# Applying Cognitive Work Analysis to a Synthetic Aperture Radar System

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**Abstract.** The purpose of the current study was to analyze the work of imagery analysts associated with Sagebrush, a Synthetic Aperture Radar (SAR) imaging system, using an adapted version of cognitive work analysis (CWA). This was achieved by conducting a work domain analysis (WDA) for the system under consideration. Another purpose of this study was to describe how we adapted the WDA framework to include a *sequential* component and a means to explicitly represent relationships between components. Lastly, we present a *simplified work domain representation* that we have found effective in communicating the importance of analysts' adaptive strategies to inform the research strategies of computational science researchers who want to develop useful algorithms, but who have little or no familiarity with sensor data analysis work.

**Keywords:** Cognitive Work Analysis, Work Domain Analysis, Human Factors, Synthetic Aperture Radar, Imagery, Systems Analysis.

## 1 Introduction

Remote sensing domains are common and complex work domains comprising multiple subsystems, components and actors. Such systems provide society with a wide range of information products, from space weather to patterns of change in land use. As remote sensing platforms become more sophisticated, the human actors responsible for managing and analyzing data feeds are increasingly facing a "data deluge" that will inevitably change how data consumers interact with the information products derived from remotely sensed systems. Automated support for analysis is a necessary evolution. However, because sensor data analysis is a highly interpretive process shaped by contextually-specific goals, automated analytical systems present significant design challenges for algorithm and software developers.

In this paper, we discuss the use of cognitive work analysis (CWA) methods, specifically work domain analysis, and the construction of an abstraction hierarchy, to decompose one sub-domain of a remote sensing data analysis workflow associated with the Sagebrush system, a Synthetic Aperture Radar (SAR) platform used to generate ground image data for a wide range of civilian and military applications. We provide a brief overview of the Sagebrush system and summarize the research and

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design challenges that motivated our study of one sub-domain in the larger Sagebrush workflow. We then describe some of the difficulties we encountered in using CWA representations to communicate our findings. This difficulty motivated us to evolve some elements of CWA into representations and terminology that enhance understanding of the methodology's power. We discuss how our products are being used by algorithm and software experts to develop and evaluate new algorithms, software and visualization platforms to enhance the analysis of SAR data and image products.

## 2 The Sagebrush System

Sagebrush refers to a family of SAR sensors that are used to support a wide array of civilian and military ground operations in multiple locations throughout the world. Taken in its entirety, Sagebrush is a large, complicated work domain that includes a wide array of sites, operators and analysts, platforms, networks, locations, workstations, offline and off-site databases, communications platforms, qualitative and quantitative data, and copious amounts of imagery.

The research that we are pursuing focuses on the perceptual and cognitive work of imagery analysts associated with Sagebrush sensing platforms. As is true with most remote sensing systems, data generated by the Sagebrush system goes through several stages of processing, review, information extraction, and knowledge product creation. Analysts at the front-end of the sensor perform – the so-called "near-real time" analysts – perform rapid triage, assessment and communication of trends and events and trendss for Sagebrush's stakeholder community. Other groups of analysts work with Sagebrush products in an "offline" process that generates longer-term, strategic assessments of trends and events. Such offline analyses shape the planning and implementation of Sagebrush missions and even the development of next-generation Sagebrush hardware and software.

The CWA activities describe in this paper focused on the domain of "offline analysis." Offline Sagebrush analysts are responsible for assessing the correctness, completeness and overall performance of fielded Sagebrush systems. Their job involves not only analysis of Sagebrush data products, but also the incorporation of several types of auxiliary data (e.g., weather, agricultural activity, animal movement) to develop richer evaluations of trends and events rendered in the sensor data. Associated tasks include the retrospective analysis of radar imagery data (i.e., analyzing the features of an image that contains evidence of ground changes or signatures of ongoing trend); classification of events and trends captured in the imagery; evaluation of the periodicity of scene changes to identify emerging trends; and helping fielded Sagebrush teams improve their performance with richer contextual data for trend analysis. The specific tasks associated with this offline analytic workflow are labor intensive, cognitively demanding, and require extensive domain knowledge about the sensor, the terrain being imaged, the operational requirements of fielded teams, and the needs and requirements of Sagebrush stakeholder groups.

