Soft-Data-Driven Resource Management for Concurrent Maritime Security Operation

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***Abstract*— Enhanced Course of Action (CoA) generation is a fundamental component of effective risk management and mitigation. This paper presents an extension of a system capable of integrating physics-based (hard) and people-generated (soft) data, for the purpose of achieving increased situational assessment and automatic CoA generation upon risk identification. The system's capabilities are enhanced through added support for managing multiple, concurrently unfolding risky events (situations) with the goal of attaining superior resource management and thus reducing the overall security operation costs. The CoA generation process is evaluated through a series of performance measures. The proposed conceptualization is validated via an elaborate experiment situated in the maritime world.**

Keywords—course of action recommendation; decision support systems; multi-criteria decision making; high-level information fusion; hard-soft data fusion

I. INTRODUCTION

Advances in the telecommunications sector – namely, the development of always-connected, hand-held, sensor-packed computing machines we refer to as smartphones – have enabled people to play the role of portable observational sources of information. Traditional, physics-based (e.g., acoustic, sonar, radar, or electro-optical – frequently referred to in the literature as 'hard') sensors are superior in their ability to characterize physical objects by estimating their attributes, computing their locations and velocities, and making predictions on their future states. Humans, on the other hand, are inferior in performing these mathematically-intensive activities, but themselves excel in their *sui generis* capacity to provide inferred relational information and estimated intents and capabilities of observed entities [1]. These complementary information types can provide for an effective synergy between physics- and human-derived observations to augment the situational awareness picture constructed by Information Fusion (IF) systems. Including human-derived (also referred to as 'soft') data into IF systems comes at a price. Hard sensors are manufactured under stringent requirements and thus have known error characteristics; two properly functioning sensors of the same type will produce identical (to a previously known and acceptable tolerance) information when observing the same event. This is not true about soft sensors, however as perception is inherent in the human observation process, and therefore situational observations are subject to the knowledge and skill level of the individuals carrying them out. It can be said that human beings are like *uncalibrated* sensors. The information provided by them is subject to unknown bias and uncertainty; furthermore, it can also be subject to conflict, as multiple people observing the same phenomena may provide inconsistent accounts of what transpired [2], [3]. Additional challenges of assimilating people into IF systems include: (1) no standard ways of representing the collected heterogeneous data; (2) performance assessment techniques are still largely non-existent; (3) there is no clear methodology for what the most effective way to task people is (they are an uncontrolled resource). As a result of these aforementioned challenges, at present, there exists no generic, standardized framework to seamlessly integrate and exploit these heterogeneous information sources. Nonetheless, automated solutions in Hard-Soft IF (HSIF) can assist in operational decision making, as they alleviate analysts from dealing with the otherwise overwhelming, voluminous amount of sensor data. One environment, greatly burdened by the curse of big data, is the maritime domain. The research presented in this paper strives to be a step towards an automated HSIF solution in this domain by building on from [11] through expanding the proposed HSIF system's capabilities by: (1) supporting CoA generation for a wider variety of risky events, and (2) allowing for it to monitor and manage *any* number of concurrently unfolding events by generating responses (i.e., CoAs) composed of tasking resources (assets – e.g., helicopters, unmanned aerial vehicles, fixed wing aircraft, maritime vessels) that will carry out the specified concurrent missions. The research in [11] presents the first instance of hard-soft data-driven response generation for the maritime domain.

The remainder of the paper is structured as follows. Section II briefly reviews relevant work. Section III presents background information pertaining to maritime security operations. Section IV unveils the proposed, soft-data-driven response generation methodology and Section V lays out its associated experimental results. Finally, Section VI presents the concluding remarks and discusses future research directions.

II. RELATED WORK

Level 2 (L2) and Level 3 (L3) IF are respectively defined as situation assessment and impact assessment in the Joint Director of Laboratories/Data Fusion Information Group models [4]-[6]. The responsibility of situation assessment is to characterize currently unfolding situations in the environment being monitored whereas impact assessment is concerned with the generation of suitable CoA recommendations and the estimation of their effects on the previously characterized, presently unfolding situations. The estimation is achieved by carrying out scenario simulations of the different sets of CoAs and calculating their associated performance measures.

In the maritime world, operators often rely on data sources generated by hard sensors (monitoring vessel traffic) for the purpose of identifying risks or suspicious events at sea. However, soft data in this area presents a trove of relevant information, such as maritime incident details or textual reports on vessel sightings. Soft data has been previously considered in [7] and [8] to respectively extract risk features from maritime incident reports and perform hard-soft risk-driven situation assessment. As demonstrated in [7], natural language processing methods can be effective in extracting from such reports meaningful information that is representative of human intuition. In [8], we demonstrated how this soft information can then be fused with information derived from hard data sources in order to provide a more comprehensive situational awareness picture.

