Joint Data Management for MOVINT: Data-to-Decision Making

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Abstract – *Joint data management (JDM) includes the hardware (e.g. sensors/targets), software (e.g. processing/algorithms), and operations (environments) of data exchange that enables persistent surveillance in the context of a data-to-decision (D2D) information fusion enterprise. Key attributes of a information system require pragmatic assessment of data and information management, distributed communications, knowledge representation as well as sensor mix, algorithm choice, life-cycle data management, and human-systems interaction. Throughout the paper, we seek to describe the current technology, research approaches, and metrics that instantiate a realizable joint data management product. We develop the methods for joint data management for structured and unstructured data in the context of decision making. The accurate track and identification of the target provides a MOVINT capability. We examine classification methods of unstructured data using seismic, acoustic, and combined fusion methods for data analysis.*

Keywords: *Information Fusion, Situational Assessment, sensor planning, path planning, target tracking.*

1 Introduction

The goal of Joint Data Management[1] for MOVINT (intelligence about moving object) is to design a tool that supports sensor placement, optimal data collection, and active sensor management for decision support, in an environment where data exchange is seamless, efficient, and appropriate across potentially diverse stakeholders. With limited sensor resources, there is a need to optimize sensor placement that maximizes the sensor utility for users to observe moving targets[1]. The utility is based on the measures of effectiveness, which can vary over the sensor types, environmental conditions, targets of interest, situational context, and users [2].

One example of MOVINT is detecting cars moving in an urban area [3]. Detecting traffic can be completed by fixed ground cameras or on dynamic UAVS. If the sensors are on UAVS, path planning is needed to route the UAVs to observe the traffic [4, 5] and cooperation among UAVs is necessary[6]. The DARPA Grand Challenge featured sensors on mobile unattended ground vehicles (UGVs) observing the environment [7]. Mobile sensing can be used to orient [8] or conduct simultaneous location and mapping (SLAM) [9] to observe the environment or another targets [10]. Current efforts include Mobile-Ad Hoc Networks (MANET) and cooperative robots from which many efforts are applied such as information-theoretic entropy approaches [11].

A significant challenge in detecting and tracking moving vehicles in an urban area over a long period of time is to acquire data in a persistent, pervasive, and an occlusion compensating manner [12]. There has been a recent surge in the design and deployment of wide field-of-view systems known as WAMI (wide area motion imagery) sensors, including the DARPA ARGUS-IS. At any given instance, they produce images with dramatically varying point spread functions across a very large field of view; and, any given location undergoes persistent observation of varying spatial fidelity from different viewing directions as the sensor moves steadily in a fixed pattern above the city [12, 13]. A substantial amount of preprocessing, coupled with frame-to-frame, or frame-to-DTED (digital terrain elevation data) registration is applied before an image sequence can be analyzed in the context of multi-target tracking, or historical baseline similar to UAV video analysis or object deformation measurement tasks [14, 15]. Detection, feature extraction, post-processing, object detection, tracking, and track-stitching of moving vehicles in these videos is still a complex problem in terms of, fusion, computation and throughput [14, 16]. Motion detection-based track initialization for vehicle and people tracking using the flux tensor, aligned motion history images, and related approaches have been shown to be versatile approaches [13, 17, 18, 19]. Scaling these algorithms to very large WAMI sequences will require improved computer vision algorithms and multicore parallelization [16, 20]. Joint data management, summarization and retrieval using content-based querying and searching of visual information with user feedback remains a significantly challenging area [21, 22]

Deployed ground sensors can observe the targets; however they are subject to the quality of the sensor measurements as a well as obscurations. One interesting question is how to deploy the fixed sensors that optimize the performance of a system. Efforts in distributed

[1] In the context of this paper and research Joint Data Managementdoes **not** refer to Joint Services (cross service phenomena). The use of "Joint" in this research refers to cross-data analysis.

wireless networks (WSNs) [23] have resulted in many issues in distributed processing, communications, and data fusion [24]. To facilitate both WSNs decision support, requires efforts in understanding the user's needs [25], the theoretical and knowledge models [26], and situational awareness processing techniques [27]. In a dynamic scenario, resource coordination [28] is needed for both context assessment, but also the ability to be aware of impending situational threats [29, 30]. For distributed sensing systems, to combine sensors, data, and user analysis requires pragmatic approaches to metrics [31, 32, 33, 34]. For example, Zahedi [35] develops a QOI architecture for comparison of centralized versus distributed sensor network deployment planning.

