ASSET NETWORK PLANNING: INTEGRATION OF ENVIRONMENTAL DATA AND SENSOR PERFORMANCE FOR COUNTER PIRACY

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ABSTRACT
An operation planning system, integrating dynamic environmental forecasts and satellite Automatic Identification System sensor performance surfaces, to improve maritime traffic situation awareness is proposed and tested. Multi-objective evolutionary algorithms are used to optimize a network of monitoring assets with respect to a combined surveillance and piracy activity risk metric, the network area coverage and the mission cost, under given spatial and kinematic constraints. Pareto efficient solutions are provided, each representing a tradeoff among mission objectives. Tests in a counter piracy operational scenario with real-world hindcast data and sensor performance surfaces show the effectiveness of the methodology in improving surveillance efficiency.

Index Terms—environmental forecasts, sensor performance surfaces, multi-objective optimization, sensor networks, path planning, counter piracy.

1. INTRODUCTION

Piracy on the high seas is a problem of world-wide concern. According to the International Chamber of Commerce (ICC) International Maritime Bureau's (IMB) global piracy report attacks in East and West Africa accounted for the majority of world attacks in 2011, signaling a rising trend. Of the 439 attacks reported to the IMB in 2011, 275 attacks took place off Somalia on the east coast and in the Gulf of Guinea on the west coast of Africa [1]. In response to the piracy problem, the U.S. Naval Oceanographic Office (NAVOCEANO) at Stennis Space Center has been providing a forecasting product called the Piracy Performance Surface (PPS). The PPS uses forecasts of winds and seas to map the locations that are most conducive to pirate activity, and incorporates information on confirmed pirate activity in the form of an attack, an attempted attack, or suspicious activity. The existing product was developed rapidly to provide support to the operators. NAVOCEANO is working to improve the model of the relationship between meteorological and oceanographic (METOC) and pirate activity, and to improve the way the pirate threat is updated when confirmed piracy activity is observed [2]. In [3] an algorithmic procedure is proposed to allocate interdiction and surveillance assets so as to minimize the likelihood of a successful pirate attack over a fixed planning horizon. This procedure is basically a tool for human planners that can be mapped closely to the decision support layer of the Battlespace on Demand (BonD) framework [4].

In the present work as a response to the piracy threat, a methodology is proposed that can integrate intelligence data, commercial shipping routes and METOC information to predict regions where pirates may be present and may strike next and plan monitoring asset trajectories according to specific requirements for vessel traffic monitoring. The monitoring assets are typically ships, airplanes, satellites and autonomous vehicles equipped with a diversity of sensors (e.g. radars, infrared, etc.). Some of these assets have predefined dynamics, for instance a satellite sensor has a fixed orbit and can only provide useful information in some given time period during the day. Other assets, instead, may be scheduled in order to fill the blanking region/time period with gaps in surveillance coverage. These areas of interest are the regions where a pirate group may be operative, *i.e.* the most dangerous for a commercial vessel. A related risk map is computed, mostly based on the correlation between METOC data and pirate attacks, using machine learning techniques [5] applied to a historical data base of pirate attacks. The costs of the monitoring activity must also be taken into account, and potentially the trade-off with the minimum number of assets that should be employed to achieve the security requirements.

Specifically, this paper proposes to optimize the surveillance assets over a fixed planning horizon in order to obtain the best coverage of the vessel traffic regions. The procedure provides the jointly optimal path planning of the monitoring asset network given specific operational constraints, dynamic environmental forecasts, satellite Automatic Identification System (AIS) sensor performance surfaces and the mission cost of each asset. Multi-objective (MO) evolutionary algorithms are used to optimize asset way points with respect to three objectives: i) a surveillance risk metric, ii) the asset network area coverage and iii) the total mission cost. Pareto efficient solutions are provided, each representing a tradeoff among mission objectives.

The paper is organized as follows. Section 2 describes the planning system and section 3 poses and formalizes the multi-objective optimization problem. Section 4 is devoted to describe and analyze a maritime scenario. Finally, section 5 draws conclusions.

2. SYSTEM DESCRIPTION

The problem addressed in this work consists in optimizing the deployment of *N* controllable moving assets, equipped with on board surveillance sensors. The network of assets operates in a given region of interest (ROI), in order to improve the vessel traffic surveillance in those areas of the ROI where there is a lack of information (e.g. lack of satellite AIS coverage) and at the same time favorable METOC conditions for a pirate activity. In this formulation, the purpose of the assets is to improve coverage of vessels that from which no AIS is received rather than detect pirate groups or suspicious vessels.

