FAULT DETECTION FOR POSITION MOORING USING STATISTICAL ANALYSIS

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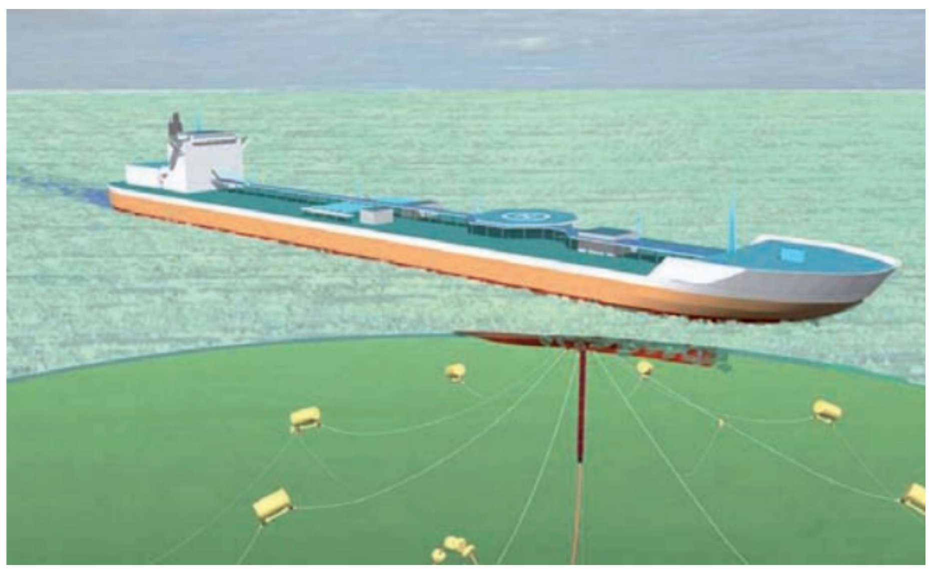
INTRODUCTION

Most marine vessels that are placed at one location for a long duration will be moored to the seabed with 6-12 anchors to hold their position. If the vessel also has dynamic positioning (DP) capabilites, this is referred to as thruster assisted position mooring (TAPM). Such vessels will usually use their thrusters to achieve greater damping and more fine grained positional control.

It is obviously of great importance to be able to detect failure in the mooring lines as quickly as possible. In the short term this enables the use of the DP system to compensate for the lost mooring line. In the longer term it means that maintenance to rectify the failure can be carried out before any serious consequences occur.



Most TAPM vessels that monitor their mooring lines either use tension measurements (directly through sensors in the lines, or indirectly using strain or angle) or sonar imagery. These sensors are usually mounted beneath the waterline, as the mooring lines are often attached beneath the vessel. This creates several challenges.

The sensors need power and the ability to send data to the vessel. This can either be done by cables, which are vulnerable to wear and tear, or acoustic transmission with battery power. Using batteries creates a maintenance challenge, as these need to be replaced regularly. Maintenance operations for underwater systems like these are often expensive, as they require ROV capabilities or divers, and can only be performed in fair weather conditions. One of the largest challenges is determining if a loss of tension is an actual line breakage, or a sensor failure. With no easy access to the mooring lines or sensors this is not a trivial task, and in one case it took two weeks of analysis to determine that a tension spike was an actual failure.

OBJECTIVE AND SCOPE

To counter some of the challenges associated with underwater sensors, it is desirable to develop an alarming system that doesn't depend on them. The objective is to develop several mathematical models of the TAPM vessel, one for each failure scenario. Each model will describe the behaviour of the vessel, given a failure, and incorporate the actual position measurements of the vessel.

By analysing how the real behaviour of the vessel compares to what the models expect, it is possible to try to determine which of the different scenarios is the correct one. This is done using statistical analysis methods like dynamic hypothesis testing (DHT) and maximum likelihood estimation (MLE)

MODELING

Nine different models for the vessel behaviour were created. Each model assumes one of the eight mooring lines have failed, while the ninth model has all lines intact. There is no limiting factor in the model for how many lines can fail at once, but a maximum of one was chosen to keep the number of models low.

The model describes the motion of the vessel, separated between motion caused by the applied and measured forces, and motion caused by first order wave loads. All unmodeled nonlinear dynamics are lumped together in a bias term, which includes currents for instance.

OBSERVER

An observer was implemented to filter out measurement noise and environmental disturbances from the position signal. A passive observer was chosen for its ease of tuning. However, this observer does not calculate the error covariance matrix of the signal live. Because this is needed for the statistical analysis, several long simulations were done, and the error covariance matrix was estimated from the resulting signals.

One observer was created for each hypothesis, where each observer used the mathematical model assuming that hypothesis was correct. This means nine observers are run in parallel.

DYNAMIC HYPOTHESIS TESTING

The DHT method essentially tries to answer the question "for each of these hypotheses, what is the probability that it is the correct one?". The algorithm calculates the probability of the most recent measurement occurring, given the time history of measurement and thruster inputs, and assuming one of the nine hypotheses to be true. Because there are infinitely many different possible scenarios this probability will be low, so it is normalized by dividing by the total probability of all the hypotheses.

The calculation of the probabilities uses the Gaussian multivariate probability density function. This equation uses the error covariance matrices from the observers.