Information fusion has been interested in the problems of databases for target trafficability (i.e. terrain information) [36], sensor management [37], and processing algorithms [38] from which to assess objects in the environment. Various techniques have incorporated grouping object movements [39], road information [40, 41], updating the object states based on environmental constraints [42]. Detecting, classifying, identifying and tracking objects [43] has been important for a variety of sensors, including 2D visual, radar [44], and hyperspectral [45] data; however newer methods are of interest to ground sensors with 1D signals.

The DARPA SENSIT program investigated deploying a distributed set of wireless sensors along a road to classify vehicles as shown in Figure 1.

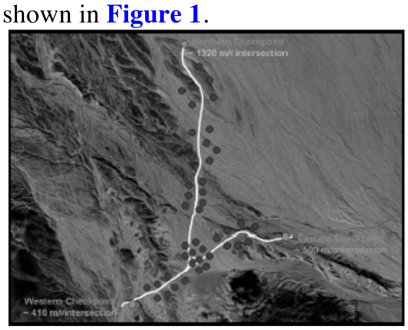

Figure 1. SENSIT Data from [M. F. Duarte and Y. H. Hu, "Vehicle Classification in Distributed Sensor Networks," 2004 [46]

The sensors included acoustic and seismic signals. While the placement of the sensors was not determined a prior, the observations were not subject to obscurations. Given the deployed set of sensors, feature vectors were used to classify signals based on the data from the seismic and acoustic signals. [46] Various approaches include combining the data with decision fusion [47], value fusion [48], and simultaneous track and identification methods [49]. Information theoretical approaches including the KL method were applied to the data for sensor management [50] as shown in Figure 2.

Much work has been completed using imaging sensors and radar sensors for observing and tracking targets. Video sensors are limited in power and subject to day/night conditions. Likewise, radar line-of site precludes them from observing in the same plane. Together, both imaging and radar sensors do not have the advantage of UGSs which can power on and off, can work for a long time on battery power, and can be deployed to remote areas.

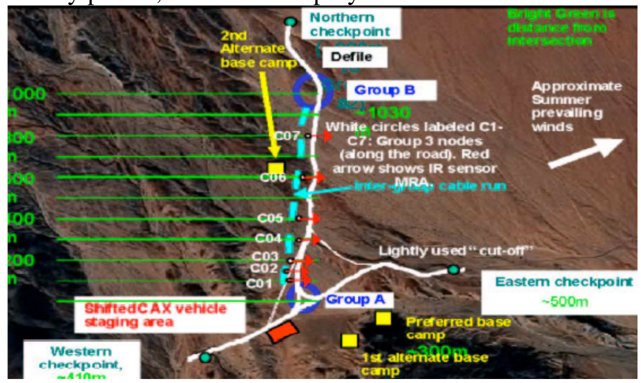

Figure 2. Deployed Sensors. From S. Kadambe and C. Daniell, "Theoretic Based Performance of Distributed Sensor Networks", *AFRL-IF-RS-TR-2003*, 231, October 2003. [65]

Track management situational awareness tools receive input from sensor feeds (examples include electro-optical, radar, electronic support measures (ESMs), and sonar) and display this information to a user. User inputs include: creation of new objects, such as tracks, contacts and targets. Methods to reduce data-to-decisions include: fusing multiple tracks into a single track, incorporating alerting mechanisms, or visualizing track data common operational picture (COP). Sensor and track data can grow rapidly as the user desires to keep historical data. Wikipedia states that the use of *relational database management systems* (RDBMS) [51] provides support for track management; however, RDBMS requires a high level of maintenance, provides limited support for ad-hoc querying, involves rigid storage paradigms, and has scalability issues.

