DATA FUSION AND SIMULATION AS DECISION SUPPORT SYSTEM IN NAVAL OPERATIONS

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ABSTRACT

This paper proposes an approach for creating a decision support system in Naval Operation combining statistical approaches with modeling and simulation; it is proposed as case study the problem of maritime piracy; in this context data fusion based on Bayesian Networks and Dempster-Shafer could be applied to develop innovative classification solution to identify suspect behaviors and to support to the Naval Planner; indeed this paper focuses on the use of a discrete event simulator in order to create the evaluation framework to measure the effectiveness of the proposed classification approaches respect a realistic scenario inspired by Aden Gulf piracy**.**

Keywords: *Discrete Event Simulation, Bayesian Networks, Dempster-Shafer theory, Anti-Piracy, Intelligent Agents*

1. INTRODUCTION

Decisions in military operational contexts are complex problems affected by many factors and boundary conditions; in particular in maritime asymmetric warfare the uncertainty on large data set are representing critical elements affecting the planning as well as the decision making capabilities. In contexts similar to this one, wrong decisions could lead to dramatic consequences, so it is evident that human responsibility in decision making can't be substituted, therefore the use of simulation and decision support systems (DSS) could improve reliability, efficiency and effectiveness of the processes. This way, this paper is focusing on creating aids for supporting decision makers instead of addressing automated decision systems driven by computational systems.
From this point of view, it results useful to consider the possibility to combine modeling and simulation (M&S) with Dempster-Shafer methodologies for facing this challenge; indeed these methods represent a generalization of Bayesian models and could support classification problems within complex environments. Moreover the aim of the proposed decision support systems is addressing the necessity to be able to proceed in identifying and classify not cooperative targets within an asymmetric mission environment.
The paper proposes a simulation solutions to be used for testing the tactical aid and classification system used in the context of naval anti-piracy operations; this projects benefits from previous models as proposed in figure 1 (Bruzzone et al. 2011a); this stochastic simulator is able to estimate the effectiveness of the classification algorithms and of the overall naval plan respect the specific boundary conditions, indeed such approach could lead also to develop training aids to introduce naval planner in effective use of the input provided by intelligent classification systems. The paper provides experimental results in this case while in future the authors will finalize details of the classification approach in this case study and related integration with the simulator.

2. PIRACY AS APPLICATION CASE STUDY

The new warfare scenarios are characterized by new unconventional threats (i.e. terrorism, insurgency etc).
In maritime domain, piracy attacks are increasing over, in particular along Somalian Coast and in Arabian Sea.
From 2008 around 1000 piracy attacks are reported by the IMB (International Maritime Bureau) into the annual report and most of episodes are attributed to Somalia pirates. Those attacks generate huge economic and social damages to the entire world due to the great value of goods moved by sea. In fact, in a pirate attack often the interests of many countries are affected: the state of the attacked vessel, hostage's countries, the State of the industrial company owner of the cargo and so on.
The maritime piracy has become a critical issue in specific regions (for instance the Somalia coast) due to local factors such as political and socio-economical

instabilities since 2006. Actually, the maritime piracy is not a new phenomenon, but changes in geographic "hot spots", the increased frequency of incidents and the severity of attacks are requiring to face the current maritime piracy situation in a more effective and efficient way. For these reasons it could be interesting to develop innovative solutions for classification and simulation.