The generation of viable responses has been previously investigated in [9] and [10] (where the latter builds on from the former by accounting for behavioral intents in its risk modeling), but considering only hard data sources. More recently in [11], we explored the generation of Courses of Action (CoAs) through the use of both hard and soft data guided by evolutionary multi-objective optimization.

A. Response Assets and Onboard Sensors

Within this research, we make use of two broad categories of assets – namely *aerial* and *naval*. The former group includes Unmanned Aerial Vehicles, Fixed-wing Aircraft, and Helicopters. The latter group comprises vessels of different types (e.g., speed boats, tug boats, military ships).

From a mission response perspective, each asset can belong to one of three groups: Coast Guard Assets (CGAs), Auxiliary CGAs (ACGAs), and Opportunistic Response assets (ORAs). CGAs and ACGAs can be either docked at their home base or traveling somewhere in the vicinity. ORAs are not owned by the coast guard, but happen to be in the vicinity at the time of the detected risk events and are able to provide assistance. The different asset platforms have different associated characteristics – costs to operate/move and transit speeds. Assets also can have onboard detection equipment (such as sensors). Two sensors which can be used for maritime operations are Doppler Radar Model (DRM) and Synthetic Aperture Radar (SAR). SAR sensors are mounted on aerial platforms and used to look down on targets located on the Earth's oceans and seas. In contrast to them, DRM sensors are near the surface of the Earth; they are typically mounted on tall masts, where the height of these structures determines the distance to the horizon (beyond which targets cannot be detected). The probability of target detection for both of these sensors is directly related to their corresponding power levels, as well as being directly affected by the prevailing weather conditions in the region they are monitoring.

B. Search Patterns

In maritime security operations, there are four popular types of search patterns with which response assets can be tasked to execute in their designated search areas [12], [13]. These are the *Track Crawl*, as depicted in Figure 1.; *Parallel Track Line*, as depicted in Figure 2.; *Outwards Expanding Square*, as depicted in Figure 3.; and *Inwards Collapsing Square*, similar to the depiction in Figure 3., but with reversed directionality.

The use of the search patterns varies depending on the characteristics of the situation being dealt with. The Track Crawl is used whenever the track of the Vessel to be Located (VL) is known ahead of time. Whenever the track is not known, the Parallel Track Line is used to task search assets to follow parallel tracks along the expected drift current. The last two search patterns (the Inwards/Outwards Collapsing/Expanding Squares) are used whenever only the last known location of the VL is captured ahead of time.

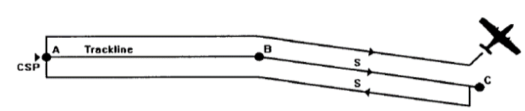

Fig. 1. Track Crawl, as presented in [13]

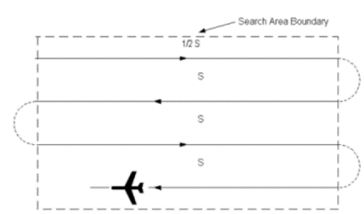

Fig. 2. Parallel Track Line, as presented in [12]

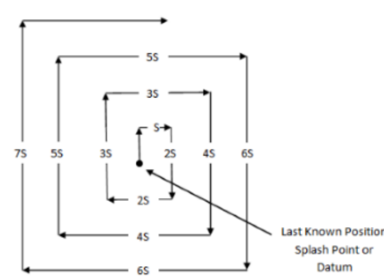

Fig. 3. Outwards Expanding Square, as presented in [12]

III. Concurrent, Soft-Data-Driven Resource Management

A vital L3 Fusion component is the timely, automatic generation of suitable responses, with the intention of lowering a risk or hazard present in the environment being monitored. This section unveils the architecture for a system capable of generating such CoAs for multiple, concurrently unfolding risk events by extracting mission-specific requirements from historical soft incident and response data. The expectation is that: (1) the inclusion of such people-generated data will yield a higher average chance of mission success; and (2) that considering multiple situations (events) at once will yield a lower average asset utilization in missions than when the same situations are being processed independently by the system, due to a more optimal asset-to-risky-event assignment.