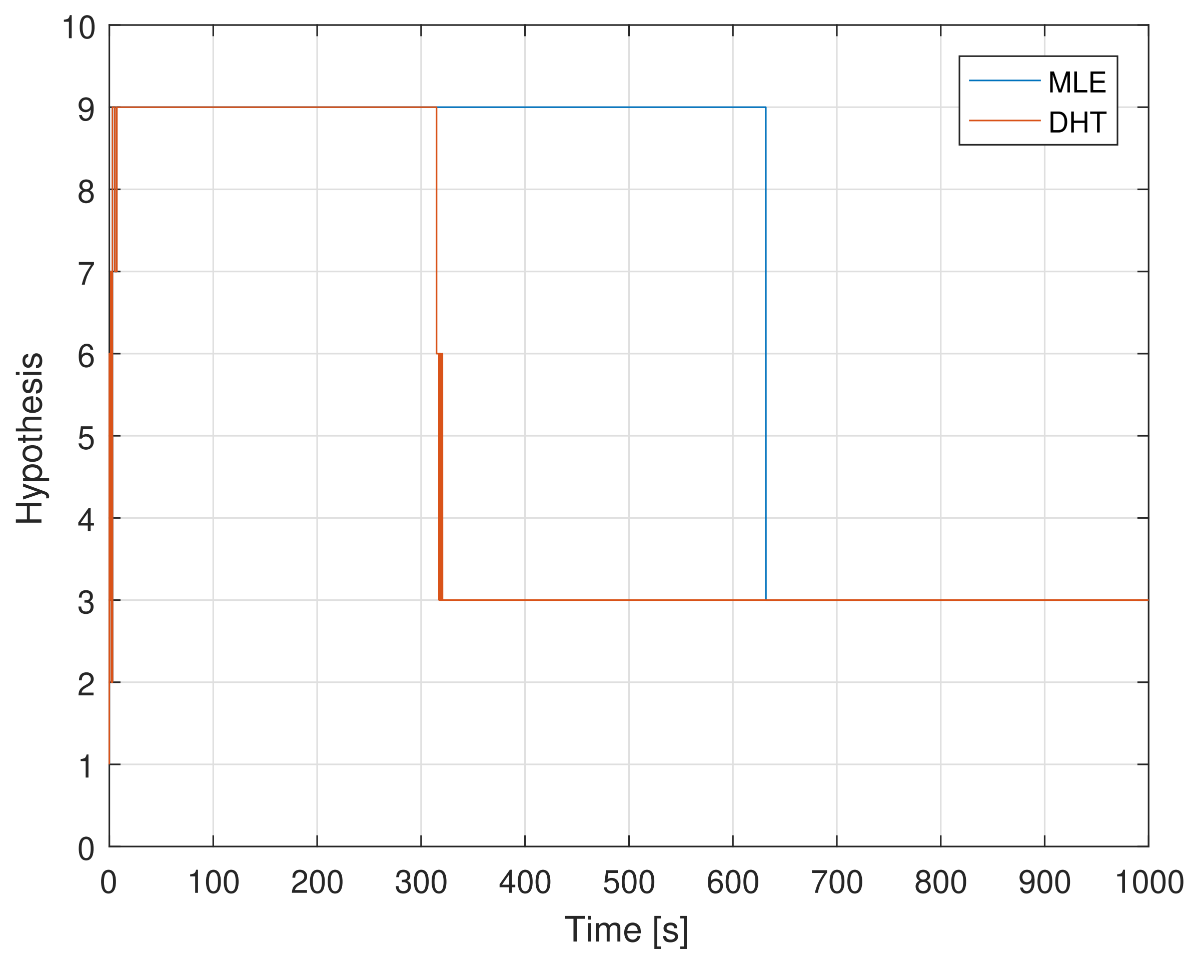
MAXIMUM LIKELIHOOD ESTIMATION

With MLE the goal is to calculate the likelihood that a parameter has a given value, given the known measurement history. This can also be viewed as finding the probability of getting those measurements given the parameter. The modelled scenario that has the highest likelihood of occurring is deemed the correct one. In practice it is easier to work with the negative log likelihood function, turning this into a minimization problem. The calculation is similar to DHT, using the Gaussian pdf with the error covariance from the observer.

Unlike DHT, the likelihoods are calculated independently for each hypothesis, and they are not normalized on each other.

SIMULATIONS AND RESULTS

The methodology was tested using a Simulink based TAPM vessel simulator, developed by Ph.D. Zhengru Ren. The simulated vessel has 8 mooring lines in an even distribution around it. In addition a simple PID controller was added to simulate the thruster assistance aspect. In the simulation presented here, mooring line number 3 breaks at $t = 300$. The results of the DHT and MLE algorithms trying to determine the correct scenario can be seen in the figure below.



Estimated real mooring line configuration, using both DHT and MLE. Hypotheses 1 through 8 are failure of the corresponding mooring line, while hypothesis 9 is all lines intact.

As can be seen in the figure both algorithms quickly determine that the starting configuration is with all mooring lines intact. When the third mooring line breaks at $t = 300$, the DHT changes its estimate to the correct hypothesis very quickly, using around 20 seconds. The MLE algorithm on the other hand, has much slower performance. It uses over 5 minutes to change to the correct hypothesis.

CONCLUSION

The statistical methods are able to determine that a mooring line has failed using only the position measurements, even with a simple observer that is not able to directly estimate the error covariances.

The DHT algorithm is able to quickly change to the correct hypothesis when a line breakage occurs. However, the MLE algorithm has a much slower response. This is likely due to the fact that the algorithms use the previously estimated likelihoods/probabilities when calculating for a new time-step. This means that the values for hypotheses that are deemed false will go towards zero. Coming back from a near zero value takes a long time, causing the delay. For the DHT algorithm this was solved by implementing a lower bound on the probabilities for each hypothesis, and then normalizing the values for the new total. For the MLE algorithm there is no equivalent physical interpretation of the value, and so this has not been done. This is likely what causes the disparity between the two methods.

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