Fig.1: Discrete Event Simulator based on PANOPEA

Different models were developed to analyze the maritime traffic and to support maritime surveillance systems (Monperrus et al., 2008; Xiao et al. 2010) propose a framework of the Dynamic Data Driven Multi-Agent Simulation system in the maritime traffic domain.
The use of Modeling and Simulation (M&S) to address complex problems is largely used in a wide spectrum of fields such as military (Bruzzone 2010; Longo et al. 2008; Merkuryev et al. 1998), logistics (Merkuryev et al., 2009; Engelhardt-Nowitzki et al. 2013; Longo, 2014, Prado et al. 2014), distribution and transportation (De Felice and Petrillo, 2013), medicine (Diaz et al., 2012), economics ones. Furthermore, simulation is an evolving sector and the continuous improvement of M&S, with special reference to distributed interoperable simulation provides new opportunities for innovative applications where it is necessary to combine different models; in our case the possibility to connect the simulator with real C2 (Command and Control) systems for training or with Data Farms for scenario awareness have a big potential.
Indeed Intelligent agents are a new paradigm for developing software applications (Oren et al. 2000; Piera et al., 2013); more than this, agent-based computing has been hailed as 'the next significant breakthrough in software development' (Sargent, 1992), and 'the new revolution in software' (Guilfoyle and Warner, 1994).
The advantage to introduce IA (Intelligent Agents) in this sector is based on several aspects; one pretty interesting is their existing, even if limited, capability to self-explain the motivations of their actions and to interact dynamically with users (Bruzzone, Massei 2007; Moraitis, Spanoudakis 2007).

There are several methodologies that could be investigated to be used for creating intelligent agents to direct automatic consensus creation such as AHP or GMCR (Bruzzone, Massei, Tarone, Madeo 2011b; Inohara 2010).
In 1763 Thomas Bayes published his paper titled "An Essay towards solving a Problem in the Doctrine of Chances" as a solution to a problem of inverse probability, but the term "Bayesian networks" was coined by Judea Pearl in 1985 where in his essay "Probabilistic Reasoning in Intelligent Systems" summarized the properties of Bayesian networks and established Bayesian networks as a field of study (Pearl, 1988; Pearl and Russell, 2002).
Dempster-Shafer theory is a generalization of the Bayesian theory of subjective probability; the basis of this theory are included in two papers: Shafer's "A mathematical theory of evidence" (1976) and Dempster's "Upper and lower probabilities inducted by a multivalued mapping" (1967). From a quantitative point of view, Dempster-Shafer theory is equivalent to probabilistic argumentation.

3. PIRACY AND CLASSIFICATION

In the proposed piracy scenario, the threats (i.e. pirates) are usually hiding within a large traffic of small medium size boats looking for proper opportunity to attacks. So the decision maker should be able to properly decide about the different alternatives in patrolling an area as well as in the best way to address suspects within this context; often among many different objects it is required to identify the most effective approach to guarantee their classification, their nature, intentions, dangerousness and efficiency of the feasible actions. Therefore this problem need to be solved considering also efficiency aspects that strongly affect the sustainability of the mission; for instance cost reduction and effectiveness improvement could allow protecting large areas for longer times with limited resources, guaranteeing economic feasibility of the mission itself.
The not-linear nature of the problem outlines the strong dependence of the proper solution from the boundary conditions (i.e. patrolling resource capabilities, pirate attack procedures, boarding times, etc); due to this fact the simulation is the best approach to be able to quickly evaluate different alternative Courses of Actions (COAs) as well as different hypotheses on the scenarios.
An interesting issue is due to the fact that the threats are not collaborative and adopt behaviors devoted to guarantee their camouflage within the general traffic; these aspects become pretty challenging for classification because in this case the target detection and proper classification don't rely on technical features as it happen in traditional cases. In traditional naval classification the threat is usually identified by considering its features such as Radar Frequency collected by ESM (Electromagnetic warfare Support Measure) or length and number of chimney estimated by