A. System Architecture

The *Soft-Data-Driven Response Generation* (SDDRG) system, whose architecture is laid out in Figure 4., is capable of performing its CoA-generation duties through the aid of seven modules: (1) the *Anomaly Detection Module* (ADM), which is responsible for determining the confidence levels for different anomaly types (e.g., piracy events, vessels in distress) for each of the assets being monitored; (2) the *Situation Assessment Module* (SAM), which determines the most pressing situations the system will tend to; (3) the *Response Requirements Determination Module* (RRDM), which uses historical incident data to infer the response requirements based on the type of unfolding situations and the manner in which similar, previous (historical) situations were dealt with; (4) the *Asset Selection Module* (ASM), which is responsible for selecting the assets that will tend to the

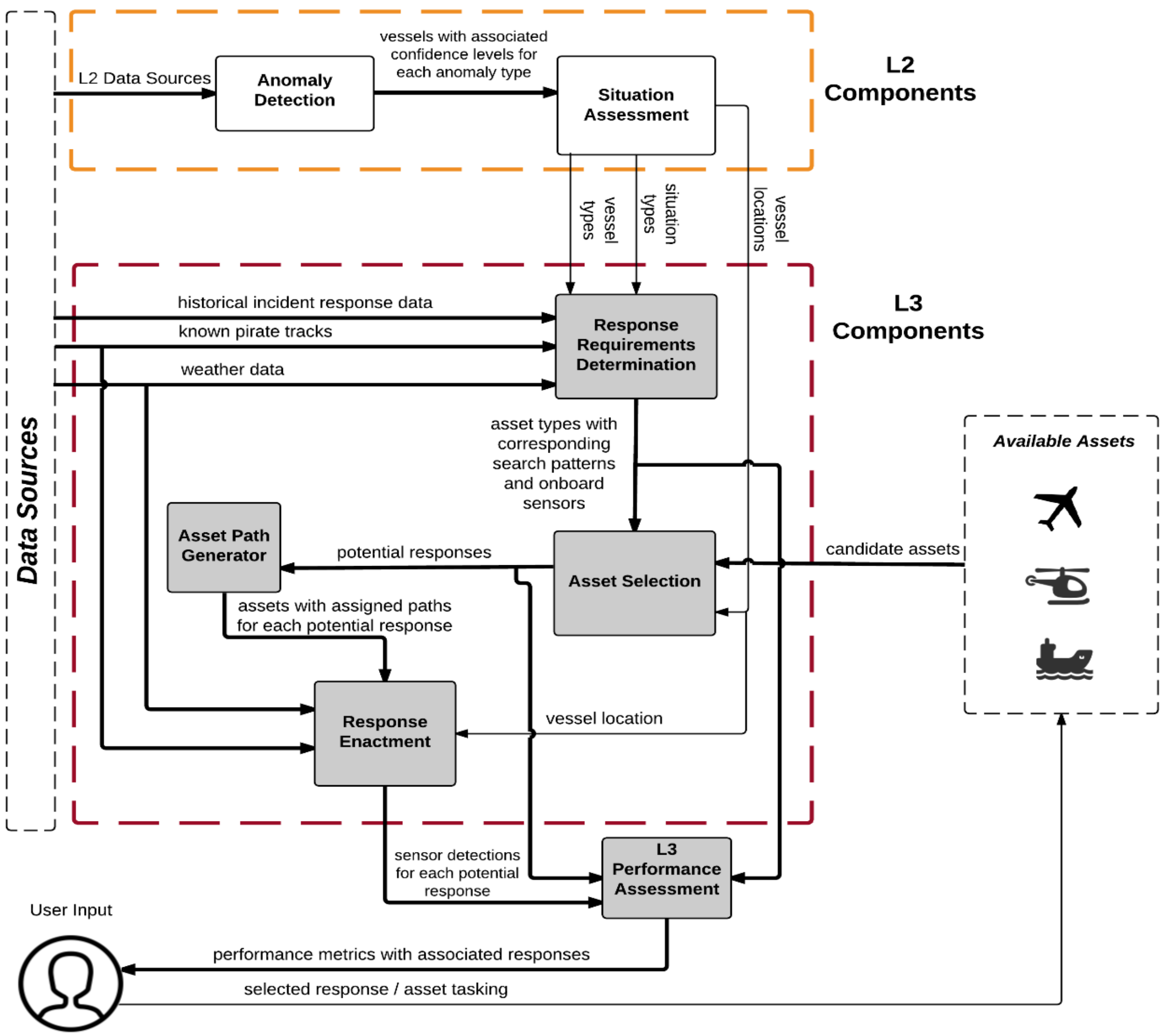

Fig. 4. Soft-Data-Driven Response Generation (SDDRG) System

unfolding situations of interest; (5) the *Asset Path Generation Module* (APGM), which generates tracks for all the assets, based on their designated search areas and assigned search patterns; (6) the *Response Enactment Module* (REM), which is responsible for carrying out the response simulation; and lastly, (7) the *L3 Performance Assessment Module* (PAM), which tracks and calculates six performance metrics, according to which each potential response is judged. This research focused on the expansion of the system's L3 modules (the RRDM, ASM, APGM, REM, and PAM), which are all shaded in grey within the architectural blueprint. The behavior of the remaining two (L2) modules was simulated for the purposes of this study.

B. Response Encoding

The tasking of the assets for the different response missions is based on the mission requirements (MRs) that are extracted from the soft data. The MRs themselves define what specific types of assets are required for each type of risk event (situation), as well as what type of onboard sensors each type of asset should possess. The module provides a designated subgrid (a subset of the response search area) for each asset. Whenever a risk event is detected by the system, a response grid surrounding that incident is immediately produced. The response grid resembles a rectangular matrix composed of cells, where each cell is a square with an area that can be entirely enclosed by the sweep area of the smallest-sweeping sensors of the selected response assets. Figure 5. demonstrates an example response grid with four subgrids and three gaps in search area coverage. Asset subgrid designation is optimized