The optimization is carried out by minimizing a risk metric with a series of conflicting objectives including asset mission costs and network spatial coverage. The problem has several constraints such as asset kinematic, operational limitations, sensor performance and spatial constraints. The risk metric is defined based on a data fusion strategy, which takes into account all of the information from the sensors and the METOC information related to the presence of pirates. METOC variables include wind speed, significant wave height and wave peak period, which are predicted by a forecast system typically over a 3 day time horizon every three hours. The network is assumed to be heterogeneous, and can include radar, electro-optical and infrared sensors on board ships, airplanes, satellites and autonomous vehicles. Given the asset initial states (position, velocity and heading), and the constraints, the optimization procedure provides the optimal number of assets and optimal set of way points for the asset navigation. The surveillance mission time horizon is constrained by the operational limits of each asset (i.e. mission endurance) as well as by the forecast period of the METOC prediction system.

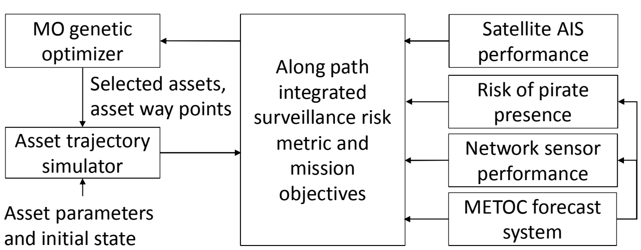


Figure 1: Schematic of the planning system.

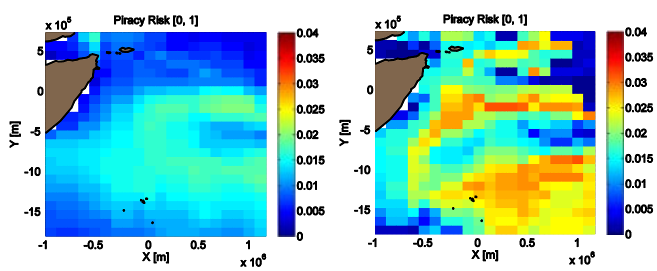
Figure 1 shows a scheme of the planning system. The asset trajectory simulator provides the trajectories of the selected assets given the waypoints and the initial states. Sensor performance and risk of pirate presence are integrated along the trajectories in order to evaluate the overall performance of the surveillance network over the whole mission period. A multi-objective genetic algorithm is used to optimize the deployment of the network. The following subsections detail the main blocks of the proposed planning system.

2.1. METOC pirate risk maps

METOC data are used in routinely counter piracy operations to provide risk maps of preferred environmental conditions for pirates to operate at sea [2]. In [5] the correlation between METOC data and pirate attacks is exploited using machine learning techniques applied to a historical data base of pirate attacks. The study is conducted by considering the publicly available data by the International Maritime Organization and includes all the monthly reports on piracy and armed robbery against ships from years 2005 until 2010 [6]. The weather and sea conditions, taken from the National Oceanic and Atmospheric Administration (NOAA) public archive, are used. This data set consists of a worldwide grid of METOC hindcasts generated using the WAVEWATCH III global model [7]. The piracy risk in a spatial dell *c* is defined as the probability of the attack event $A_c \in \{0,1\}$ given the METOC conditions $\mathbf{m}_c$ in *c*:

$$P_{A,c} = \mathrm{P}\{A_c = 1 | \mathbf{m}_c\} = \frac{p(\mathbf{m}_c | A_c = 1)\,\mathrm{P}\{A_c = 1\}}{p(\mathbf{m}_c)}. \quad (1)$$

The METOC variable vector includes the significant wave height, the peak wave period and the wind speed.



a) b)

Figure 2: $P_{A,c}$ risk map of pirate presence from WAVEWATCH III global model hindcasts. Forecast base time: 10 Oct 2010, 00:00:00Z. Forecasts at a) +00h, b) +72h show increasing risk in the ROI.

Figure 2 depicts an example of a risk map in the Indian Ocean. Panel b) represents the risk after 72h w.r.t. panel a), showing an increasing trend of the risk in a period of 72h. The map was obtained by using a multivariate Gaussian mixture model to fit the likelihood $p(\mathbf{m}_c | A_c = 1)$, considering the other terms in (1) uniform. The probability density function $p(\mathbf{m}_c)$ and the prior probability $\mathrm{P}\{A_c = 1\}$ can be estimated by using the same training set of attack positions-METOC vector pairs used for the likelihood.