the analysis of the ship silhouette captured by an ISAR (Inverse Synthetic Aperture Radar); vice versa in the proposed scenario the pirate boat is often exactly identical to a small medium size boat, just because the pirates are just hiding inside these ones; the capability to identify the type or even the name of the boat don't contribute too much in detecting pirates.
In technical terms here the classification problem deals with classification of suspect conditions and behaviors, while feature analysis is much less sensitive in this process.
Obviously in order to classify behaviors or boundary conditions that are correlated to high probability of pirate activity requires quantification of these elements in proper way; this approach is pretty challenging considering the high variability that corresponds to the necessity to introduce many parameters.
The authors in order to face this issue decided to introduce fuzzy modeling; indeed this approach gives the opportunity to support efficiently the decision making process, because of its capability in quantify these parameters in semantic terms by acquiring measures of their perception; in this way it could be possible to estimate by a fuzzy allocation matrix the degree of suspect affecting a boat approaching a cargo; at the same time the use of fuzzy membership functions could be used to extract the meaningful of specific boundary conditions respect the threat nature.
Based on this approach it becomes possible to elaborate the information and behaviors of different actors by using data fusion (Fenton and Neil 2007). The proposed approach focuses in the development of a data fusion architecture able to apply these methodologies to the specific case and in particular to the development of a platform supporting decision making and classification for ship commander of both military vessels and commercial cargo.

4. SIMULATION AND CLASSIFICATION AS COMBINED DSS

The Naval Operation requires to deal with uncertainty even in the information age; as anticipated in the proposed case study, it is challenging to obtain clear identification of the asymmetric threats (i.e. piracy) a through traditional technological surveillance: pirates hides among generic small medium size boat traffic and don't are characterized by features that could be easily detected by sensors (e.g. infrared and/or ISAR imaging, EMS etc); in this case it is fundamental to combine classical sensor data with information, behaviors, reports, boundary conditions; therefore specific features could also influence the classification (e.g. high speed); due to these reason, it is interesting to develop an innovative data fusion approach to classify suspect targets in order to estimate their probability to represent non collaborative threats such as a pirate boat while they operate as fishermen waiting for an opportunity to attack.
In this context the use of this innovative classification algorithms represent a significant improvement in planning naval operation by providing to the decision makers an indication where to concentrate their resources in patrolling an area; this approach support the definition of most effective approach for inspecting suspects boats.
Indeed the integration of this approach with simulation allows evaluating the reliability and efficiency of the proposed naval planning; in the proposed case the use of stochastic discrete event simulation allows to estimate the Measure of Merits (e.g. patrolled area, number of effective inspections) in statistical terms by conducting risk analysis and by defining their confidence bands.
Therefore, it becomes possible to estimate the probability to successfully identify the pirates by using resources (e.g. helicopter) for inspecting a specific suspect boat; the proposed solution allows considering also the information provided by reports received by local authorities and intelligence resources.
The simulator estimates costs and times to accomplish specific planning, so it represents a decision support system able to identify most promising alternatives among the necessity to inspect multiple suspect boats with different resources; simulation could be used also for coordinating a vessel task force in patrolling a specific area respect a particular threat.

5. CLASSIFICATION PROBLEMS

In classification problems, unfortunately, complete statistical knowledge regarding the conditional density functions of each class is rarely available, which precludes application of the optimal Bayes classification procedure. In these cases the adoption of the Dempster-Shafer methodologies looks really feasible. When no evidence supports one form of the density functions rather than another, a good solution is often to build up a collection of correctly classified samples, called training set, and to classify each new object using the evidence of nearby sample observation.

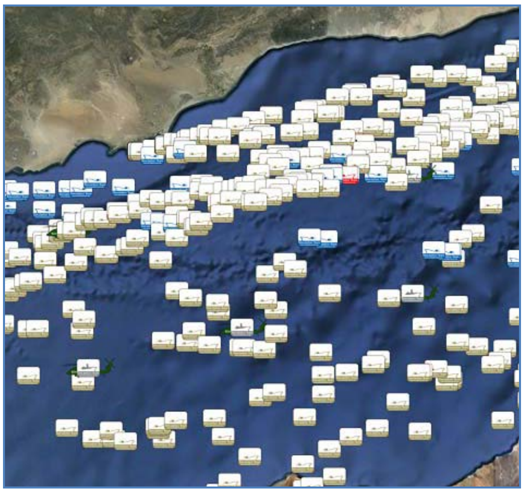

Fig.2: Simulator integrated within GIS Representation

Indeed, a Bayesian network is a graphical model that encodes probabilistic relationships among variables of interest (Castillo 1997). When used in conjunction with statistical techniques, the graphical model has several advantages for data analysis; first of all, the model encodes dependencies among all variables, it readily handles situations where some data entries are missing.

