on this phenomenon:

> The large data volume does not solely classify this as the big data era… What sets the current time apart as the big data era is that companies, governments, and nonprofit organizations have experienced a shift in behavior. In this era, they want to start using all the data that it is possible for them to collect, for a current or future unknown purpose, to improve their business.

Breiman, based on his extensive industrial experiences, presented in his seminal paper [7] several insightful (and provocative at the time of publication) arguments for the machine learning (algorithmic modelling) approach, addressed mainly to the statistics community who heavily relied on statistical models. Some of the arguments, to our opinion, are valid to the maritime community who have a long tradition and strong knowledge and experience in dynamics and control models. Here we briefly summarise his main arguments.

A nature's phenomenon can be seen as black box, depicted in Figure 1, with a vector of independent input variables x and the response variables y. There are two goals: a) to extract *information* about how a phenomenon is associating y to the input x; b) to predict what y will be with future input x. There are two approaches: 1) data modelling, which assumes a stochastic data model for the inside of the black box and seeks to build it using e.g., linear or logistic regression. Models are validated using goodness-of-fit tests and residual examination; 2) algorithmic modelling, which considers the inside of the box complex and unknown and seeks to find an algorithm that operates on x to predict the response y. Models are measured by predictive accuracy.

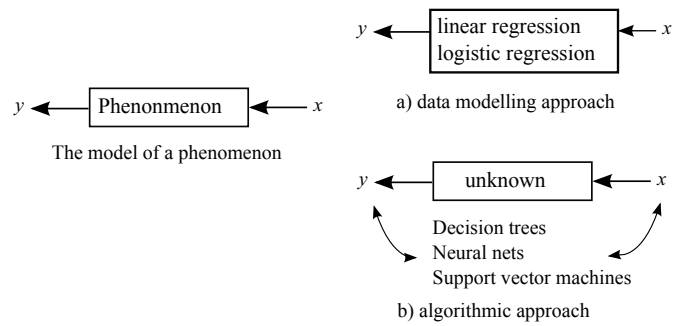

Figure 1. Two approaches to analyse a phenomenon (adapted from [7]

Breiman argued that being limited in the data modelling approach has 1) led to irrelevant theory and questionable conclusions about the subject phenomenon; 2) kept statisticians from using more suitable algorithmic models; 3) prevented statisticians from working on new problems. In particular, he commented on the "strange" belief existed in the statistics community,

> The belief in the infallibility of data models was almost religious...once a model is made, then it becomes truth and the conclusions from it are infallible.

A statistician can build a reasonably good parametric class of models for a complex mechanism devised by nature, and parameters can be estimated and conclusions can be drawn. However, Breiman stressed that the conclusions are about the model's mechanism, and *not* about nature's mechanism. Therefore, if the model is a poor emulation of nature, the conclusions could be wrong. He also observed, with an example from bio-statistics, when faced with a choice between accuracy and interpretability, users tend to go for interpretability.

Breiman presented several principles to address the problems, 1) the goal is not interpretability, but accurate information; 2) the goal should be adjusted to search for a model that gives a good solution, either algorithmic or data; 3) predictive accuracy on test sets should be the criterion for how good the model is.

Reflecting Brieman's arguments in the context of the maritime community, we argue that we should also be open to the algorithmic approach, combined with the dynamics and control modelling approach, so as to gain better understanding of the complex behaviour of vessels and the ocean.

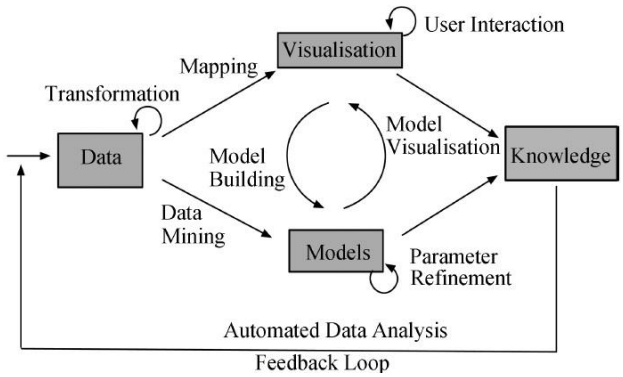

Figure 2. Visual Analytics Framework [26, Fig.1]

III. Towards Visual Analytics of Propeller Ventilation

A. Visual Analytics Framework for Martime Operations

Here in the Big Data Lab in NTNU Aalesund (BDL), we aim to move one step further based on Breiman's principles, to develop the so-called *visual analytics* (VA), that combines automated analysis techniques with interactive data visualisations, for maritime applications. Keim et al., in their seminal paper [8], stated that the goal of VA is the creation of tools and techniques to enable people to 1) synthesise information and derive insight from data; 2) detect the expected and discover the unexpected; 3) provide timely and understandable assessments; 4) communicate assessment effectively for action. They introduced the seminal VA framework, depicted in Figure 2.