Our goal is to determine the possible JDM for D2D from the unstructured data to the classification decision over varying environmental conditions. JDM includes (1) sensor management and placement of these UGSs, (2) intelligent use of the data based on value for classification, (3) coordination of sensor data for detection, classification, or both, and (4) metrics to support the sensor and data management as supporting a user control. Together, these factors have to be addressed in decision support tools that aid an operational team that deploys, maintains, repairs, and then utilizes the data over a distributed network.

2 Location / Detection

We desire to produce a JDM system for D2D with a MOVINT capability, which introduces the question what characteristics are relevant for such a system. MOVINT is an intelligence gathering method by which images (IMINT), non-imaging products (MASINT), and signals (SIGINT) produce a movement history of objects of interest. MOVINT provides both tactical and operational intelligence (situational awareness) of the dynamic environment.

2.1 Sensor Information Management

The goal is to utilize the UGSs sensors which may be acoustic, magnetic, seismic, and PIRoelectric (passive infrared for motion detection. With a variety of sensors, information fusion of JDM for D2D can (a) utilize the most appropriate sensor at the correct time, (b) combine information from both sensors on a single platform, (c) combine results from multiple platforms, and (d) cue other sensors in a hand-off fashion to effectively monitor the area. Sensor exploitation requires an analysis of feature generation, extraction, and selection or (construction, transformation, selection, and evaluation). To provide track and ID results, we develop a MOVINT capability of the target location and identification.

2.2 Sensor Classification

Sensor exploitation includes detection, recognition, classification, identification and characterization of some object. Individual classifiers can be deployed at each level to robustly determine the object information. Popular methods include voting, neural networks, fuzzy logic, neuro-dynamic programming, support vector machines, Bayesian and Dempster-Shafer methods. One way to ensure the accurate assessment is to look at a combination of classifiers. Combination of classifiers [52] could include different sensors with classifiers, different methods over a single or multiple sensors, and various hierarchies of coordinating the classifiers such as Bayes nets and distributed processing.

Issues in classifier combination methods need to be compared as related to decisions, feature sets, and user involvement. Selecting the optimal feature set is based on the situation and environmental context of which the sensors are deployed. An important question for sensor and data management is measures of effectiveness. For instance, what is the quantification of fusion/decision gain using a set of classification methods and placement methods? There is a need for a robust combination rule that includes the location and detection of the sensors subject to the target and environmental constraints. Typically, a mobile sensor needs to optimize its route and can be subject to interactive effects of pursuers and evaders with other targets [53] as well as active jamming of the signal [54].

Detecting targets from seismic and acoustic data in a distributed net centric fashion requires pragmatic approaches to sensor and data management. [55] To robustly track and ID a target requires both the structured data from the kinematic movements as well as the unstructured data for the feature analysis. [56]

3 Unstructured Data

Because effective MOVINT must incorporate diverse data structures it is important that a JDM system address concerns of unstructured data in addition to structured data. Unstructured data (versus) structured data refers to computerized information that does not have a data structure (i.e. exist within a database). Examples of "unstructured data" may include (1) textual: documents, presentations, spreadsheets, scanned images, etc., (2) imagery: multimedia files, streaming video, etc., (3) HUMINT: reports, audio files, gestures, (4) sensors: seismic, acoustic, magnetic, sonar, etc., and (5) environmental: weather, GIS, etc. All of the data has to be collected, acquired, exploited, stored, recalled, and tagged, not to mention a host of other activities. Most of data that is collected has some structure; however, for information fusion the inherent structure is not common among entities.