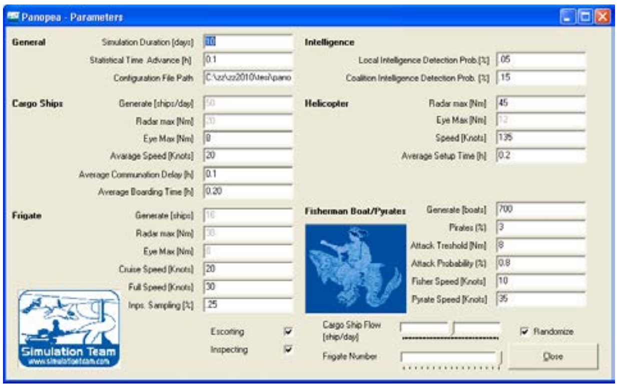

Fig.3: Simulator Main Input Variables

Another important advantage of the proposed approach is related to the fact that the Bayesian networks are useful to learn causal relationships, to gain understanding about a problem domain and to predict the consequences of intervention. In addition to these aspects, the proposed models combine causal and probabilistic semantics, so they are the ideal representation for fusion of a priori knowledge (which often comes in causal form) and current data. Last, but not least, Bayesian statistical methods, in conjunction with Bayesian networks, offer an efficient and principled approach for avoiding the data overfitting (Ben-Gal 2007).

The focus in this paper is on naval operations so the Bayesian network and Dempster-Shafer theories should be applied in this context; as anticipated it is challenging to identify different kind of boats by high level data fusion in order to understand and forecast their intentions and nature based on their behaviors (Darwiche 2009).

Formally, Bayesian networks are Directed Acyclic Graphs whose nodes represent random variables in the Bayesian sense: they address observable quantities, latent variables, unknown parameters or hypotheses. In these networks the Edges represent conditional dependencies, while not connected nodes represent variables that are conditionally independent of each other. Each node is associated with a probability function that takes as input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node. For example, if the parents are *m* Boolean variables then the probability function could be represented by a table of 2^m entries, one entry for each of the 2^m possible combinations of its parents being true or false. Similar ideas may be applied to undirected, and possibly cyclic, graphs; such are called Markov networks (Gelman et al. 2003).

Efficient algorithms exist that perform inference and learning in Bayesian networks; Bayesian networks that model sequences of variables (*e.g.* speech signals or protein sequences) are called dynamic Bayesian networks, while generalizations of Bayesian networks able to represent and to solve decision problems under uncertainty are called influence diagrams (Neil et al. 2005).

The first step of this analysis consists in defining the critical variables to be considered in these algorithms:

- danger distribution areas
- object dimension
- object speed
- object direction respect the potential target
- number of objects proceeding in formation
- distance of object from coast
- intelligence data and information
- weather conditions
- waves periodicity
- historic data

6. SIMULATION MODEL

The proposed model is based on discrete event stochastic simulation and it reproduces a piracy scenario in the Horn of Africa, a very critical area in terms of pirates' attacks against cargo ships especially during 2009-2011. This scenario includes navy vessels and helicopters, intelligence assets, ground bases, cargos as well as other boats (i.e. fisherman and yachts) and pirates hiding in the general traffic. The proposed simulator is derived from PANOPEA simulator (Bruzzone, Tremori, Merkuryev 2011a); in this simulation engine the user is able to set all major simulation features including Simulation Duration, Stochastic Influence and Replications.

