

Lessons Learned in the Creation of a Data Set for Hard/Soft Information Fusion

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Abstract - *Recent experiences in urban operations highlight the need for automated methods to help execute the data collection and association functions in the intelligence process. Technology development in this area has been challenged by the heterogeneity of data to be processed and by the diversity of potential applications. Here, we report lessons learned during the creation of a hard/soft data set. The data set was built using “hard” physical sensor reports and “soft” documents captured during training exercises simulating urban conditions. We discuss data collection issues, and we examine the information elements that can be exploited from the data. A key product in the data set is the identification of threads of insurgent activities that were observed by both hard and soft sensing modalities. We discuss the process by which the threads were identified, including an annotation procedure that structures the text information to enable association with the hard information elements.*

Keywords: Human-based information, HUMINT, information fusion, low-level fusion, physics-based information

1 Introduction

Military commanders need accurate estimates of the situation in order to make good decisions. Such estimates are usually generated by a fusion process that combines data from multiple sources. Some data sources are “hard” physical sensors such as radar, video, acoustics, etc. Data from such physical sensors typically contain kinematic (location/velocity) and type classification data for the entities of interest. Other data sources are “soft” because they are based on human observations. These include human reports, intercepted text and audio communications, and open sources such as newspapers, radio/TV broadcasts, and web sites. In addition to possible location and identity information, “soft” information may contain activities, intent, context, and relationship among entities.

Physical sensors are effective in detecting and tracking vehicles in open areas and providing some identification. However, they are not as effective in urban environments due to clutter and occlusion. Airborne sensors are less effective in detecting people, especially from the stand off distances that are required for their protection. It is possible for sensors to be employed closer to targets, but this limits their range. In addition, vulnerability concerns reduce the ability to place them in optimal locations, particularly in conflict areas. In these situations, soft information sources such as human patrols, communication intercepts, and open sources are critical in detecting people and activities.

Because hard and soft data contain complementary information, human analysts routinely have to perform hard and soft data fusion manually. However, there are just not enough analysts or available time to fuse the increasingly large amounts of data from diverse sensor feeds. The information fusion community has only recently begun to recognize the need for automated hard and soft data fusion tools. For example, the 11th International Conference on Information Fusion held in Cologne in July 2008 had a special session on hard/soft fusion. Fusing hard and soft data has many technical challenges. Whereas physical sensors generate structured data that can be characterized mathematically, soft data are generally from human sources, unstructured, and lacking interpretive models. Thus, information extraction is needed before any fusion can take place. Furthermore, human reports are typically qualitative, open to interpretation, and often outright inconsistent. These properties make the mathematical modeling of soft information very challenging. The challenges for hard/soft fusion and a processing framework were discussed in [1].

In order to make progress in hard/soft fusion, the research community needs a problem and an associated data set to drive the research. This data set can be used for exploring ideas and comparing the performance of different approaches. An effort was started in 2008 by the Army Research Office (ARO) to develop such a

data set. Reference [2] describes initial progress towards generating such a data set to assist in verifying and validating fusion approaches. Specifically, it discusses sources of hard and soft information, conceptual examples of hard/soft fusion, data collection requirements and strategy, and conceptual requirements for future algorithms with reference points in ongoing work.

This paper reports the lessons learned in actually creating this data set. This data set was built using physical sensor reports and documents captured during large-scale training exercises simulating urban environments. We discuss data collection issues for both hard/soft data sources, and then describe single-int information elements that can be obtained from the sources. A key goal of the data set is to highlight threads of insurgent activities that were detected in both types of data sources. As a result, we describe the procedure used to create associations between the hard/soft elements and the limited truth information available. To carry out the association process, the soft data had to be conditioned, annotated, and indexed. This process was very manual, and it is similar to how human operators perform hard/soft fusion.

2 Collection of Primary Data

The primary data that serves as the basis for the hard/soft data set was collected during live training exercises simulating urban operations. Live exercises enable units to test their skills against a role-playing opposition force (OPFOR). The OPFOR conducts operations, such as launching mortar attacks and implanting improvised explosive devices (IEDs), reproducing insurgent activities in a relatively controlled environment. A key advantage of collecting the data during an exercise is the availability of limited truth artifacts documenting the actual activities on the ground. The truth information for this data set was obtained from neutral observers' notes, global positioning system (GPS) tracking devices, and exercise planning documents. The truth information is a valuable companion of the primary data because it allows the exploited hard/soft information to be measured against the real events. Metrics resulting from this comparison can then become part of the evaluation criteria for new hard/soft information algorithms and technologies.