2.2. Satellite AIS performance surfaces

Vessels exceeding a certain gross tonnage are equipped with AIS transponders for position-reporting, as established by the Safety of Life at Sea (SOLAS) convention. Ships repeatedly broadcast their name, position and other details for automatic display on nearby ships. While this allows ships to be aware and keep track of other ships in their immediate vicinity, coastal states are also able to receive, plot and log the data by means of base stations, along the coast. However, terrestrial AIS is limited in range and therefore cannot detect ships at distances beyond the range of normal VHF communication from coastlines. Operating range from shore is expected to depend on the capability and height of the installed base stations. Satellite AIS was developed to overcome this issue. However, AIS messages are organized in time slots and only one vessel is nominally permitted to transmit its AIS message in a given time slot within a Self Organized Time Division Multiplex Access (SOTDMA) region. Since more than one SOTDMA region usually falls into the satellite field of view, different AIS messages from different vessels can reach the sensor at the same time, leading to a collision and consequent message loss, namely, those vessels aren't detected [8]. The satellite AIS performance is then defined by the target detection probability [8], indicated for the *i*-th sensor and for the elementary cell *c* by $P_{D,c,i}^{AIS}$. This probability has been estimated for each cell *c* covered by the satellite field of view (FOV) using a Bayesian inference approach [8]. It is null for those cells not covered by the FOV.

2.3 Sensor trajectory simulator

The asset trajectory between two waypoints is simulated by modeling the asset horizontal position by a simple discrete first order kinematic equation with constant cruise speed in Cartesian coordinates. Additive Gaussian acceleration noise with given covariance matrix is used to model random disturbances generated, for example, by environmental conditions. A waypoint is acquired when the distance between the position of the asset and the way point is less than a given threshold (calculated by considering the speed of the asset and the sampling interval). A simple control system is included for simulating auto-piloting that is based on heading correction calculated from simulated noisy position measurements. Heading from last way point and range to the next are constrained within given intervals in order to guarantee the feasibility of asset maneuvers.

2.4 The surveillance risk metric prediction

The surveillance sensor network is devoted to monitor the vessel traffic. This task can be modeled with a binary hypothesis test. The null hypothesis H_0 holds if a generic target is not present in cell *c* while the alternative hypothesis H_1 holds if a target is present. The surveillance risk metric provides a measure of the risk that a vessel is not detected in regions where pirates can operate. Considering the cell *c*, a warning event W_c can be defined as the event of deciding for the absence of a vessel (*i.e.* H_0) when there is a pirate group operating, conditioned to the presence of the vessel target:

$$P_{W,c} \triangleq P(W_c) = P\left\{\hat{H}_c = H_0, A_c = 1 \middle| H_1\right\}, \tag{2}$$

where $\hat{H}_c$ is the binary testing decision.

The testing decision is based on the information fusion of the local sensor decisions. Given the probability of detection of the network (assets+satellite AIS) $P_{D,c}$, and the probability of favorable conditions for pirate activity $P_{A,c}$, recall equation (1), the probability of *W* can be obtained by:

$$P_{W,c} = \left(1 - P_{D,c}\right) P_{A,c}. \tag{3}$$

The network detection probability $P_{D,c}$ depends on where the network assets are deployed and on the performance of the sensors carried on board.

The surveillance risk metric for a given discrete time step *k* is defined as a Bayesian risk $f_{W,k}$ by averaging equation (3) over all the spatial cells:

$$f_{W,k} = \frac{1}{N_c}\sum_{c=1}^{N_c} P_{W,c,k} = \frac{1}{N_c}\sum_{c=1}^{N_c}\left(1 - P_{D,c,k}\right) P_{A,c,k}, \tag{4}$$

where N_c is the number of cells. The total risk metric f_W is then calculated by averaging equation (4) over the entire duration of the asset network mission.

3 ASSET NETWORK OPTIMIZATION

The goal of the multi-objective planning system is to minimize the surveillance risk metric and the mission costs, while maximizing the asset network area coverage. The multi-objective optimal deployment of the asset network can be formalized as follows. The decision variable vector $\mathbf{u}_i$ of the optimization problem for each asset *i*=1,…,*N* is composed of control actions to move the asset from the last reached waypoint to the next. These include range and heading controls:

$$\mathbf{u}_i = \left[r_{i,0}, \theta_{i,0}, r_{i,1}, \theta_{i,1}, \ldots, r_{i,N_{WP}-1}, \theta_{i,N_{WP}-1}\right]^T, \tag{5}$$

where N_{WP} is the maximum number of waypoints; $r_{i,w} \in \Omega_r$ and $\theta_{i,w} \in \Omega_\theta$ are the range and the heading to waypoint w+1 for the *i*-th asset, respectively; Ω_r and Ω_θ are the range and heading feasible regions. The controls $r_{i,0}$ and $\theta_{i,0}$ are applied at the asset starting position $\mathbf{x}_{i,0} = \left[x_{i,0}, y_{i,0}\right]^T$ to reach the first waypoint. The asset is supposed to come from a given direction with a given cruise speed. The network action control vector $\mathbf{u}$ is composed of the action controls of all assets:

$$\mathbf{u} = \left[\mathbf{u}_1^T, \mathbf{u}_2^T, \ldots, \mathbf{u}_N^T\right]^T, \tag{6}$$

where N is the total number of assets. An additional binary decision variable vector can be included if the number of deployed assets and the number of waypoints for each asset have to be optimized:

$$\mathbf{d} = \left[\mathbf{a}^T, \mathbf{w}_1^T, \mathbf{w}_2^T, \ldots, \mathbf{w}_N^T\right]^T, \tag{7}$$

where $\mathbf{a} = \left[a_1, a_2, \ldots a_N\right]^T$, with a_i equal to 1 in case the *i*-th asset is included in the network, 0 otherwise, and

$\mathbf{w}_i = \left[w_{i,1}, w_{i,2}, \dots w_{i,N_{WP}} \right]^T$, with $w_{i,j}$ equal to 1 if the *j*-th waypoint has to be included in the waypoint list of asset *i*, 0 otherwise.

The optimization is directly performed in a multi-dimensional space, by exploiting the concept of Pareto dominance [9], thus avoiding specifying weights among objectives (which is almost a subjective practice) as in an optimization scheme with a weighted sum of the objective functions. Moreover, there is no need to know derivatives of these functions with respect to the unknown vectors $\mathbf{u}$ and $\mathbf{d}$ given that a genetic evolutionary technique is used. The optimizer provides a full spectrum of optimal solutions (representing different tradeoffs among objectives) close to the so called Pareto optimal front (also known as Pareto efficient frontier) that is a hyper-surface in the multi-objective space. If a non-dominated solution is moved along the front to improve one objective, the remaining ones are inevitably subjected to deterioration. Such a set of tradeoffs can be analyzed by the mission planner for making his final decision taking into account his subjective preferences and qualitative evaluations [10].

Assuming the optimizer solves minimization problems, the objective vector function (also referred to as fitness function) used in this work includes the surveillance risk metric f_W, the opposite of the asset network area coverage f_{AC} and the total mission cost f_{MC}:

$$\mathbf{f}\left(\mathbf{u},\mathbf{d};\Theta\right) = \left[f_W, f_{AC}, f_{MC} \right]^T, \quad (8)$$

where Θ is the vector of sensor performance parameters. The solution of the optimization problem consists in finding the set P^* of non-dominated solutions for $\mathbf{u}$ and $\mathbf{d}$ in the feasible region constrained by the asset kinematic, the asset operational limits and additional spatial constraints such as interdicted areas:

$$P^* = \left\{\mathbf{u},\mathbf{d}\right\}_{Pareto} = \arg \underset{\mathbf{u},\mathbf{d}}{\mathrm{opt}} \left[\mathbf{f}\left(\mathbf{u},\mathbf{d};\Theta\right) \right], \quad (9)$$

where $\mathrm{opt}(\cdot)$ is the optimum in the Pareto sense [9]. The optimal solutions represent a cost effective tradeoff between the tendency of concentrating assets in high risk areas, which can be limited to a small portion of the whole ROI, versus larger area coverage in the ROI.

4. RESULTS

The proposed optimization criteria has been tested on a maritime scenario making use of real METOC hindcast data and satellite AIS performance surfaces. The ROI is in the Indian Ocean facing the Horn of Africa. Simulated assets include frigate class ships equipped with a surface radar having a maximum range of 100 km, and constant detection probability P_D=0.8 and constant false alarm probability P_{FA}=0.001, with cruise speed of 20 knots (10 m/s). The feasible regions for the control actions are $\Omega_r = [150, 350]$ km and $\Omega_\theta = \left[\bar{\theta} - 80, \bar{\theta} + 80\right]$ deg, where $\bar{\theta}$ is the ship direction of arrival to the last reached waypoint. A linear mission cost with the travelled distance is assumed, with cost per unit length and per asset equal to 10^{-6}. The total number of assets is N=6 and the number of waypoints per asset is N_{WP}=7. All assets and waypoints are included into a solution, *i.e.* the components of $\mathbf{d}$ are constant and equal to one. The scenario starts on 10 October 2010 at base time 00:00:00Z. Three days of significant wave height, peak wave period and wind speed hindcasts from the WAVEWATCH III global model, with 110x110 km spatial resolution and 3 hours temporal resolution, are used to produce grids of piracy risk. Satellite AIS performance is predicted on the same grid every 10 min to capture the dynamic of the satellite orbits.