Figure 1 shows the basic flow of information and data from the sensor to the offline analytic domain described in this paper. As shown, the Sagebrush sensor generates radar data that is rendered in pixelated imagery. This imagery is then transmitted to both off-site and local servers for storage. In addition, analytic teams deployed with these platforms perform "near-real time" triage of data products identify and characterize events and trends for Sagebrush stakeholders. These near-real time products and associated imagery and sensor data are then transmitted to a variety of other consumers, including Sagebrush offline analysts. Together, these sensor data, imagery and near-real time analytic products comprise the critical information resources for Sagebrush's offline analytic work.

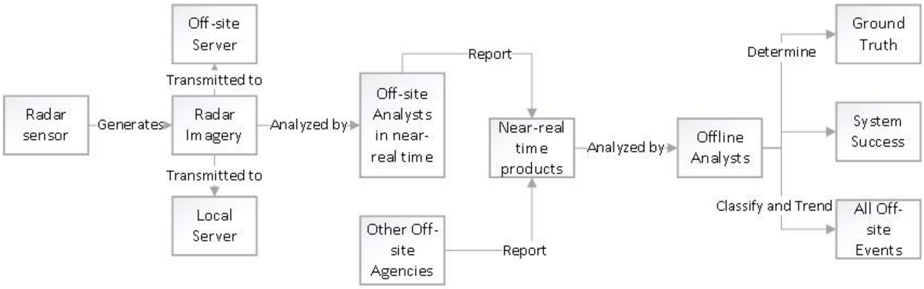


**Fig. 1.** Basic Work Flow for Sagebrush Data and Imagery Analysis

Every day, Sagebrush offline analysts log into their computers to determine if new image products, reports, and sensor data are waiting for review and evaluation. They also review all events and trends reported by other off-site agencies. This requires a review of radar imagery generated by their sensors and reports generated by off-site agencies. One result of this analysis is a list of all the events and trends that have occurred during a particular time period in an area being imaged by Sagebrush radar platforms, creating a set of assessments that the analysts describe as 'ground truth.' Sagebrush owners use this ground truth to determine the effectiveness of their system in meeting all stakeholder information requirements. In addition, the offline analysts continually revise and update a database of ground trends and events that can be disseminated to a much wider operational community. Essentially, Sagebrush's offline analysts take products generated by their counterparts and put them into a broader, longer-term context that enables not only evaluation of fielded system performance, but the enrichment of the entire Sagebrush community's collective knowledge about operationally-significant events and trends in the areas under study.

### 2.1 Motivating Context for This Research

Because SAR systems provide all-weather sensing capabilities and are relatively easy to mount on a variety of airborne platforms, they are becoming increasingly popular for a wide range of remote sensing tasks. As the volume and diversity of SAR imaging missions expands, stakeholders are grappling with floods of sensor data and are seeking new ways to analyze sensor data, beyond the standard "eyes-on-imagery" paradigm that dominates remote sensing analysis. Our team is part of a larger project called **PANTHER** – **P**attern **AN**alytics to support **H**igh-performance **E**xploitation and **R**easoning – funded by Sandia National Laboratories in Albuquerque, NM.

PANTHER researchers are pursuing new algorithms, software architectures, and visualization platforms to enable human analysts to realize the information value of remotely sensed datasets. Studies of working analysts are critical to understanding how humans interact with sensor datasets, so that software designers can develop usable, useful and adoptable technologies that demonstrably enable people to extract meaningful information from these datasets.

## 3 Cognitive Work Analysis

Within PANTHER, our team was tasked with studying the current work processes of Sagebrush analysts and generating ideas and requirements for algorithms, architectures and visualizations to enhance analytic work. To address this challenge, we conducted a CWA study. CWA is an evolution of cognitive task analysis (CTA) methods that was specifically designed for complex systems with uncontrolled, uncertain environments [1-3]. CTA provides detailed analysis of discrete, predefined task sequences performed by individuals; in contrast, CWA decomposes an entire work domain, then asks questions about how operators navigate toward domain-specific goals using resources at hand. In doing so, CWA reveals the creative work of domain experts operating complex systems under conditions of uncertainty and constraint, and how we can design systems in ways that will enhance operator performance. CWA is increasingly recognized as a valuable framework for eliciting and documenting the human activities associated with a technological system: the tasks and activities that human operators perform, the behavior resulting from their interaction with the system, their work context, and the goals and purpose that motivate their actions [2], [3].