In this section, we outline some of the challenges involved in organizing and conducting the collection of primary hard and soft data. In an effort to present a view of data collection issues in general, we do not limit the discussion to the specific issues encountered in the data collection used for the hard/soft data set. When relevant, we will make comments of how soft information processing may provide interesting opportunities in selected segments of the hard information collection chain (and vice-versa). We begin by addressing physical sensor collections, and then follow with a discussion on the challenges of capturing information from human observers.

2.1 Physical Sensors

The main steps needed to organize and perform a physical sensor collection are shown in Figure 1. The process begins by identifying the relevant information requirements (IRs). IRs are typically provided by commanders in the form of unstructured text, like questions. Analysts and collection planners then refine the IRs, effectively converting high-level needs to more specific information requirements that can be used to task platforms and sensors. Other potential sources of IRs can be information gaps identified from soft information sources or from analyses of the situational picture[3].

The advent of soft information processing techniques creates an opportunity to improve the generation of information requirements derived from soft information sources. Although IRs can be generated automatically by programming alerts based on exploited hard information, the automatic generation of IRs from text or human intelligence (HUMINT) tips is much more difficult. Text extraction techniques could be applied to this problem, potentially saving analysts and collection planners valuable time.

Once information requirements have been identified and refined, the next step is to determine the mission plan that satisfies the IRs given existing constraints. Common constraints that limit what may be performed in a mission include the agility in constituting platform/sensor packages, availability of platform/sensor resources, availability of platform/sensor operators, and the physical or engineering limitations of the platform/sensors.

The final step is the execution of the mission plan, which in the simplest case involves carrying out a predetermined sequence of steps that guide the platforms and sensors to collect the desired information. In reality, however, executing the mission plan requires orchestrating people and equipment, and it involves dynamic replanning when unexpected circumstances occur (e.g. a broken comms link or non-performing sensor). The execution phase may involve collecting more than the desired information elements. For example, we may collect sensor operating parameters that can be used to improve exploitation [4], like signal to noise ratios or environmental conditions.

The three main steps listed in Figure 1 are supported by an infrastructure that enables communication, storage, and interpretation of the collected data. Of specific interest for fusion applications is the ease by which hard information elements can be retrieved and associated based on time, location, or other distinguishing characteristics. Queries are a standard tool in databases, but the distributed, dynamic, and real-time requirements of military applications complicate the creation of

Determine Information Requirements

- Interpret commander needs
- Identify from detected objects, situation assessment, and threat/impact assessments
- Identify from other soft information sources like tips or intelligence gaps

Determine Mission Plan

- Identify elements that fulfill information requirements
- Select platforms/sensors to deploy
- Assign sensors to platforms
- Plan platform routes
- Plan sensors tasks

Execute Mission Plan

- Perform planned activities
- Coordinate resource assignments across platforms, sensors, people, and infrastructure
- Adapt to new information or unexpected events
- Record useful platform, sensor, or environmental information for exploitation

Enabling Infrastructure

- Communication management addressing bandwidth tradeoffs, latency requirements, and quality of service rules
- Data storage for capturing large volumes
- Data indexing and retrieval
- Interpretation of heterogeneous formats
- Syntactic and semantic compliance
- Geo-registration
- Clock synchronization
- Exploitation tools
- Air space management
- Robust processes, system designs, and plans
- System and sub-system verification

Figure 1: Steps to plan and execute a physical sensor collection. The items on the left detail the three main steps required to plan and execute a typical physical sensor collection. The right column describes common infrastructure elements that support and impact the data collection.

comprehensive, up to date indexes. An additional complication in the hard/soft fusion case is the normalization required to associate the hard and soft information elements. Initial progress on automated hard/soft association has been reported [5,6], and additional techniques will be required to effectively manage the large numbers of heterogeneous data elements that will become available in an interconnected enterprise of hard/soft data sources.

2.2 Human Observers

The top-level process needed to plan and execute a soft data collection is similar to that of the physical sensor case. At the conceptual level discussed here, the soft data collection process is a superset of the physical sensor process. Figure 2 makes specific the new considerations that come into play when conducting collections relying on human observers. As can be seen, the determination of the information requirements is unchanged at this level of detail, but the mission planning, execution, and infrastructure pieces do contain new items.