with the popular Non-dominated Sorting Genetic Algorithm II (NSGA-II) [14]. This algorithm is employed to yield a set of spread non-dominated candidate solutions (responses) with varying degrees of mission latency, cost, response area gap sizes, and levels to which they meet MRs. The reader is referred to [9] for insights into the reason for which this algorithm was selected for carrying out multi-objective optimization.

As presented in Table 1, potential response missions are encoded as four-layer chromosomes, where each gene corresponds to an asset that can be engaged in the response. As previously defined in [11], the first layer encodes whether or not an asset will participate in the mission, and the second layer codifies the type of search pattern the asset will have to execute within its designated subgrid.

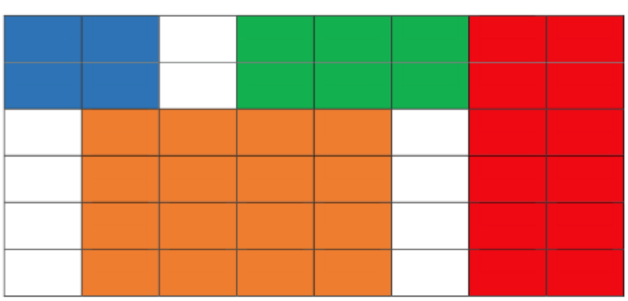

Fig. 5. Example Response Grid

TABLE 1. CHROMOSOME ENCODING OF A CANDIDATE RESPONSE

Asset	A_1	A_2	A_3	…	A_N
Inclusion / Exclusion	Exclude	Exclude	Include	…	Exclude
Designated Search Pattern	Parallel Track Line	Parallel Track Line	Track Crawl	…	Track Crawl
Designated Search Area	5	3	2	…	3
Designated Subgrid	0,5,1,8	5,5,2,1	3,0,5,4	…	6,2,7,7

The third layer is new and has been added in this work in order to denote which particular response (i.e., situation) grid the asset will be exploring, as there may be multiple response grids whenever there are multiple ongoing risk events. The fourth layer has been modified to encode the designated asset subgrid – within the selected response grid in the third layer – for that asset, by encoding the row and column indices of the top left corner location of the response grid, as well as the length and width of its designated subgrid, analogously to [10].

C. Response Objectives

There are four objectives used by the NSGA-II optimizer: Mission Time (MT), Mission Expenses (MEs), Unexplored Search Area (USA) percentage, and MRs, which are as previously defined in [11]. The MT is calculated by determining how long it would take each of the assets to travel to its designated subgrid, and then perform its assigned search pattern within the subgrid. The MEs are calculated by determining what the total accrued cost of displacing the assets is. The USA quantifies the percentage of the search areas that remains unexplored by response assets. The MRs, as previously discussed, are derived from the soft data, and quantify the similarity between the number and type of assets partaking in the response mission along with the type of sensors attached to each asset, and the number and type of assets and sensors located in historical (soft) data missions.