Additionally, although CWA has been applied to many domains, a recent review [4] indicates that sensor data analysis – a highly visual and individualized form of work – is not one of them. Thus, one purpose of the current study was to evaluate the usefulness of CWA approaches, specifically work domain analysis, for informing the design of statistical and graph-based algorithms to mine patterns in very large sensor datasets. A second purpose was to describe how we adapted the work domain analysis framework, as proposed by Vicente [3] and Naikar et al. [2], to include a *sequential* component, a means to explicitly represent relationships between components, detailed explanations of the different abstractions that exist within a system hierarchy, and how outputs from this analysis can be used as direct inputs for a system interface. Lastly, we present a *simplified work domain representation* that we have found effective in communicating the importance of analysts' adaptive strategies to inform the research strategies of computational science researchers who want to develop useful algorithms, but who have little or no familiarity with sensor data analysis work.

### 3.1 Work Domain Analysis (WDA)

**Overview.** Lintern describes a work domain as "an intentional-functional-physical space in which work can be accomplished."[5] He explains that intention refers to the system's purpose and that function denotes an "activity-independent capability to accomplish something specific." Essentially, WDA is a means for practitioners to identify the purposes and constraints of a system and to describe system components, and their interactions and relationships in operators' work. WDA is the first phase of CWA and has been used in a variety of domains to inform system interface design (for a review, see [4]). The representational product of WDA is an abstraction hierarchy (AH). This tool is a hierarchical representation that describes the system in terms of its functional purpose, values and priority measures, purpose-related functions, object-related processes and physical objects. The following is a summary of the different levels of abstraction proposed by [2]:

**Table 1.** The abstraction axis of the Abstraction Hierarchy

| Abstraction Level | Description |
|---|---|
| Functional Purpose | The purposes of the work system and the external constraints on its operation |
| Values and Priority Measures | The criteria that the work system uses for measuring its progress towards the functional purpose |
| Purpose-related Functions | The general functions of the work system that are necessary for achieving the functional purpose |
| Object-related Processes | The functional capabilities and limitations of physical objects in the work system that enable the purpose-related functions |
| Physical Objects | The physical objects in the work system that afford the object related processes |

## 4 Completing the WDA

We adapted the nine steps proposed by [2] for completing a WDA. The abstraction hierarchy was developed as a tool to deconstruct the work domain.

1. **Establish the purpose of the analysis:** The purpose of this analysis was to deconstruct the offline synthetic aperture radar work domain in order to determine if operator goals and tasks are currently supported by the system and to develop design recommendations for tools that support these goals.
2. **Identify the project constraints:** The project was constrained by the type of analysis tools that the authors could use to observe offline radar imagery analysts' work. Analysts work in a classified environment. Thus recording software tools were prohibited. Other project constraints included resource constraints and time.
3. **Identify the boundaries of the analysis:** This analysis focuses solely on the work domain in which offline analysts perform.
4. **Identify the nature of the constraints in the work domain:** The timeframe in which analysts perform their duties varies. Sometimes, analysts are unable to perform their work because imagery is absent or equipment is especially slow. Procedural work constraints exacerbate this problem. It may take days or weeks for technicians to fix software and/or hardware related issues. Other constraints include political constraints, and mission constraints which are outside the scope of

this analysis. Analysts have a specific set of operationally defined work requirements. These are explicit and analysts do not deviate from them.

5. **Identify the sources of information for the analysis:** We interviewed and observed two offline radar imagery analysts for approximately 50 hours. Analysts performed verbal walkthroughs of their work for many different types of imagery events and trends. These walkthrough also included discussions about imagery, different reports, and analyst-developed software applications. We also attended analysts' weekly meetings where they are briefed about factors that may influence the way that they perform their work
6. **Construct the AH with readily available sources of information:** The AH was constructed with the sources of information described in step 5.
7. **Construct the AH by conducting special data collection exercises:** The data collection exercises included structured interviews, observations, and attendance at analysts' weekly meetings. Data collection lasted over a period of months from April until August of 2013.
8. **Review the AH with domain experts:** We asked analysts to provide feedback about the accuracy of our representations of their tasks, work flow etc. throughout the entire study.
9. **Validate the AH:** We plan to complete this step during a future study.