When dealing with human observers, the mission planning function can conceivably support three main sources: physical sensors (e.g. communications intelligence or images for analyst interpretation), recorded documents or media, and direct human observations. The items related to physical sensors are carried over in Figure 2 to reflect the fact that human interpretation of sensor data remains, and is likely to remain, an important part of the intelligence process. Additional items are added to capture the choices of human sources, interviewers, and interview approach. The flow of information between an

interviewer and an interviewee can vary significantly based on the level of training of the interviewer, the language interpreter, the willingness of the interviewee to cooperate, and the personal approach taken by the interviewer. Items are also added to reflect the soft information that can be obtained from documents (e.g. the web) or media (e.g. radio), and to emphasize that explicit decisions to obtain, process, and analyze such information must be made. The typical constraints that might be present in planning a soft data collect are: limits on human or machine collection capability, required timeliness of information, and finite analysis and interpretation resources.

The direct involvement of interviewers with cooperative, deceitful, or non-cooperative human sources results in situations that are not present when considering physical sensor collections. For example, a conversation between an interviewer and an interviewee takes time, and the exchange involves not only the transfer of information, but also real-time adaptation, by both parties, of the question and answer flow. In addition, the interaction may include aspects of negotiation, where both parties simultaneously diagnose each other and choose their next steps based on the completed interactions and expected responses. Such complications place an important responsibility on the interviewer, and they underscore the need for the interviewer to be properly informed and trained on both the topic of discussion and more general cultural and social context.

In the execution step, we list additional items particular to the soft data case. In human discussions, non-verbal communication plays a non-trivial role,

Determine Information Requirements

- Similar to physical sensors (See Figure 1)

Determine Mission Plan

- Includes items from physical sensors (See Figure 1)
- Solicit/Select interviewers and interviewees
- Train and prepare interviewers
- Determine interview approach
- Determine appropriate recording medium
- Select documents, audio, or video to review
- Select analysts/tools to conduct research

Execute Mission Plan

- Includes items from physical sensors (See Figure 1)
- Adapt questioning sequence in response to answers or non-verbal cues
- Record non-verbal information like tone, accent, facial expressions, or body language
- Eliciting additional information from interviewers post-mission

Enabling Infrastructure

- Includes items from physical sensors (See Figure 1)
- Optical character recognition services
- Audio transcription services
- Language translation services
- Text extraction services
- Image and video retrieval
- Note-taking tools
- Machine representation of non-verbal communications
- Biometric services
- Cultural information dictionary
- Social network information
- Systematic training

Figure 2: Steps to plan and execute a human observer collection. The items on the left mirror the steps for physical sensors, introduced in Figure 1. The main differences are the additional considerations that come into play when planning soft data collection.

providing a parallel information channel that conveys emotion, emphasis, and symbols. Non-verbal information is naturally captured by human observers, and, in the case of sign language, it is an information rich medium. However, audio devices cannot capture gestures, and video exploitation of such gestures is still an area of research [7,8]. As a result, human observers need to interpret and record important non-verbal information elements. Another peculiarity of human observers is that their recollection of the interactions is relatively poor compared to audio or video recordings. As a result, human observers depend on either memory, or memory supplemented with note-taking. Because note-taking is a relatively poor recording medium, human observers find it useful to revisit their notes after their exchanges, and to write down additional details from memory. The notes serve to “jog their memory” and trigger additional information to be recalled. Such a process could be amplified by providing human observers with relevant and timely information elements, from other sources, related to their post-observation reports.

The enabling infrastructure block in Figure 2 contains added functional tools covering human-machine interactions, data storage and retrieval, and biological and social fields. The human-machine interface topics include items like optical character recognition (OCR) and language translations, and they represent the key interface between human-generated communications and computers. Data retrieval technologies will also play an important role, as observers, analysts and algorithms will need access to information elements regardless of whether the primary source is hard or soft, or whether the storage medium is text, audio, image, or video.

One of the observations resulting from reviewing collected soft documents is the comparative lack of detailed metadata relative to the hard data. For example, physical sensor products often rely on accurate platform measurements to compute quantities, such as position, relative to the sensor orientation or the platform motion. Documents capturing summaries of patrol interviews, however, did not contain analogous detailed trajectories of patrol movement, locations within a building where observations were made, or location and orientation information associated with pictures. Such useful metadata can in principle be collected and stored, providing valuable context for later analysis.