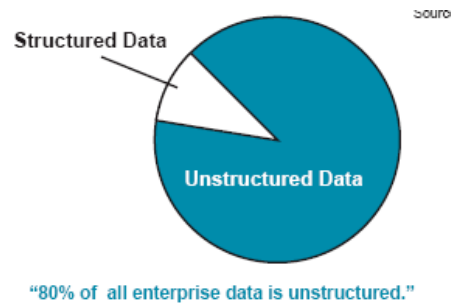

Figure 3. Description of Unstructured Data.

Research has shown that over 95% of the digital universe is unstructured data. According to these studies, 80% of all stored organizational data is unstructured (Gantzandetal 2007; White 2005) [57, 58]. This presents a critical challenge for large data technologies specifically in the area of data exchange because unstructured data must be structured before knowledge can be extracted and must therefore undergo some sort of transformation. The impact of this transformation affects the manner in which the data is stored, accessed, and utilized. The effects of this transformation are visible in the metadata, where the information contained in the data itself is described; illustrating the implications of data exchange on data integration. The relationship between data exchange and data integration is not trivial and from a decision-making perspective must be tightly linked together because the data is exchanged for a purpose, likely with other data. When characterized in this manner, the performance of data exchange has an implicit dependency on integration and therefore schema synthesis.

Managing data requires dealing with the structured and unstructured data with methods to allow the user and the algorithm to understand the credibility and complexity of the data.

3.1 Unstructured Information Challenge

Exclusive of the unstructured or structured nature of data, the premise of data exchange suggests a need for a unifying, ideally universal, data schema. The likelihood of achieving such a unified schema in the near term, particularly in an environment as dynamic and diverse as the Department of Defense is unlikely. However that does not preclude the research merit in attempting to achieve such an objective; rather it underscores the importance of doing so.

The unified data integration model for situation management developed by Yoakum-Stover and Malyuta [59] presents a database-centric theoretical solution for unified storage of structured data that is viable in ultra-large scale systems environments. This solution is based on their **Data Definition Framework** (DDF). The DDF consists of 6 primitives (signs, mentions, terms concepts, statements and predicates) that describe the fundamental elements of data generically. The research proposes that these primitives can be utilized as a lossless foundational structure with which to decouple vocabularies/data models from the source data artifacts.

While the objective of a lossless unifying data model that allows integration of disparate data sources and model semantics is laudable as well as desirable, many practical considerations that have historically characterized data integration and fusion, present challenges to any solution's viability. Exclusive any sociological, behavioral, or organizational obstacles to unified information spaces, which are not the focus of the research; the authors' solution takes a step in the direction of addressing the practical technical issues. Despite the innovations present in the DDF, it suffers from some limitations that are particularly critical to a unified model. Most significantly, the linkages between the data and the model prevent the DDF from capturing concepts for which no data exists, which is essential for any unifying schema. To this extent the DDF would be effectively useless in cases where sparsity was high or in cold start situations such as those that would existing in ranking or recommendation decision support systems [60]. Further, the DDF also lacks the notion of element ordering or implementation to capture constraints, participation, and cardinality. To effectively utilize such an approach it is essential to extend the work of Yoakum et al. to address these issues.

The DDF is only one notion of a unifying **schema approach** and there are others, including the Extended Entity Relationship data model (EER) (Markowitz and Shoshani 1992), [61] the Amsterdam Hypermedia Model (Hardman et al. 1994), [62] the object-oriented predicate calculus (Bertino et al., 1992), [63] UCLA M Model (Dioniso and Cardenas 1998) [64] and the iMeMex Data Model. While having individual benefits over one another these models generally tend to focus on logical schema definition. The Amsterdam Hypermedia Model and the UCLA M Model target multimedia, timeline, and simulation data and as such lack broad generalizability to other datatypes. EER has grown in popularity and has become the basis for contemporary relational database modeling due to its visual effectiveness, but lacks the rich semantics of object oriented or other modeling constructs and is bound by the limitations in scaling of entity-relational structures.