D. Response Objectives Performance Metrics

There are six different metrics that are used to evaluate the quality of the responses; these, along with the details of each response are presented to the human operator, who proceeds to select which response, if any, should be carried out, given his or her training, expertise and intuition. The first five metrics remain as previously defined in [11] and constitute the level to which the four objective functions (MT, ME, USA, MRs) are met, as well as a fifth metric, Potential Contact Detections Per Response Asset (PCDRA), which quantifies the amount of potential VL contacts that are detected during mission simulations. The sixth metric, proposed as part of this research, is the Asset Utilization (AU), which quantifies the percentage of assets partaking in a response mission. More formally, it is defined as:

$$\boldsymbol{AU} = \frac{\{a\ \varepsilon\ A : a.participates = true\}}{|A|} \qquad (1)$$

where A represents the set of assets available to participate in missions.

E. *Evolutionary Operators*

There were two evolutionary operators used in the study: standard crossover and a custom mutation operator. The former randomly selects a crossover point and swaps the information in each of the four layers of each parent's chromosome (before and after the swap point) thus generating two offspring. The latter operator is responsible for mutating each gene layer based on an input probability, and for ensuring that if the asset's subgrid boundaries extend beyond those of the full search grid (as a result of the mutation), it will trim the subgrid to fall entirely within the search grid. The custom mutation algorithm is presented in Figure 6.

IV. Case Study: Maritime Piracy and Vessel in Distress

This section presents a simulated maritime experiment that includes two concurrent risk events – a Vessel in Distress (VID) and a Maritime Piracy situation. Both events occur at roughly the same time. To gather experimental data, the SDDRG system was run with three different configurations:

- with soft data enabled by considering the VID and piracy event independently (in a sequential fashion);
- with soft data by concurrently assigning assets to both the VID and Piracy event; and
- same as configuration (2), but without considering soft data

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comments:   rnd.nextDouble() returns a uniformly distributed real number in the range of 0 to 1

            rnd.nextInt(N) returns a uniformly distributed integer ranging from 0 to N-1

            getPatternsForAsset(assetType, subgrid) returns a list of search patterns (if
            any) which were used for this asset type in the closest historical soft incident report (for the
            situation described in the provided subgrid)

            checkGridBoundaries(gene, subgrid) checks whether the designated subgrid of
            the asset, as designated by the row, column, and their respective offsets falls fully within the
            boundaries of the search grid; if it does not, the offsets are trimmed to guarantee that the asset's
            subgrid does not extend beyond the search grid
--------------------------------------------------------------------------
inputs:     chromosome                  c,
            random number generator     rnd,
            mutation probability        p,
            search grids                grids
--------------------------------------------------------------------------