3 Available Information Elements

The previous section describes issues related to the collection of hard and soft data. We now describe the information elements that are available after initial exploitation of the raw data used to create the hard/soft data set. These elements are generated prior to reaching an all-source fusion process, and they would become the basic inputs that hard/soft data association and fusion processes will have to ingest.

3.1 Hard Information

The Table 1 information elements with check marks in the “hard” column can be obtained from exploitation algorithms processing physical sensor information. The kinematic information represented in the first three rows can be obtained by a variety of exploited sensor products, including radar, electro-optical, and hyperspectral sensors. Color can be measured by

Element	Description	Hard	Soft
Time	Time of detection or event occurrence	√	√
Location	Geo-spatial point where the detection or event occurred	√	√
Track	Correlated time series of locations	√	√
Color	Visible light spectrum	√	√
Spatial Extent	Volume occupied by an object	√	√
Attribute	Common feature that identifies a class of many objects, like emission frequency or vehicle type	√	√
Signature	Uncommon feature or spectrum that identifies a class of a few objects	√	√
Self-reported IDs	Blue-force or emitter IDs that uniquely identify the reporting object	√	√
Negative Information	Lack of detection of a given element, coupled with an estimate of the probability of detection map over the measured area	√	√
Relationships	Association of two objects or entities	√	√
Entity Names	Names of people, groups, or organizations		√
Descriptions	Event, biographical, or other factual description		√
Assessments	Opinions or estimates regarding entities, situations, or threats		√

Table 1: Information Elements Observable by Hard/Soft Data Sources. The table lists nominal information elements that can be reasonably produced by single-source exploitation of Hard/Soft Sensors. The checkmarks indicate whether hard or soft information sources could generate reports of the specified type. Grey check marks denote that the elements are not available in the hard/soft data set. The complete set of checkmarks down the soft column reflects the descriptive nature of soft information, allowing complex concepts to be expressed.

imaging sensors, and spatial extent can be estimated from images or from radar range extents and/or cross-sections. Attributes and signatures of various types can also be measured using physical sensors by leveraging features in the detected signal that either represent a particular class or help identify a reduced set of objects. Unique, self-reported IDs can also be detected for objects that are designed to provide them, like blue force trackers and certain types of emitters. Negative information can also be obtained with imagery sensors and radars, and it is helpful to eliminate false hypotheses. The final hard data element listed in the table is relationships, and these can sometimes be inferred by noticing trends in the observations. All of these information elements are present, to varying degrees, in the primary physical sensor data used to create the hard/soft data set.

3.2 Soft Information

The raw soft data used to create the hard/soft data set also contains many of the information elements in Table 1. However, because the raw data comes from documents like patrol reports, analyst products, and neutral observer notes, a non-trivial process needs to occur to convert the data into information elements amenable to a computer. This conversion process is a significant challenge to automatic algorithms because it requires stepping through an inference ladder of increasing sophistication. To illustrate, consider the following five layers of abstraction:

- Audio recording
- Transcribed text with metadata
- Annotations
- Events
- Higher-level descriptions

To a human listener, the audio recording directly communicates actionable information. To a computer, the audio recording is nothing more than a sequence of bits. A computer can potentially infer through these abstraction layers, but to do so it requires deliberate use of concrete models and algorithms to transform a signal into text, text into semantically meaningful annotations, grouped annotations into single events, and sets of events to higher-level descriptions. This conversion process is a principal obstacle to automatically obtain the information elements of Table 1 from soft data. In contrast, models and algorithms for doing the analogous inference on physical sensor data are much more mature.

Our review of the soft data identified several issues that would test any automated inference approach. Real data contains mismatches, missing items, misspellings, abbreviations, and synonyms. In addition, information elements can be expressed in endless syntactically different, but semantically equivalent ways. For example, a text snippet may indicate an absolute reference like the “Vehicle A is at location with coordinates X, Y,” but it would also be common to see relative statements like “Vehicle A is near Building 1.” Analogous situations can occur for times, vehicle descriptions, organizations, people, and the higher-level constructs that result when conveying facts about all of these entities. Finally, there are concepts that are not appropriately communicated using text languages, like facial expressions, emotion, body language, and complex shapes or volumes. Hard/soft fusion processes will need to resolve difficulties such as these, and initial approaches can be found in [5].