3.2 InfoGrid NoSQL and Probe Framework: Data Exchange in a Non-Relational Schema

Given a generalized information model, there must exist and architecture that can support information management in that context. InfoGrid [65] is an open-source software modular architecture that is comprised of a graph database that abstracts data stores' interface to web applications. **Figure 4** illustrates the high level architecture of InfoGrid. The design objectives of InfoGrid were to support a broad set of information types, connect information from different sources with an integrated application programmers' interface that is schema-driven and support a broad range of applications. Within the InfoGrid structure, information is modeled as a semantic network. The design of InfoGrid resolves the join-scalability of relational databases and separates the tight integration between the data and the application.

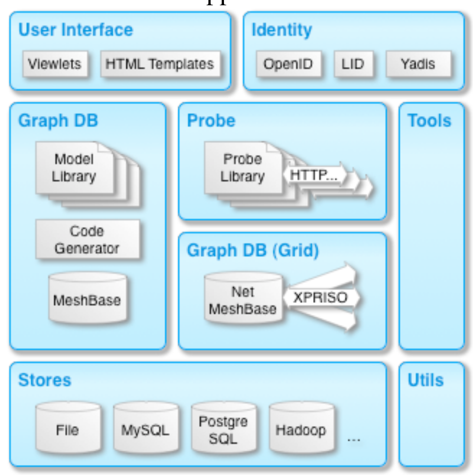

Figure 4. InfoGrid Application Architecture [65].

InfoGrid specifically targets web applications. The Probe Framework, which is built on the InfoGrid platform, makes the content of external data stores and sources appear as InfoGrid objects that self-update. The Probe Framework does this by shadowing the content of external sources as they change through the implementation of probes that monitor and control updating effectively creating decentralized data sources with federated governance within the scope of the InfoGrid infrastructure. From this perspective probes operate like services that extend the external data source into the InfoGrid platform on which applications are layered.

This architecture has many benefits for data exchange in a large data context. It subsumes the challenges of unified schemas by providing both a middleware pass through (using the Probe Framework) as well as a centralized graph database (the MeshBase referred to in **Figure 4**]) on which applications are built. The broad range of data stores addresses the diverse nature of data structure and incorporates utilities within the framework for specialized processing tasks. By adopting this architecture InfoGrid allows scalable applications to be created and maintained more quickly, more reliably and at lower cost by addressing the concerns of data exchange. Moreover, this generalized architecture can increase the availability of decision-related resources and therefore increase the probability of successful decision outcomes [66].

3.3 Data Management Processing

Data exchange can result from delivering the raw data versus publishing summaries of the data. Delivering the raw data requires an architecture that can *support large volumes of data*. Another method is to design an architecture such that the processing is *embedded in the sensor* such that data delivery is faster, there is increased speed from data to decisions, and a quicker ability to cue other sensors for on-line processing. Distance and data amount are tradeoffs that must be accommodated for processing speed of D2D. Processing the data at the sensor would require communication challenges between distributed sensors. For both cases, the architecture must address large amounts of data exchange and the speed of the communication for data exchange.

There are many techniques for processing unstructured data given known situations or a priori hypothetical situations. Since the data is unstructured it is essential to provide some context around which exploitation can be built approaches, which includes: *data* transformation, analysis, and sampling, *feature* generation, association, selection and extraction; *decision* classification such as Bayesian, Dempster-Shafer, and Support Vector Machines (SVM) methods for clustering and association rule extractions. Using the above methods, either known models or learned unknown models can help assess the data. In this context, since the complexity of the situation is known **models** are constructed using regression analysis over the parameters of interest and machine learning approaches can determine the likely components of the model.

Data mining supports the processing of data, however, **ontologies (or semantic models)** can improve the categorization, storage, and indexing of the data. An ontology improves communication between humans and machines, because an ontology contains machine-processable, structures to disambiguate given data values, as well as data structures.