for each gene g in c
      if (rnd.nextDouble() <= p)
            g.flipInclusionBit()
      end if
      if (rnd.nextDouble() <= p)
            s = grids.get(rnd.nextInt(grids.length))
      end if
      if (rnd.nextDouble() <= p)
            g.rowIndex = rnd.nextInt(s.numberOfRows)
      end if
      if (rnd.nextDouble() <= p)
            g.colIndex = rnd.nextInt(s.numberOfCols)
      end if
      if (rnd.nextDouble() <= p)
            rangeToMaxRow = s.numberOfRows - g.rowIndex
            g.rowOffset = rnd.nextInt(1 + rangeToMaxRow)
      end if
      if (rnd.nextDouble() <= p)
            rangeToMaxCol = s.numberOfCols - g.colIndex
            g.colOffset = rnd.nextInt(1 + rangeToMaxCol)
      end if
      if (rnd.nextDouble() <= p)
            patterns = getPatternsForAsset(g.assetType, s)
            g.searchPattern = patterns.get(rnd.nextInt(patterns.length))
      end if
      checkGridBoundaries(g, s)
end for
```

Fig. 6. Custom Mutation Operation

The three different configurations were all executed with the same set of scenario assets, which included a collection of naval as well as aerial platforms. The risk events occur in the northeast coast of Africa. The region has a Somalian coast guard station located at latitude of 11.777, and longitude of 51.243; a Somalian auxiliary coast guard station located at latitude of 4.408, and longitude of 47.784; and a Yemeni auxiliary coast guard station located at latitude of 15.770, and longitude of 52.044. The pirate attack under consideration occurs approximately 500 km off of the Somalian coast line – at latitude of 7.525, and longitude of 54.950; at the time of the incident the weather was relatively calm. The VID is approximately 530 km off of Oman's coast at latitude of 14.063, and longitude of 59.721; the VID situation is occurring in bad weather conditions. Some of the scenario's assets were docked at the two auxiliary coast guard stations, in Yemen and Somalia, and at the coast guard station in Somalia. Other assets were dispersed throughout other locations in the region. Note that assets with higher-quality sensors (those with higher operational power) are costlier to operate. Figure 7. depicts the region being monitored by the SDDRG system, along with the non-docked assets and the known pirate tracks that are used by the REM to carry out pirate vessel simulations.

Figures 8 and 9, respectively, present the historical incident response reports deemed by the system to be the most pertinent to the VID and Piracy risk events. The VID report describes an incident taking place during adverse weather. As a result, the coastal agency decided to dispatch assets with high-quality sensors (all of the assets had 'very high' quality sensors, with the exception of Aircraft-2, which had a 'high' quality onboard sensor). This report tells the system to explore solutions comprising of assets with high quality sensors via the MR objective function used within NSGA-II. The piracy event report describes an incident taking place during good weather, and as a result, the coastal agency deployed assets

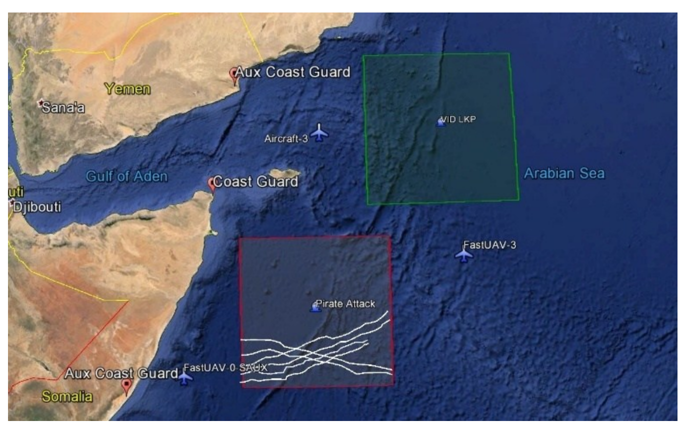

Fig. 7. Vessel in Distress and Piracy Events in the North-East Coast of Somalia

While underway, an oil tanker was boarded by a group of pirates at 10.769 N, 54.048 E on August 17th. The intruders were carrying automatic rifles. The ship's alarm was sounded and the master was able to send a distress call to the coast guard over the VHF radio. The coast guard immediately dispatched response assets. FastUAV-0 was assigned a track crawl search pattern. SlowUAV-0 was assigned a track crawl search pattern. Speedboat-0-A was assigned a track crawl search pattern. Lastly, Speedboat-0-B was assigned a track crawl search pattern. There was no rain and no clouds during the mission.

Fig. 8. Most Pertinent VID Incident Report in the Somalian Region

On the 20th of May, coastal radars lost contact with a cargo ship at 13.538 N, 50.672 E. Following unsuccessful attempts to contact the crew, a search mission was launched. Aircraft-3 was assigned a square in search pattern. Aircraft-2 was assigned a square in search pattern. SlowUAV-3 was assigned a parallel track line search pattern. Speedboat-3-A was assigned a square out pattern, and Speedboat-3-B was assigned a square out pattern. Tugboat-3-A was assigned a square in pattern. Helicopter-3 was assigned a parallel track line search pattern. Lastly, Tugboat-3-B was assigned a parallel track line search pattern. At the time of the incident, there was moderate rain present with extremely dense clouds.