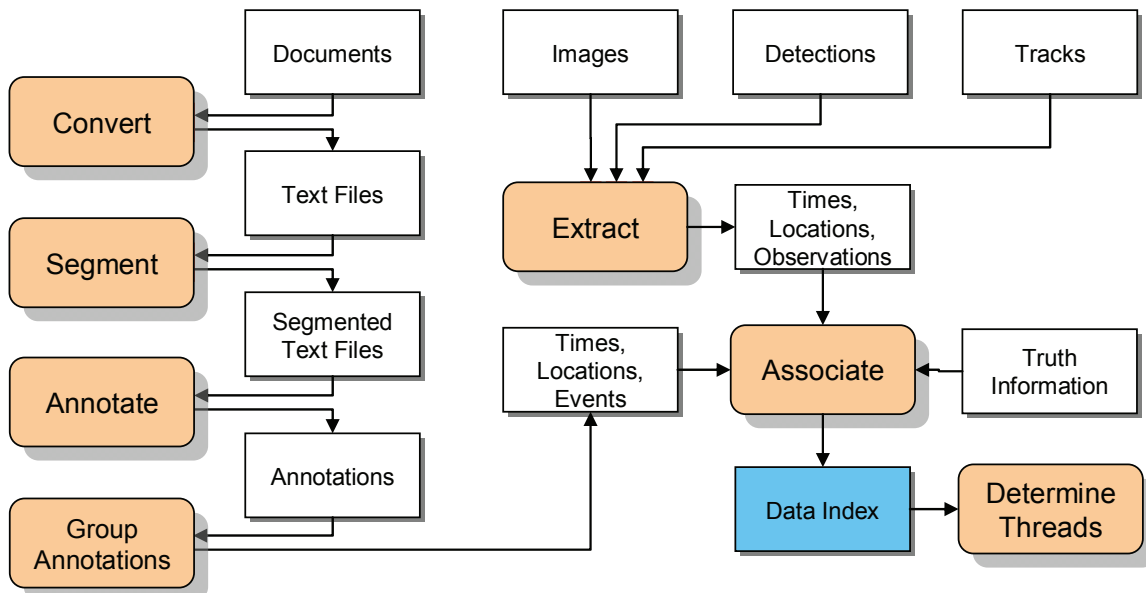


Figure 3: Procedure for Identifying Threads. The figure depicts the procedure used to identify threads of insurgent activity observed by both hard and soft data. Rounded boxes represent functions, while rectangles represent intermediate products. The soft data chain is on the left, starting with documents from the NTC soft data collection and ending with events containing time and location elements. The events are associated to the hard data (top right) and truth artifacts, producing an index of data products keyed on space and time. The index can then be queried for coincidences to determine the threads.

To realize the added value of jointly exploiting both hard and soft information elements, we need to create associations between the physical sensor information and the human observations. The next section discusses the approach we took in the development of the hard/soft data set.

4 Identification of Threads

A key product of the hard/soft data set is the identification of threads of insurgent activities that are observed by hard, soft, and truth sources. Given the volume and heterogeneity of the primary data, it is not feasible to inspect the artifacts and notice the presence of insurgent threads. Instead, we follow the approach depicted in Figure 3. The left side of the figure describes a soft data annotation process that yields correlatable events. The top right part of the figure depicts the hard data processing chain, which provides times and locations of physical sensor observations. We then associate the hard, soft, and truth elements, recording the links in an index over spatial and temporal variables. The index of the data enables simple queries for coincident reports to identify the threads.

4.1 Soft Data Annotation

The formal process of extracting information from the soft corpus of documents began by placing the entire collection under configuration management to provide stability and facilitate collaboration. The actual extraction steps consist of a combination of automated procedures

and manual annotation. The automated part uses freely available file translation and parsing tools:

- Apache POI for transforming MS office documents into text files (minus the pictures) [9]
- LingPipe for segmenting the text into sentences [10]

The segmented files were inputs for the manual process of annotation. We used a configurable annotation tool that focuses the annotator’s attention on one sentence at a time. The tool assigns an ID number to each document, each sentence, and each annotation within each sentence. Custom templates appear in the annotation-tool window so that the annotators are prompted to provide information in a highly structured manner. The templates specify the granularity of a time or a location. For example, temporal templates include dates, times (hour, min, sec), as well as time intervals. Our templates for locations are domain-specific and include buildings, UTM coordinates, base facilities, towns, and training event locations.