The simulator is also integrated with a GIS (Geographic Information System) in order to visualize the whole scenario that include over 1500 small medium size boats, hundreds of commercial cargos plus the patrolling vessels (see figure 2); all these elements operates driven by the IA in the Aden Gulf reacting each other and to the evolution of boundary conditions: for instance small boats sail back to their ports when weather conditions are degenerating, or a vessel moves to a Naval Base in case of severe failures.

The entities are directed by IA-CGF (Intelligent Agents Computer Generated Forces) and apply strategies for succeeding based on their scenario awareness (Bruzzone, Tremori, Massei 2011c).

In addition, the simulator model different C2 (Command and Control) strategies, indeed the Simulation Team implemented different simulators addressing alternative C2 Architectures, including hierarchical and edge solutions corresponding N2C2M2, NATO NEC Command and Control Maturity Model (Bruzzone et al. 2009).

The model reproduces piracy activities for evaluating different strategies in N2C2M2. This simulator is a stochastic discrete event simulator integrated with IA-CGF (Intelligent Agent Simulation Computer Generated Force) in HLA (Bruzzone et al. 2011d).

The following actors are part of the simulation model:

- **Pirates**, different attack modes are considered: Outrunning, Maintaining Innocent Speed, Following a Ship, Hiding between Ships, Swarming. The main characteristics of these units are: agile structure, knowledge of the sea area, support from local population and in some case from political structure.
- **Navy**, including the vessels of different coalition forces patrolling the area. The command and control system. Different C2 (Command and Control) level of maturity are modeled including conflicted, deconflicted and collaboration approaches as well as C2 edge. Patrol modality is based on use of vessels (i.e. frigates and destroyers), helicopters, rigid hull inflatable boats (RHIB), Unmanned Aerial Vehicles (UAV) & special force squads. These platforms includes stochastic variables related to their reliabilities and availabilities.
- **Cargos** correspond to commercial ship travelling on the area in the direction of Suez Channel, Cape of Good Hope and/or Far East.
- **Small Medium Size Boats** represent the general traffic created by fishermen boats, small boats devoted to service and feeders sailing in the area, they could include also pirate support boats.
- **Intelligence Agencies**, that represent critical support for the Navy in order to identify and predict pirates activities by using resources, instruments and techniques such as: field agents, data analysis, special commandos, satellite and communication technologies.
- **Local Authorities**, represent Local Coast Guards and Authorities that could provide additional information and resources for additional control of the area; it evident that some of the coastal countries could represent additional resources, while someone has low credibility being characterized by unstable government, strong presence of gangs, warlords etc. The trustiness of Local Authorities is subjected by dynamic evolution considering the possibility of corruption or sympathy with pirates; due to these reason the adoption of an agile approach in C2 could lead toward the necessity to manage the structure dynamically.

In this context the False Alarms (FA) are defined as suspect boats that don't hide pirates; the FA are requested to be checked and/or inspected due reports originated by intelligence, local authorities or cargos.
The table below is a synthesis of some high level variable defining the scenario.
The use of the discrete event stochastic simulator allows users to carry out experiments over the scenario by changing several parameters related to boundary conditions as proposed in figure 3 (e.g. weather conditions, pirate distribution probabilities, intelligence effectiveness) or vessel characteristics (e.g. Cargo Average Speed, Navy Vessel Cruise Speed and Full Speed, Radar Range and Eye Range of View).