# 5 Results

Figure 2 shows a completed AH for the system under consideration based on [2] and [3].

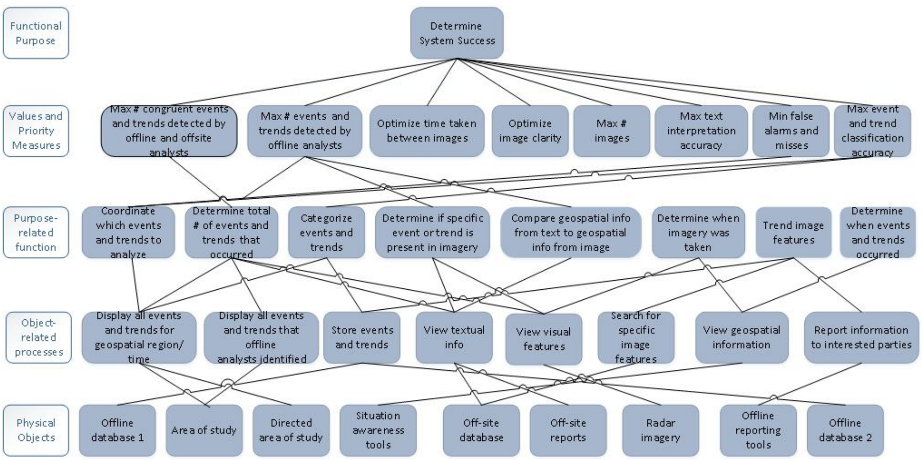


**Fig. 2.** Abstraction Hierarchy for offline analysis of the Sagebrush SAR system

We began constructing this representation by examining the physical objects that analysts use (Figure 3). This layer is shown at the bottom of the hierarchy and includes software objects such as databases, scripts, and offline applications. One-to-one mappings between tools and different analyst processes do not exist within this system. Instead, each process uses a selection of tools that overlaps with other processes.


**Fig. 3.** Physical objects of the system

We then spoke to analysts about how these objects are used to accomplish specific processes (Figure 4). For example, the offline database serves as storage for events and trends and a means for offline analysts to track the progress of their analysis. In addition, the area of study for all events and trends and the directed area of study for events and trends are represented by visualizations that allow analysts to obtain a cursory understanding of time and place for imagery features.

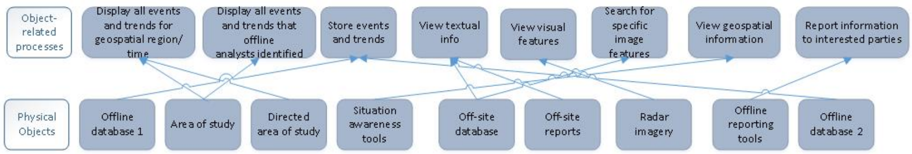


**Fig. 4.** The physical objects and associated processes layer of the AH

The purpose-related function layer of the abstraction hierarchy (Figure 5) consists of higher-level functions that are associated with object-related processes and the values and priority measures of the system. For example, analysts view geospatial information of image features in order to determine when the imagery was taken. They view the visual features in order to determine if specific events and trends are present in the imagery. This layer often reveals gaps between system functions and their associated object-related processes and priority measures.

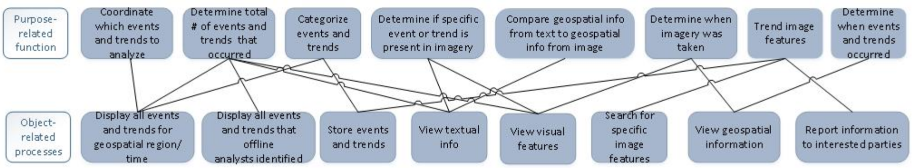


**Fig. 5.** Object-related processes and their purpose-related functions

Figure 6 shows how the purpose-related functions of the system can be accomplished through a set of values and priority measures. The values and priority measures of the system have great utility in terms of characterizing and sometimes measuring behaviors in complex systems. As shown, one way to achieve system success is to minimize the false alarm and miss rate for offline analysts. Analysts achieve this through correctly determining when events and trends occurred, by determining when the imagery was taken, and by coordinating events among other analysts.

