KINGFISHER: Total Maritime Awareness System (Demonstration)

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1. INTRODUCTION

Continuous monitoring of naval activities of vast areas, hundreds of nautical miles away from shoreline, is one of todays most challenging problems. To enable total maritime awareness in these areas, the use of satellite-based sensors is an efficient and cost-effective way to perform this task. The KINGFISHER (Figure 1) is a maritime multi-layer intelligence system created for an in-depth analysis of large maritime areas of interest in order to provide maritime awareness and detect illegal activities such as illegal fishing and immigration.

The major novelty of KINGFISHER is the detection of abnormal vessel behavior by analyzing and correlating various data sources such as Electro-Optics (EO) imagery, Synthetic Aperture Radar (SAR) imagery, Automatic Identification System (AIS) and Open Source Intelligence (Osint), to track moving vessels with satellite sensors in order to detect uncooperative ones, and select the most suitable satellite and its best time frame for vessel detection. Satellite imagery covers a relatively small area, and can be acquired only at predefined acquisition opportunities. Thus, effective usage of satellite sensor will lead to a more economic solution and is mostly required in this domain.

The Research and Innovation team at ImageSat International (ISI) developed algorithms for KINGFISHER based on Artificial Intelligence (AI) techniques such as Multi Agent System and Deep learning. The objective of the AI techniques is to enable decision support for maritime operators and provide an optimal, autonomous and economic solution for maritime system.

Detection of a moving vessels with satellite sensors, is a challenging problem which requires a large amount of satellite imageries to enable vessel detection. We propose to minimize this coverage area by using the prediction process of the moving target. Using multi-agent based modelling and simulation, we developed a prediction algorithm for the vessel behavior and selection algorithm which recommends on the best satellite and its observation window for this mission. Deep learning enables the system autonomously detect vessels in existing satellite imagery and by correlating this detection with various other sensors, the uncooperative vessels are detected autonomously as well.

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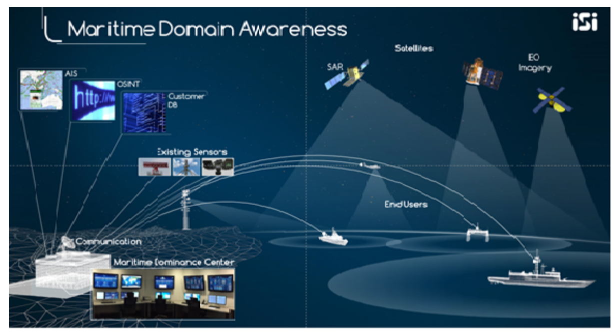

Figure 1: KINGFISHER: Total maritime awareness

2. THE SYSTEM ARCHITECTURE

The KINGFISHER is a multi-layer system integrating data from several types of satellite based sensors and additional intelligence sources such as AIS, SAR satellite imagery, EO satellite imagery, OSINT, weather and more. Figure 2 presents the system architecture. The System Core model is a management layer and it responsible for data management, algorithms setting, user permission and more. The Algorithms layer is responsible for the execution of algorithms and the AI module is responsible for the intelligent decision process and it contains algorithms such as autonomous vessel detection from satellite imagery, vessel behavior prediction, multi source data correlation, optimal satellite selection for moving vessel detection with satellite sensor and more.

3. ALGORITHMIC FRAMEWORK AND AI

There are two main algorithmic phases at KINGFISHER. First is to continuously monitoring an area in order to detect and alert the operator about presence of maritime anomalies. Then, the system performs further investigation for all the suspected vessels to learn their behavior patterns and to continue tracking these vessels with satellite sensors, the system recommends the best imaging opportunities available.

In monitoring phase (Figure 3), the data from various sources is being received, analyzed and archived as a separate intelligence layer. The AIS data is pre-processed to

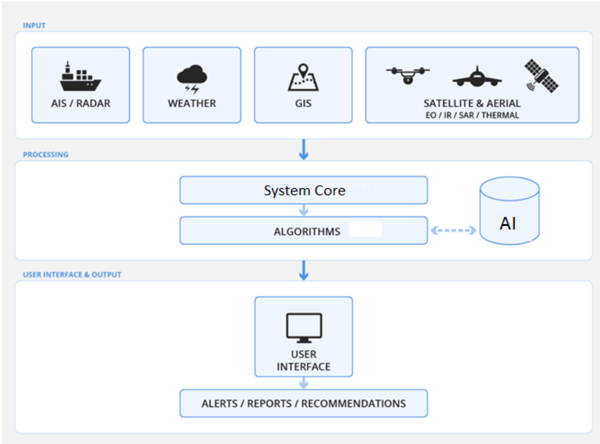

Figure 2: System architecture

remove a noisy data. Deep Learning classification algorithms are applied on the imagery data layers in order to autonomously detect vessels in the imagery. The system enables detection of naval vessels which are mostly non-cooperative targets through the integration and correlation of all data sources.