3.4 Published/Filtered Data

Processing of large volumes of data requires metrics, architectural models, and operational realistic scenarios to test data search, access, and dissemination. Properly measuring significant parameters is critical to quantifying compliance and outcomes; yet doing so presents a challenge for eliciting quantifiable data, particularly in the case of architectural or system-related measures. Assessment of large data architectures requires a set of metrics that will objectively quantify performance of the architecture, its related technologies, and process/decision impacting outcomes. Relative to the JDM emphasis on *large data*, it is important to revisit a working definition of large data. Large data is when data has sufficient volume such that it cannot be completely processed for real-time decision making. Extending this definition to architectural metrics, additional focus should be given to scope measurements that determine the tradeoffs between cost, timeliness, throughput, accuracy, and confidence. The performance of a *large data architecture* (LDA), like any complex system is affected by its objectivity, context, and resolution of measurement. As a system increases in size, complexity/flexibility/scalability, and number of human participants becomes increasingly difficult to identify all of the relevant system elements, to measure the desired properties of the elements, or even quantify what should be measured. Large systems are resistant to holistic system-level measurements.

There are two general perspectives on **architectural metrics**: measurement of the *descriptive architecture* itself and the measurement of the *architectural artifacts*. There is ample work detailing the measurement of artifacts, but the work measuring architectural quality is somewhat sparse. Yet there are advantages to descriptive architecture evaluations. These benefits include financial benefits, increased understanding and documentation of the artifact, detection of problems with the existing architecture, and clarification and prioritization of requirements [67] Evaluating a descriptive architecture has an additional benefit in that it can provide the foundation for system performance assessment before the system is developed.

3.5 Data Management Metrics

Data exchange is an important area of information management that aims at understanding and developing foundations, methods, and algorithms for transferring data between differently structured information spaces to be used for diverse purposes. The exchange of data is but one critical step in information management. However the exchange of data is a linchpin for the success of any data management strategy or infrastructure. Efficient and effective exchange of data must address many issues beyond just getting the data to where it is needed (transport). Issues of *dissemination* (access, availability, control), *quality* (truth, relevance, accuracy), *timeliness* (speed-to-need and information lifecycle) are an exemplar list of challenges that fall under the data exchange scope of activity. Similarly many of these metrics translate directly to decision outcomes (timeliness, user confidence, accuracy). From a large data perspective, the process of data exchange is complicated by limitations in *interoperability*, diversity in applications and contexts, and even by the structure of the data itself.

A summary [68] of ten key requirements include:

- Visibility: Illustration such as folders and plots
- Control: Test, push, and pull of information
- Auditing: Complete and searchable
- Security: Data permissions and access
- Performance: communication and traffic flow
- Scale: amount of data

- Ease of Installation: timeliness of submission
- Ease of Use: distributed and timely access
- Ease of Integration: interoperability
- Cost of Ownership: money and effort

These methods are similar to the **QOS/QOI information fusion** standard metrics such as timeliness, accuracy, confidence, throughput, and cost; with most of the efforts in JDM focusing on throughput and timeliness. It is hard to judge the quality of information stored; however, a user can input this information when the data is sent to be archived. Zahedi [35] uses QOI to establish an architecture for comparison of centralized versus distributed sensor network deployment planning.

Data maintenance is akin to equipment maintenance. In the case that equipment maintenance includes reliability, survivability, reparability, supportability, and other "ilities"; the same case can be made for data.

(1) *Reliability* is that the data is available and timely. Much of the use of the data is based on the need for the data and information at the correct time. To ensure data reliability means that it has to be stored and accessed in such a way that it can be retrieved. In addition, unlike equipment, the data can be stored as information and that information needs to be updated with new data. For instance, an acoustic data can be exploited for a target and saved in a target folder. However, if later, it was determined from HUMINT reports that it was a benign target or incorrectly labeled, the data (acoustic) and information (target ID) should be updated for the new confidence (target ID) and timeliness (where the target is at a certain time). Finally, the incorrect information needs to be removed from the target folder.