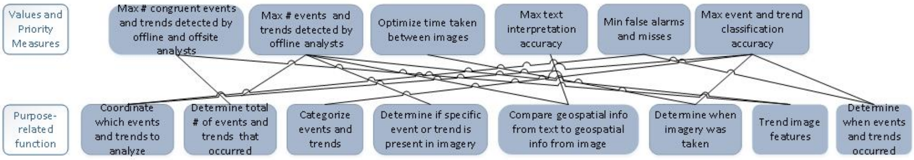


**Fig. 6.** The values and priority measures of the system's purpose-related functions

The top of the AH shows the functional purpose of the system. Although there are several purposes, we have only reported one due to space limitations. As shown in Figure 7, the functional purpose of the system is to determine system success. This is measured by all of the values and priority measures shown.

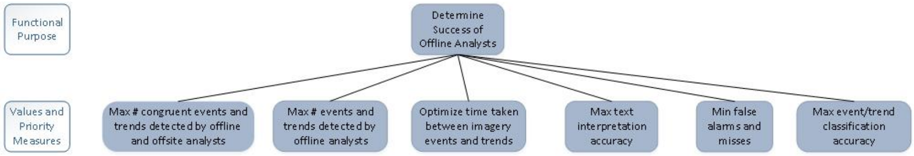


**Fig. 7.** The functional purpose of the AH is measured through the values and priority measures

### 5.1 Evaluation of WDA Framework

Although [2] and [3] provide a framework that has great utility for representing complex systems, it is not a universal solution for every domain. By showing the connections between the different layers, one can certainly see how system components are related on a higher level. However, one cannot make a determination about the quality of these relationships nor can they ascertain whether the system adequately supports particular functions and processes. Similarly, most WDA practitioners do not include contextual features such as sequence. Sequential steps are usually analyzed independently of WDA analysis during CTA or HTA. However, these methods can complement WDA. Sequence may provide more context for design requirements.

Moreover, although the nine-step methodology developed by [2] provides an overview of the steps required to perform WDA, the steps are ambiguous at best. The particular details of the steps are lacking. For example, step 6 states to complete the AH with readily available information. However, it gives no further guidance about how to do this. New practitioners would be unlikely to know where to begin.

### 5.2 Adapted WDA Framework

In order to accomplish our analysis of the system under consideration, we added details to the original WDA methodology for completing an AH. Firstly, as mentioned previously, step 6 states to complete the AH with readily available information. We suggest beginning this step by populating the bottom of the AH. This can be accomplished by creating an inventory of the system's physical objects and their associated processes. Afterwards, complete the top of the AH by determining the functional purpose of the system. The middle layers are easily the most difficult to understand and represent. Further guidance is needed to move these levels from a philosophical framework to more concrete representations that can inform design.

We also suggest the addition of a step between 7 and 8 in Naikar's nine-step methodology: construct complimentary data representations. After constructing the AH based on information obtained from the data collection exercises, we organized the components of the hierarchy by the sequence in which they are used and by their function rather than through a vertical dimension proposed by [3]. Then, we completed the bottom of the AH by conducting a separate hierarchical task analysis [6]. We grouped physical objects by function and by sequence to provide more context to develop system design requirements. In addition, we represented the relationships between items in the AH (e.g., not supported, weakly supported, adequately supported) by drawing different types of lines (e.g., dashed lines represent weak support, solid lines denote adequate support, and missing lines denote a lack of support). This also allows a level of system transparency that is not present in previous frameworks. Essentially, it allows practitioners to easily see the relationships between components of the work domain without extensive interpretation.

Figure 8 is an AH completed using the adapted framework suggested above:

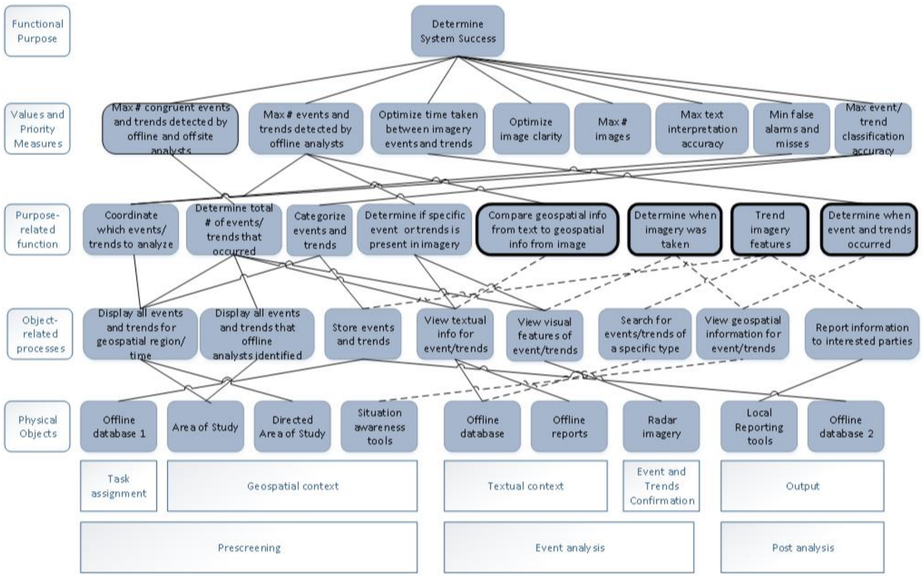


**Fig. 8.** Adapted HA for a synthetic aperture radar system

As shown in Figure 8, we created an inventory of the physical objects of the system. This is represented as the bottom layer of the hierarchy. These are mostly software objects. We ordered this inventory to correspond to the operating sequence of the system: prescreening, events and trends analysis, and post-screening. Objects were also grouped according to function including task assignment, geospatial context, textual context, events and trends confirmation, and outputs.

As mentioned previously, the lines between the layers represent relationships between objects, processes, functions, measures and purposes. Traditional CWA represents all of these relationships by drawing the same solid line. However, all relationships are not equal. Thus, by depicting the differences between these interactions, practitioners can more easily determine areas for improvement. For example, offline database 1 is used to store events and trends. Essentially, it is a spreadsheet that contains a list of events and trends that have occurred within a particular geospatial timeframe. The solid line indicates that this function (store) is adequately supported by its tool (database). However, searching for specific events and trends types is weakly supported by the tools in the current system. Offline analysts can search only for a subset of events and trends types, which excludes many other types. A dashed line represents the weak support for this process. Similarly, the situation awareness tools require manual transfer of information and von-screen visually matching. This may increase the likelihood for human error. Thus, this relationship was designated as weak because the system does not optimize human capabilities and limitations for this process. Thus, the line is dashed between the off-site reports and searching for events and trends types.

The bolded boxes show functions that are weakly supported by the current system. This is perhaps where the most improvement can occur. For example, one function of the system is to trend image features. However, analysts' ability to do this is inhibited by the tools they use and the processes that allow them to complete their work. Although they may be able to trend particular features, the system does not represent or catalog the full suite of imagery features.

### 5.3 A simplified Explanation of the AH

Unless one has extensive experience creating and reading abstraction hierarchies, it is often difficult to understand the messages they convey. We suggest a simplified explanation of the AH developed by Ganter [7]: As shown in Figure 9, the AH shows the connections between why the system exists at the top (i.e., its functional purpose), what it consists of (i.e., values and priority measures, purpose-related functions), and how it functions (e.g., physical objects) at the bottom. Essentially, it is a system hierarchy. Each level of the hierarchy has a different time horizon [7]. The functional purpose of a system evolves slowly often over years. This includes the mission, goals and constraints of the system. Similarly, the physical objects at the bottom of the hierarchy also evolve slowly because this change requires both design and execution of this design.

However, the middle of the hierarchy can evolve quickly. We adopt Ganter and colleagues' definition of the collection of middle phases as the zone of adaptation (see Figure 9). It is in this zone of adaption where operators can enact change quickly by adjusting goals and tasks [7]. In effect, the human actors adjust and revise their mental models of the system through dialog and learning. By examining this zone of adaptation, we can learn what operators do with new system capabilities to achieve enduring goals. These changes may in turn suggest new ways to levy engineering capabilities.

**Table 2.** The Abstraction Hierarchy decomposes a system into why, what and how layers with different times scales [7]

| | | |
|---|---|---|
| Why | Functional Purpose<br>Mission, goals, constraints | Evolves slowly (years) |
| What | Zone of Adaptation: object related processes, purpose-related functions, values and priority measures<br>Goals: what needs to be accomplished<br>Tasks: Actions by operators to achieve goals | Changes rapidly in response to situations and events |
| How | Physical Objects<br>Hardware, software, algorithms | Evolves slowly (days to months) |

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