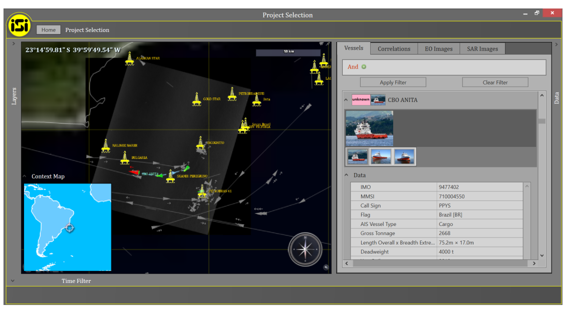

Figure 3: KINGFISHER monitoring phase: Multi layer analysis

To continue to track the suspect vessels with satellite sensor, the vessel behavior prediction is a necessary ability. The main challenge is that the vessel is a moving object and the current commercial satellites mission planning may take several hours, thus the cover area after 3 hours may be over $17,000km^2$ while one satellite image is commonly of size $50km^2 - 100km^2$, i.e., less than 1% of the total area's size. Therefore, an efficient way for decreasing the search area for the vessel is by using *vessel behavior prediction*. Reduction of the position uncertainty will also lead to a more economic solution.

There are several approaches for vessel behavior prediction in the maritime domain [2, 3, 4], however, existing models do not yet account for long-term vessel behavior prediction which is essential for ordering satellite image, since satellite service providers require planning in advance. Our proposed approach for predicting vessel behavior provide up to 77% of accurate detection for 1–11 hours.

To predict vessel behavior, we create a behavioral model based on historical data of the vessel (AIS data). We use Second Order Markov Chain to build a graph representing the historical behavior. Based on the historical graph and the estimation of initial vessel's location on the graph, we extract the possible paths of the vessel at different times. Each such path contains set of edges with their speed segments and probabilities. Using multi agent simulation we predict the vessel behavior.

We create agents that simulate the possible movements of the vessel on the extracted paths. Each agent gets the movement path based on path's probability, thus higher the probability the more agents will move on this path. Each agent draws different velocities according to the behavior graph, based on the Gaussian distribution of velocities on each edge.

At any given time, the model return the positions of the agents. The predicted area of the vessel is a two dimensional histogram, which is created based on the agents' location. Each cell in the histogram represents geographic location $1kmX1km$ and the rank of each cell is the normalized number of agents (based on the total number of agents). Example of prediction results, in one of the experiments, after 9 hours, is presented in Figure 4. As shown in the figure, there are 2 possible polygons in which the vessel can be found after 9 hours. The dark cells represent the lower rank, meaning lower probability that the vessel will be in that area, while bright cells corresponds to higher rank. The triangle corresponds to the real location of the vessel after 9 hours. As we can see in the Figure, the triangle is in one of the polygons that is recommended by the model.

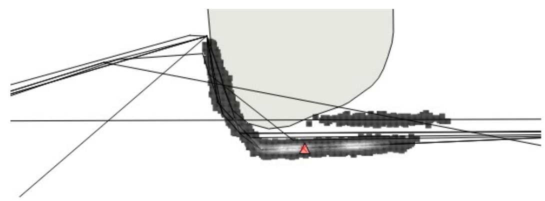

Figure 4: Prediction results after 9 hours: set of two dimensional histograms

To find the best satellite and its observation window, we use an STK (Satellite Tool Kit) [1] as satellite simulation for moving object detection. The STK simulation enables the calculation of the satellite-to-object visibility. Our simulation calculates the times that the satellites can acquire the simulated moving vessels based on position information and satellite constraints.

Figure 5 presents the STK simulation of one of the experiments: it shows the agents move on the created graph based on the historic statistics.

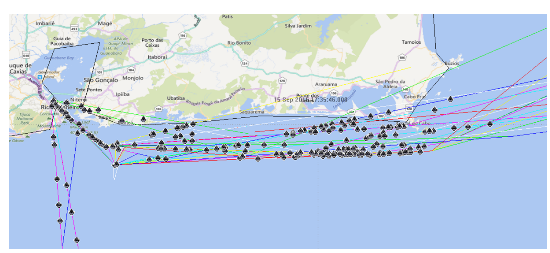

Figure 5: STK simulation

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