One key element of VA, compared to the above-mentioned algorithmic approach, is the recognition of the importance of *information visualisation* in the human understanding and analysing process. Fekete et al. [9] has rigorously explored the value and benefits of information visualisation. Even as fully-automated algorithmic methods can quickly identify useful information and provide more accurate prediction, they lack the ability to interact with human and deliver effectively the knowledge. The combination of visualisation and automated algorithmic methods enables a virtuous cycle of user interaction, parameter refinement for algorithmic models so as to achieve rapid correction and improvement of human's knowledge and decisions.

This paper and papers [11], [12], all in the same venue, represent our initial results of developing a VA framework for maritime operations. Paper [11] presents a data cleansing, integration, and visulisation prototype for maritime operations and paper [12] presents our initial results of ship motion prediction using neural networks.

As mentioned above, most existing propeller ventilation detection methods require specific parametric information about the vessel, esp. the propeller and sensor data of several components which are often missing in practice. Therefore, this paper proposes a novel signal-based detection algorithm using a one-state *Kalman filter*, which does not require information about the ship and propeller parameters. Hence, the signal-based algorithm can be used onboard all different types of vessels without any *a priori* information of the vessel. Based on these works, existing algorithmic methods can be applied to automatically refine parameters for the detection and the ventilation behaviour can be effectively explored interactively in our visualisation platform [11].

B. Signal-Based Estimator for Ventilation

We propose a novel signal-based motor torque estimator to detect propeller ventilation. A dynamic model is used to low-pass filter the motor torque Q_m and produce a slowly varying estimate $\hat{y}$ of Q_m. The estimate $\hat{y}$ can be used as a reference signal to detect a rapid drop in motor torque due to ventilation. The continuous-time low-pass filter is chosen as:

$$\dot{x} = -\frac{1}{\tau}x + w \tag{4}$$

$$y = x \tag{5}$$

where τ is user specified time constant (typically $100-1000$ s), w is Gaussian white noise and $y = Q_m$ is the measured motor torque. The discrete-time model is:

$$x(k+1) = \Phi\, x(k) + w(k) \tag{6}$$

$$y(k) = x(k) \tag{7}$$

where the transition matrix $\Phi \approx 1 - dt/\tau$ is approximated by Euler's method. Here dt denotes the sampling time in seconds. The linear discrete-time Kalman filter corresponding to (6)–(7) is implemented using a constant Kalman gain K. The Kalman filter equations are:

$$\begin{aligned} \text{Corrector:} \quad \hat{x}(k+1) &= \bar{x}(k) + K\left(y(k) - \hat{y}(k)\right) \\ \hat{y}(k) &= \hat{x}(k) \\ \text{Predictor:} \quad \bar{x}(k+1) &= \Phi\, \hat{x}(k) \end{aligned}$$

Since the estimated state $\hat{y}(k) = \hat{x}(k)$ is slowly varying due to the large time constant τ in the model, a rapid change in propeller torque due to ventilation will be observed in the residual signal:

$$\varepsilon(k) = y(k) - \hat{y}(k) \tag{8}$$

Hence, propeller ventilation can be detected by using:

$$\text{if } -\varepsilon(k) > \beta \text{ the propeller ventilates} \tag{9}$$

where β is a threshold value. The experimental results showing the performance of the detection algorithm is reported in Section IV.

C. Statistical Interpretation of the Kalman Filter

The Kalman filter in Section III-B has a simple statistical interpretation. When the time constant is large enough, we can conclude that the continuous-time representation of the Kalman filter described by:

$$\dot{\hat{x}} = -\frac{1}{\tau}\hat{x} + K(x - \hat{x}) \tag{10}$$

and the low-pass filter described by:

$$\frac{\hat{x}}{x}(s) = \frac{K}{s + \frac{1}{\tau} + K} \overset{\tau \gg 0}{\approx} \frac{K}{s + K} \tag{11}$$

with time-constant $\tau = 1/K$ can provide significantly close estimations. From a statistical point of view we know that low-pass filtering the measured signal $y = x$ gives an estimate of the mean motor torque $\bar{Q}_m$. Similarly, a second low-pass filter can be used to compute the standard deviation σ of the measured motor torque:

$$\bar{Q}_m = E(Q_m) \approx h_{lp}(s) Q_m \tag{12}$$

$$\sigma^2 = E[(Q_m - \bar{Q}_m^2] \approx h_{lp}(s)(Q_m - \bar{Q}_m^2) \tag{13}$$

where $h_{lp}(s) = 1/(Ts + 1)$ is the low-pass filter transfer function.