Cargo ship	
Number of Cargo Ships	Ships/day
Radar Max	Nm
Eye Max	Nm
Average Speed	Knots
Average Communication Delay	Minutes
Average Boarding Time	Minutes
Frigate	
Number of Navy Vessels	Ships
Radar Max	Nm
Eye Max	Nm
Cruise Speed	Knots
Full Speed	Knots
Inspection Time	Minutes
Intelligence	
Local Intelligence Detection Prob.	%
Coalition Int. Detection Prob.	%
Helicopter	
Radar Max	Nm
Eye Max	Nm
Speed	knots
Average Setup Time	Minutes
Small Medium Size Boats and Local Traffic	
Number of Boats	
Pirates	%
Threshold Distance for a Pirate to Attack a Cargo	Nm
Attack Probability	%
Small Medium Size Average Speed	knots
Pirates Maximum Speed	knots

Table 1. Parameters to be set in the Simulator

In addition to these aspects, the users are able to enable Escorting and Inspecting modes in order to activate strategies about escorting ships with same as well as inspections on suspect boats carried out by frigates and helicopters.

6. EXPERIMENTAL ANALYSIS

The stochastic simulator has been validated dynamically by using ANOVA (Montgomery 2000).
Through the analysis of Mean Square pure Error (MSpE) it is possible to determine the optimal duration of simulation run by identify the point of stabilization of the experimental error on the controlled variables.

$$\bar{Y}_i(t) = \frac{\sum_{j=1}^{r} Y_{ji}(t)}{r}$$

$$MSpE_i(t) = \frac{\sum_{j=1}^{r} \left(Y_{ji}(t) - \bar{Y}_i(t)\right)^2}{r-1}$$

$$ACFp_i(t) = \frac{2\lambda}{\bar{Y}_i(t)} \sqrt{\frac{\sum_{j=1}^{r} \left(Y_{ji}(t) - \bar{Y}_i(t)\right)^2}{r-1}}$$

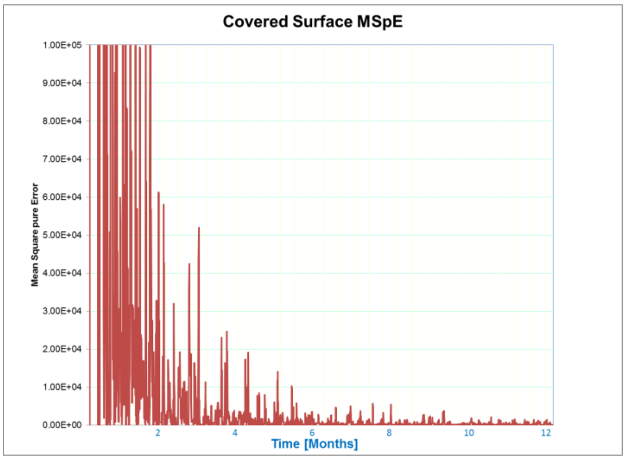

Fig.4: Total Covered surface MSpE

$\bar{Y}_i(t)$ Mean of the i-th controlled variable at t time over r replications obtained by changing random seeds of statistical distributions

r number of replications obtained by running the simulator just changing random seed and keeping same values for boundary conditions and independent variables

$Y_{ji}(t)$ Value of the i-th controlled variable at t time On the j-th replication

t simulation time

$MSpE_i(t)$ Mean Square pure Error at t time on the i-th controlled variable

$ACFp_i(t)$ Amplitude in percentage of the confidence Band of the i-th controlled variable at t time

λ percentile of the desired confidence band normally estimated based on a t of student distribution

The analysis has been carried out over several target functions including among the others:

- Total Detections
- Total Correct Classifications
- Total Correct Engagements
- Total Pirates in the Area
- Detected Pirates in the Area
- Properly Classified Pirates in the Area
- Successfully Engaged Pirates in the Area
- Total False Alarms in the Area
- Detected False Alarms in the Area
- Properly Classified False Alarms in the Area
- Improperly Engaged False Alarms in the Area
- Recently Covered Area
- Total Covered Area
- Total Costs
- Total Number of Escorts
- Total Number of Inspections by Helicopters
- Total Number of Inspections by RHIB
- Total Number of Inspections by UAV

In the following graph it is presented the convergence of the MSpE respect a subset of these variables; for instance in figure 4 it results evident that the Covered Area stabilize its variance within 4 simulation months.
Similar analysis in terms of MSpE time evolution is proposed in figures 5, 6 and 7 addressing costs, total FA detections and comparative analysis on successful classification ratio on pirates and FA.
The FA and Pirate Detection Effectiveness are presented as ration among number of entities successfully checked respect their total number.