Fig.9. Most Pertinent Piracy Incident Report in the Somalian Region

with lower quality sensors, because of their cheaper operational costs).

A. Expected Trends

For this experiment (executed with the three different configurations) there are four expected trends:

1) Expected Trend 1: It is anticipated that whenever simulations are run with the soft data enabled (vs. disabled), there will be a higher chance of mission success, as judged by the PCDRA value obtained via response simulations.

2) Expected Trend 2: It is also expected that within the results gathered by running the system with soft data enabled, there will be a correlation between the level to which MRs are met and the PCDRA value – the higher the MRs are, the higher the PCDRA values are expected to be. It is further expected that the converse might not necessarily be true.

3) Expected Trend 3: Similarly, there is an expected correlation between the MR and the ME objectives, as higher-quality sensors are attached to more expensive platforms, and the VID is taking place during adverse weather conditions (i.e., the soft data points the system towards the use of such sensors in bad weather).

4) Expected Trend 4: It is expected that whenever the system is setup to consider multiple, concurrently unfolding risk events, the average AU value will be lower, as assets will be more optimally assigned to the risk situations they are most needed for.

B. Experimental Results

Figure 10 presents the normalized values for PCDRA, ME, and MR. It can be observed that whenever the MRs are met to a high extent, the PCDRA and ME values are also high; in fact, meeting MRs with a degree of 7 or more presents a 3.335 times increase in PCDRA values as compared to the rest of the responses (i.e., the ones with MR degree of less than 7). This increase comes at the expense of costlier responses – approximately 10 times more expensive on average. Both of these observations fall in line with *Expected Trend 2* and *Expected Trend 3*. The observed increase in PCDRA and ME for high values of MR is attributed to the fact that the requirements being derived from the soft data for the VID situation are to select sensors with higher qualities (due to the prevailing weather conditions), which happen to be available on costlier platforms.

Figure 11. presents the PCDRA values obtained by running the system with and without soft incident response data. Running the system with soft data enabled yielded a 60% increase in PCDRA, which translates to a substantial increase in the probability of the missions benefitting from soft data

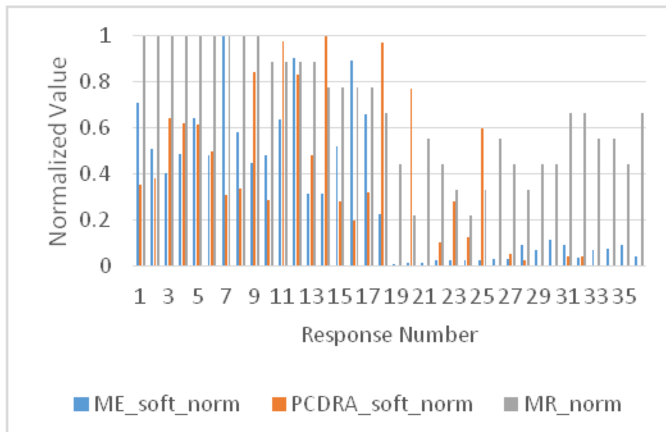

Fig.10. Normalized Soft Data PCDRA, ME, and MR for the Concurrent VID and Piracy Events

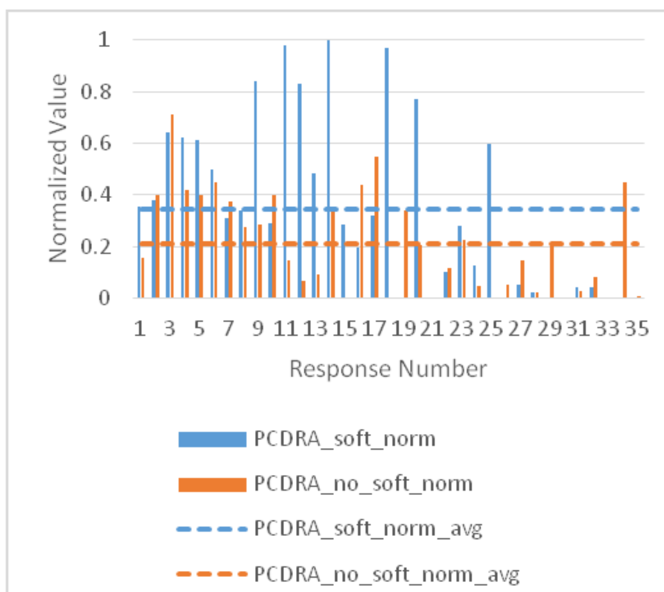

Fig. 11. Normalized Soft vs No Soft PCDRA Comparison for the VID and Piracy Events

TABLE II. AVERAGE AU VALUES FOR SINGLE VID, SINGLE PIRACY, AND CONCURRENT VID AND PIRACY EVENTS

Experiment Configuration	**Average AU**
Multi-risk-event (VID and Piracy)	35%
Single-event VID	27%
Single-even Piracy	30%

being successful. These observed results match the anticipated PCDRA relations outlined in *Expected Trend 1*.

Table 2 0presents the average AU values obtained by running the system with the three different configurations. The findings presented are in line with *Expected Trend 4*. The average AU in the multi-risk-event configuration was approximately 35%, whereas in the single-event VID and single-event piracy incident, it was approximately 27% and 30%, respectively. At best, the set of 27% and set of 30% of assets used in the two sequential situations is disjoint (i.e., the intersection of the 27% and the 30% set of assets is the *null* set); this would amount to a total of 57% of average AU – significantly higher than the 35% average utilization in the multi-situation simulations. This desired decline in average AU occurring when the system is considering concurrently unfolding risk events also translates into smaller average response costs – about 20% lower, as compared to the sum of the averages of the costs in the sequential, single situations. In practice, however, these two sets will be rarely disjoint, meaning that if the system were only considering single event scenarios, there would be a conflict in the selected assets between the different events (i.e., one asset being chosen to concurrently participate in more than one risk event), inevitably complicating the response selection process left to the human operator. These results thus present a tangible benefit from an AU, a cost effectiveness perspective, and ultimately, a response selection perspective.