The advantages of using the Kalman filter to low-pass filters and statistical methods are:

- The Kalman filter uses the discrete-time corrector-predictor representation, which is highly accurate at low sampling rates.
- The Kalman filter can use multiple measurements with optimal weighting (sensor fusion).
- The Kalman filter model can be extended to include other dynamical effects.

IV. Experimental Results

In the experiment, the motor torque measurements Q_m were sampled at 10 Hz. The estimator and detection algorithm in Section III-B have been implemented and tested using $\tau = 100$ s, Kalman filter gain $K = 0.3$ and threshold value $\beta = 10$ kNm for detection. Figure 3 shows the performance of the Kalman filter. The Kalman filter detects two cases of propeller ventilation in this data set. The first on at 11 seconds, and the second at 19 seconds.

V. Conclusion and Future Work

In this paper, we argue for the combination of algorithmic and dynamics/control modelling approaches and promote visual analytics for maritime community. We explore propeller ventilation detection methods with no *a priori* information about the subject vessel so we can efficiently monitor a larger number of vessels. The model is trained using monitoring data collected from an offshore supply ship during normal operation with minimum human intervention. This work is an important part of our initial results towards our visual analytics framework for maritime operations. For the next step, we will develop automatic parameter tuning methods and adapt our visualisation prototype for propeller ventilation detection.

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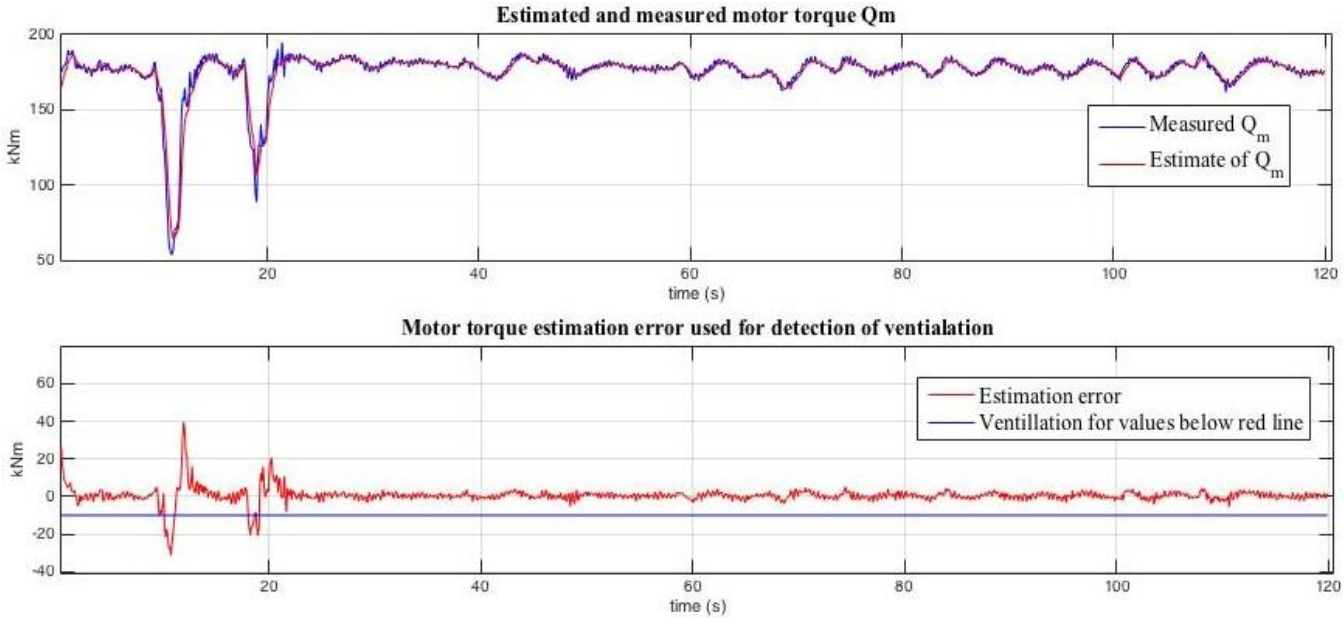

Figure 3. Upper plot: Estimated (red) and measured motor (blue) torques (kNM). Lower plot: Residual (blue) and threshold value (blue).

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