(2) *Survivability*. The data needs to be collected and correlated with the pedigree on the data collection and decision making processing. To ensure that the data is available, it needs to "survive" in the data base from which it is correctly called when needed. Again, to maintain the survivability, means that it needs to be stored correctly. Also, as more data is stored, older data can get lost as things scale.

(3) *Supportability*: One question is: Does the current data need various updates for hardware changes? If we are conducting data management, that also prioritizes ***archival management*** over various hardware changes. Likewise, software changes affect access to/from the data. Many times, data is stored with protocols and header files to be access by application and presentation architecture layers. When there is tight coupling between these layers and the data layer, access to the data may be affected. Maintaining compatibility software grand-fathering and other methods of ensuring backward compatibility are needed. Furthermore, one can think of future or emergent compatibility needs. Supportability could be maintained with standards and governance that are common (such as that for all the services) to support JDM and D2D.

4 Example/Simulation

In this example, we investigate the JDM problem for D2D by assuming a large number of sensors available to survey an area. We use the SENSIT data which was described above. To perform the data management we use data mining [69] techniques such as a *support vector machine* (SVM) [70, 71] to process the unstructured data. Through analysis, we can determine the optimum use of the data given environmental conditions (i.e. obscurations) and sensor's capabilities to detect a moving target.

4.1 Data Processing

To determine methods of Joint Data Management, we compare two cases of (1) processing the data separately and (2) jointly processing the acoustic and seismic results **Figure 5** shows the case of the acoustic results.

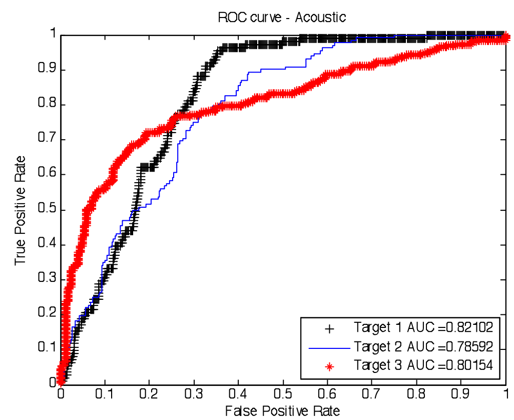

Figure 5. Acoustic Results.

Figure 6 demonstrates the results for the seismic results. Note that for the data set, the seismic results have a lower probability of false alarms for target 3 and target 2; however, target 2 exhibits more confusion.

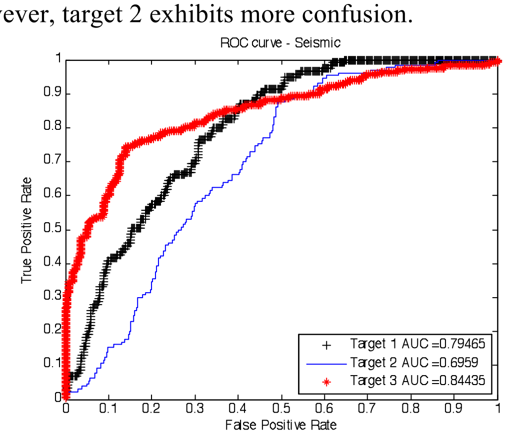

Figure 6. Seismic Results.

4.2 Joint Data Management

Next we explore the case of the joint seismic and acoustic data management and utilize SVM for classification, shown in **Figure 7**. The key is there is a false alarm reduction which is desired by users. In general, the joint analysis supports better decision making as confidence was PD was improved for a constant false alarm rate, accuracy was improved as to the target location from joint spatial measurements, and timeliness in decision making as fewer measurements were needed to confirm the target ID (i.e. decision made with two modalities required fewer measurements than that of a single modality).