An example sentence as it appears in the annotation tool follows:

Seg12. At 0950 the enemy forces attempted to get back into town

The annotators selected a snippet from the sentence and associated it with a template in the tool

(for example, involving time or location). They could also type in additional information about the snippet, such as temporal or locative resolution. The tool output is an xml file. The tool has a spelling checker and prompts users to resolve pronouns. Two snippets in a sentence, one temporal and the other locative, produced the following annotation results:

```
Time-LocationId=100
docID="Patrol Report A123"
segId=12
TemplateID=16
Event="the enemy forces attempted to
get back"
Time-Min= "at 0950"
TimeResolution=10-08-2008T09:50
```

```
Time-LocationID=101
docID="Patrol Report A123"
segId=12
TemplateID=21
Event="the enemy forces attempted to
get back"
Loc-Town= "into town"
LocResolution="New City"
```

A temporal or locative expression was disambiguated if annotators could confidently determine the intended time or location. Our annotation guidelines for timestamping of events (i.e. identification of events and anchoring them in time) are drawn on TimeML specifications [11,12], which provide general domain-independent guidelines on annotation of events and times. In our annotation task, the snippets that represent events are sentences that include a verb and its arguments. If an argument is a pronoun, it is disambiguated as in ‘They [enemy forces] were trying to get back’. The results of the annotation, therefore, do not just recognize times, locations and corresponding events, but also resolve all temporal, locative, and nominal references. Having structured spatial and location information in the text, the next step is to associate to the truth information and the physical sensor products.

Although we limited the soft data structuring to times, locations, and nominal references, the event strings do contain additional information that could be further structured by automated or semi-automated methods. As mentioned, the event string “the enemy forces attempted to get back” is a typical noun-verb-object construct that can itself be understood by higher-level inference approaches. For examples on how sentences like these can be processed and exploited, see [13].

4.2 Hard/Soft Data Association

The inputs to the association function are time- and location- tagged artifacts with fields that a computer program can easily match. For the purpose of the data set creation, the associations are conducted on time and space, using simple metrics to determine whether two artifacts

match. No constraints beyond time and space coincidence were placed on the association. For example, a soft data artifact was allowed to associate with all detections, tracks, or images that occurred within sufficient space-time proximity, and vice-versa. The resulting associations between the data elements can be summarized in an index.

To identify the insurgent threads to be highlighted in the data set, the index was queried for sets of associations that included both hard and soft data elements. Triple associations with truth represented the best candidates for the insurgent threads, but hard/soft only associations identified underlying events that had not been truthed but could still be informative to researchers.

Although this project focused on the association of elements in space and time, it should be pointed out that the data supports richer associations, leading to comparatively richer inferences on the actual observed behavior. For example, all of the information elements listed in Table 1 that can be observed by hard and soft sources are candidate variables for identifying relationships. It is desirable to imagine query methods capable of highlighting “red trucks” or “churches near community centers” in a set of images. In fact, the sentences contained in the event strings encode higher-level concepts that can lead to additional associations not explicitly called out here.

4.3 Relevance to Fusion

Although the annotation and association process described here allows the identification of threads, we note that a prerequisite for fusion algorithms is to conduct a data association process that determines which measurement reports resulted from independent observations of the same underlying object or event. The measurement reports then become the inputs to an estimation algorithm that fuses the independent information or to situation awareness algorithms that make inferences from the detected relationships. The procedure described in this section, although it was constructed to identify the insurgent threads, is an example of the type of extraction, annotation, and data association process that would have to be carried out in an automated hard/soft fusion application.

5 Conclusion

In this paper, we discuss issues involved in planning and executing hard and soft data collections. We identify information elements that can be exploited from hard and soft data, and we describe a procedure for associating the information. The association process is manual and labor-intensive, not unlike the experience of all-source analysts as they carry out the intelligence function. As part of the association procedure, we show a way to structure time and spatial information in unstructured text, and we have used the

association procedure to identify threads of insurgent activity. The threads will enable researchers to explore challenges and approaches to hard/soft information fusion.

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