V. CONCLUSIONS

The soft-data-augmented Course of Action (CoA) generation techniques proposed in this research have been validated through a simulated maritime domain experiment, carried out with three different configurations containing two concurrently unfolding risk events. The proposed methodology successfully generated viable responses with a number of conflicting objectives whilst providing higher chances of overall mission success whenever soft incident response data was utilized in the system. The experiment further demonstrated how the CoA methodology is able to more optimally assign assets to ongoing incidents, through its multi-situation handling capabilities.

Future work entails adding Level 2 (L2) and Level 3 (L3) High-Level Information Fusion support for a wider variety of risk events (e.g., smuggling, vessel coopering, illegal fishing), and employing analytics algorithms in the soft data sources to identify *risk event trends* for the purpose of anticipating future events and thus generating proactive CoAs, so as to deter or fully prevent them from occurring (e.g., in the case of anticipated pirate attacks). Another research direction is evolving the search patterns used by the assets during the execution of the response missions. The patterns used in this work are part of the chromosome encoding, but are currently only mutated between assets; future work could entail decomposing these search patterns into collections of *sub-pattern elements*, and evolving (mutating and crossing over) these finer-granularity elements for the purpose of generating new, dynamic, and potentially more effective patterns.

REFERENCES

[1] D. L. Hall and J. M. Jordan, *Human-centered information fusion*, Norwood, MA: Artech House, 2010, pp. 41-44

[2] A.-L. Jousselme, A.-C. Boury-Brisset, B. Debaque and D. Prevost, "Characterization of hard and soft sources of information: A practical illustration," in *Proc of the Int Conf on Information Fusion,* 2014.

[3] J.C. Rimland and J. Llinas, "Network and infrastructure considerations for hard and soft information fusion processes," in *Proc Int Conf on Information Fusion (FUSION),* 2012.

[4] E. Blasch and S. Plano, "DFIG Level 5 (User Refinement) Issues Supporting Situational Assessment Reasoning," in *Proc of the Int Conf on Information Fusion*, 2005.

[5] E. Blasch, I. Kadar, J.Salerno, et al., "Issues and Challenges in Situation Assessment (Level 2 Fusion)," Journal of Advances in Information Fusion, vol. 1, pp. 122-139, 2006.

[6] E. Blasch, E. Bosse, and D.A. Lambert, *High-Level Information Fusion Management and Systems Design,* Artech House, 2012.

[7] A.H. Razavi, D. Inkpen, R. Falcon, and R. Abielmona, "Textual Risk Mining for Maritime Situational Awareness," in *Proc. of the 2014 IEEE Int CogSIMA Conf,* 2014.

[8] R. Falcon, R. Abielmona, S. Billings, et al., "Risk Management with Hard-Soft Data Fusion in Maritime Domain Awareness," in *Proc of the 7th IEEE Symp on Computational Intelligence for Security and Defense Applications*, 2014.

[9] R. Falcon, and R. Abielmona, "A Response-Aware Risk Management Framework for Search and Rescue Operations," in *Proc. of the IEEE Congress on Evolutionary Computation*, 2012.

[10] R. Falcon, R. Abielmona, and S. Billings, "Risk-driven Intent Assessment and Response Generation in Maritime Surveillance Operations," in *Proc of the IEEE Int CogSIMA Conf*, 2015.

[11] A. Plachkov, R. Abielmona, M. Harb, et al., "Automatice Couse of Action Generation using Soft Data for Maritime Domain Awareness," in *Proc of the 2016 Genetic and Evolutionary Computation Conf Companion*, 2016.

[12] A.M.S. Authority. (2016). *Automatic Course of Action Generation using Soft Data for Maritime Domain Awareness* [Online]. Available: https://natsar.amsa.gov.au/documents/NATSAR-Manual/Australian%20National%20SAR%20Manual%20June%202014%20FINAL.pdf

[13] D. Timmins. (2000). *Canadian Coast Guard National Search and Rescue Manual* [Online]. Available: http://loki.cgc.gc.ca/cansarp/sarmanuals/nsm.pdf.

[14] K. Deb, A. Pratap, S. agarwal, and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," IEEE Transactions on Evolutionary Computation, vol. 6, no. 2, pp. 182-197, 2002.