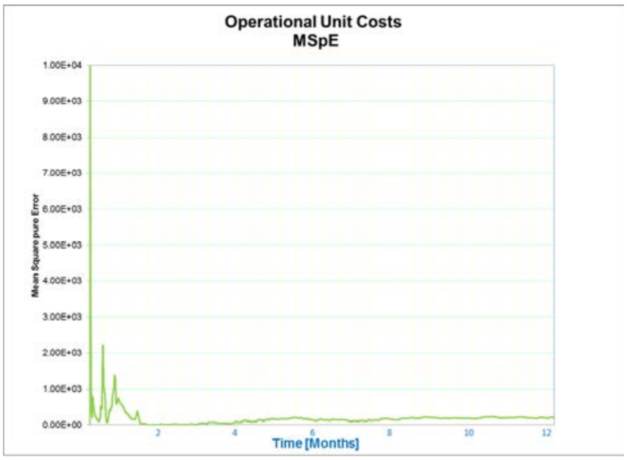

Fig.5: Operational Unit Costs MSpE

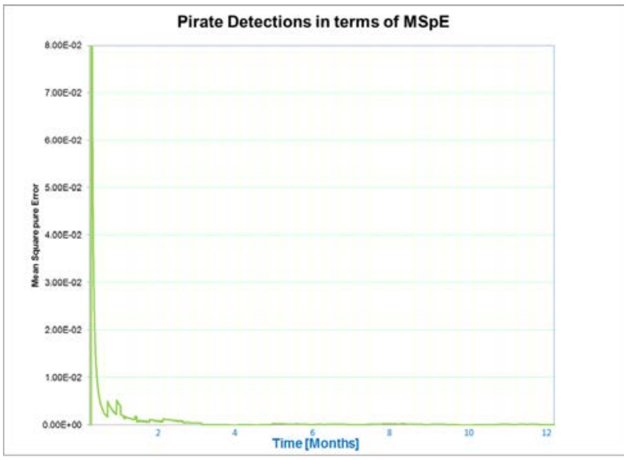

Fig.6: Pirate Detections MSpE

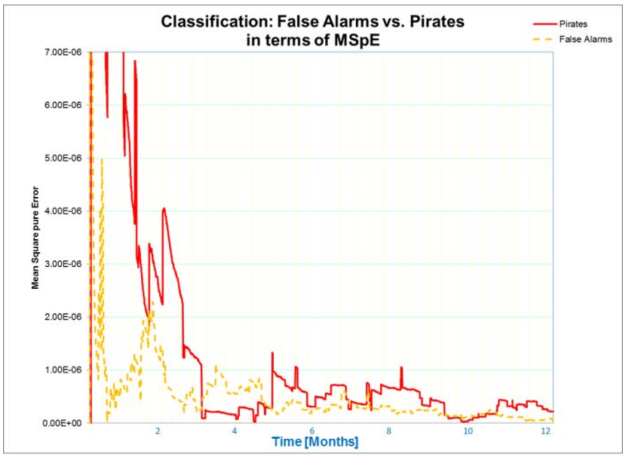

Fig.7: Classification False Alarms vs. Pirates MSpE

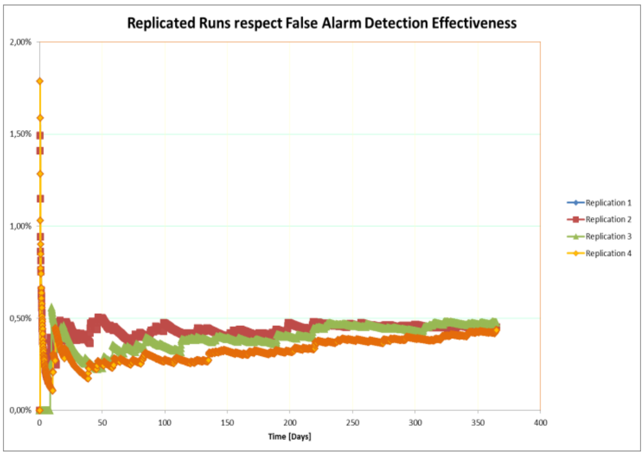

Fig.8: Replicated runs: FA Detection Effectiveness

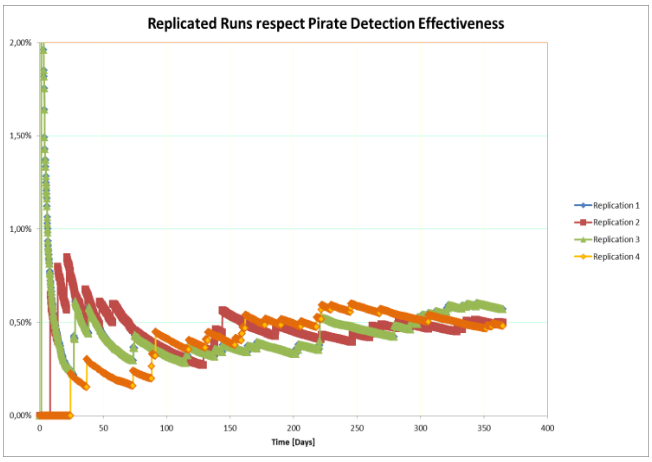

Fig.9: Replicated runs: Pirate Detection Effectiveness

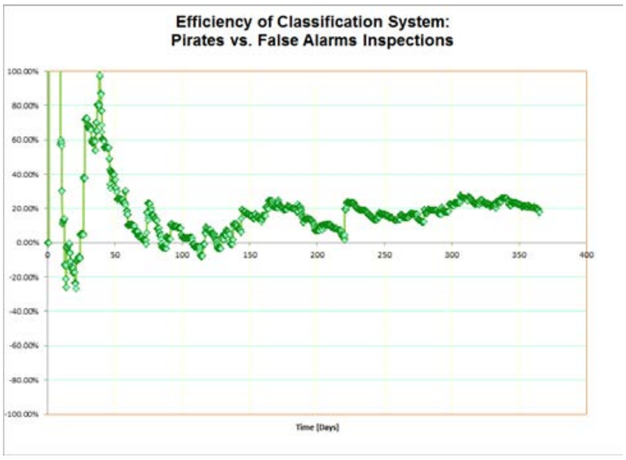

Fig.10: Benefits of the Classification System

The Figure 10 proposes the ratio of Inspections on real Pirates hiding in general traffic respect suspect contacts resulting in innocent boats (FA):

$$IE(t) = \frac{IFA(t) \cdot TPy(t) - IPy(t) \cdot TFA(t)}{IPy(t) \cdot TFA(t)}$$

IE(t) Inspection Efficiency Metrics at t time
IFA(t) Total Completed Inspections resulting in FA at t time
TFA(t) Total FA in the area at t time
IPy(t) Total Completed Inspections resulting in Pirates at t time
TPy(t) Total Pirates in the area at t time

It is evident that the number of targeted pirates is 20% higher than FA confirming that the classification algorithms directs the resources of the Navy to inspect most effective targets.

7. CONCLUSION

The simulator proposed was successfully used to carry out preliminary experimental analysis for validating the new classification modes proposed; currently the authors are working on tuning the data fusion algorithms as well as the fuzzy models in order to improve the efficiency of the algorithms, while the simulator is under further development in order to include additional details.
This research will be extended to conduct additional experimental campaigns in other geopolitical areas as well as to cover other operational needs such as maritime interdiction and/or sea border protection.

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