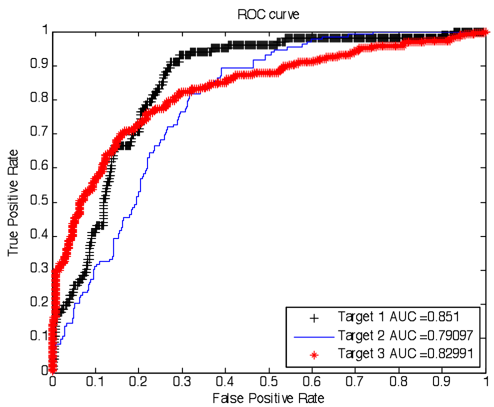

Figure 7. Combined Results

4.3 Data Management MOVINT Display

Visual analytics provide methods to visualize the data and analysis. Since our goal is to not only provide a JDM approach, but also a D2D analysis for MOVINT capabilities. MOVINT is an intelligence gathering method by which images (IMINT), non-imaging products (MASINT), and signals (SIGINT) produce a movement history of objects of interest. MOVINT provides both tactical and operational intelligence (situational awareness) of the dynamic environment. For the operational analysis, we can provide a track presentation of the objects. For this data set, the truth information is available with the data history. Here we present the classification information of the MOVINT results to demonstrate the salient features of the MOVINT system for analysis. **Figure 8** presents a short history of the acoustic information and **Figure 9** shows the case of the robust features for analysis. From these plots, a user can determine not only the location of the object, but the key aspects of the MOVINT target features for positive identification.

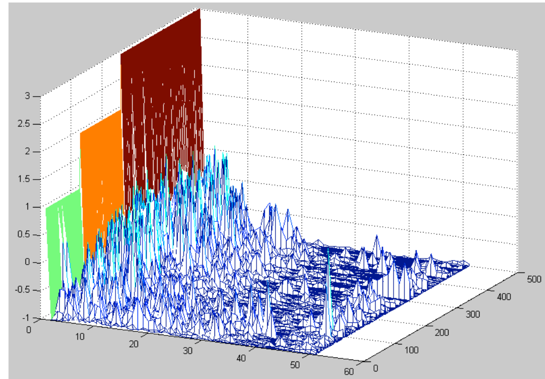

Figure 8. Acoustic feature Analysis.

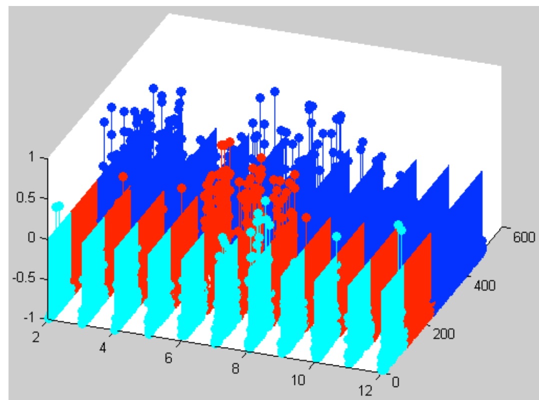

Figure 9. Feature Discrimination Plot.

We see that features 2-4 discriminate target 3, while features 5-7 discriminate target 2, and feature 8 and 12 are for target 1.

5 Conclusions

We have explored methods for Joint Data Management (JDM) for MOVINT data-to-decision making. We utilize a support vector machine to process the unstructured classification data as well as the structured data of the target location. We showed that the JDM approach reduces the false alarms for enhanced and timely decision making. Next steps would be to investigate different classifiers, combination of classifiers and utilize optimum feature vectors so as to improve performance of the JDM pragmatic use of the data. Information theoretic measures [72] and tracking analysis [73] can support the sensor and data management as well as determine the Quality of Information and Quality of Service needs. Use of the JDM for D2D provides decision support for situational awareness for command and control [74]. Various other sources of soft data (human reports) can be combined with the hard (physics-based sensing) [75] to update the sensor management, placement, and reporting of the situation based on the context and the needs of users to support JDM. JDM will require new methods in database management, information management, and measures of effectiveness for [76] mission support.

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