The improved [1]Archive-based Micro Genetic Algorithm (AMGA2) [11] has been used to optimize the asset network planning as it improves upon several concepts from existing multi-objective optimization algorithms. In this study, a parallel version of AMGA2 for MATLAB has been implemented that significantly speeds up the optimization step. The maximum leading time to provide a plan is given by the temporal resolution of the METOC forecast model.

Figure 3 shows the results of the mission planner for the considered scenario. In particular, fig. 3-a) shows an approximated Pareto front which is almost stable after 30000 iterations of the AMGA2 optimizer. A solution in red, with total mission duration of 35 hours, is highlighted on the front (it is supposed that the user preference is for low f_W solutions). Figure 3-b) shows the temporal graph of the surveillance risk metric improvement factor (IF) that is the ratio between the risk using the assets and the risk using only the AIS, averaged over the ROI. The IF, except for the first 5 hours of the mission, has a growing linear trend with some fluctuations due to the intermittence of the AIS coverage. Figure 3-c) shows the percentage of the asset network area coverage with respect to the total area of the ROI. The fraction of the covered area ranges between 9.5% and 10.5% within the mission duration period. Figures 3-d) and 3-e) depict the piracy risk map and the satellite AIS coverage 29 hours since the base time, with overlaid planned trajectories. The initial position of the assets is highlighted with small green circles. The asset sensor coverage at 29 hours since the base time is also depicted showing the ability of the planning system to distribute assets by prioritizing regions with high risk and lower AIS coverage, and maximizing at the same time the area coverage.

In general, the simulations show that the provided solutions improve the vessel traffic situational awareness in those areas where the piracy risk is higher, supplementing low satellite AIS coverage.

[1] AMGA2 has been developed at Clemson Research in Engineering Design and Optimization Laboratory, Department of Mechanical Engineering, Clemson University and is the property of its developers. (C) Santosh Tiwari and Georges Fadel, Clemson University, 2009.

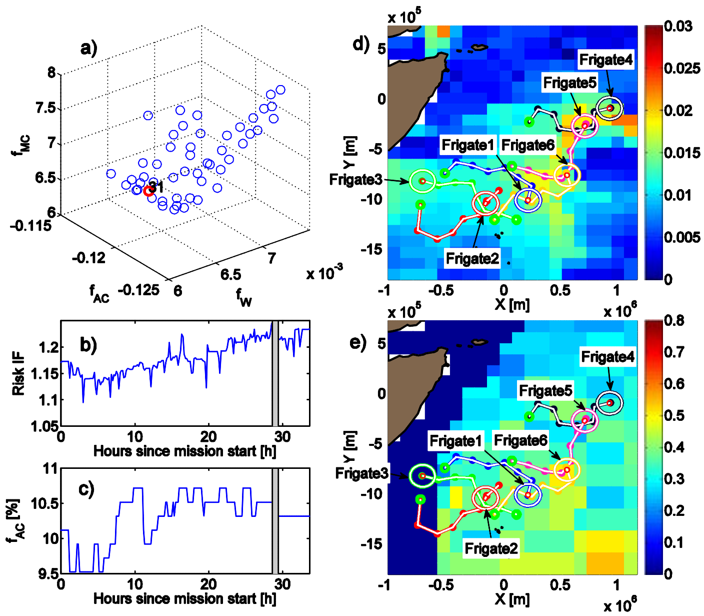


Figure 3: Indian Ocean scenario results: a) Pareto front with chosen solution in red; b) surveillance risk improvement factor; c) percentage of area coverage; d)-e) piracy risk map and satellite AIS coverage with planned asset trajectories.

Moreover, the time consuming optimization procedure, based on evolutionary multi-objective algorithms, provides solutions within the given leading time constraints.

5. CONCLUSIONS

This work proposes a system to allocate surveillance resources in areas of high piracy risk when the satellite AIS coverage is low, resulting in an improved maritime traffic situational awareness. The system is based on multi-objective optimization algorithm providing solutions that are on the so called Pareto optimal front. The solutions are a tradeoff among three objectives: surveillance risk, area coverage and mission cost. The methodology has been applied to a realistic scenario in the Indian Ocean using real-world data. In general, the tests performed have been shown an improvement in terms of surveillance risk taking into account the related asset costs and the sensor coverage. The system has a highly flexible architecture that can be expanded to account for different application dependent risk and performance metrics. Future improvements will include additional piracy risk factors such as intelligence and vessel traffic density information as well as performance surfaces of the asset sensors which are dependent on METOC conditions over the ROI.

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