Cognitive Computing for Coalition Situational Understanding

Alun Preece*, Federico Cerutti*, Dave Braines†, Supriyo Chakraborty‡, Mani Srivastava§
*Crime and Security Research Institute, Cardiff University, Cardiff, UK; contact email: PreeceAD@cardiff.ac.uk
†IBM Emerging Technology Services, Hursley, UK
‡IBM TJ Watson Research Center, Hawthorne NY, USA
§Department of Electrical Engineering, University of California, Los Angeles, USA

I. Introduction[1]

Cognitive Computing (CC) has emerged in recent years as a term for computational systems that, in general, draw on the domains of artificial intelligence and signal processing [1]. A cognitive system is characterised by capabilities including:[2]

HCC human-computer collaboration
KRR knowledge representation and reasoning
MAS multi-agent systems
ML machine learning
NLP natural language processing
VSP vision and speech processing

In this paper, we characterise the Coalition Situational Understanding (CSU) problem, and argue that this problem fundamentally requires a CC solution.

II. Coalition Situational Understanding

Situational understanding is commonly defined as the "product of applying analysis and judgment to the unit's situation awareness to determine the relationships of the factors present and form logical conclusions concerning threats to the force or mission accomplishment, opportunities for mission accomplishment, and gaps in information" [2].

UK military doctrine [3] defines *understanding* in the following terms:

Comprehension (Insight) = Situational Awareness and Analysis
Understanding (Foresight) = Comprehension and Judgment

Here, understanding includes *foresight*, i.e., an ability to infer (predict) potential future states, which is compatible with the common definition that SU involves being able to draw conclusions concerning threats [2]. Foresight necessarily includes an ability to process and reason about information temporally, spanning approaches in KRR, ML, and VSP.

These views of SU are intrinsically linked to information fusion in that they involve the collection and processing of data from multiple environmental sources as input to deriving SU. Moreover, the sources will commonly span multiple modalities (for example, imagery, acoustic and textual data [4]) requiring NLP and VSP in addition to ML.

The importance of knowledge representation and reasoning, and the human user, in the information fusion process is reflected in the *user fusion model*, an extension of the standard JDL model [5]. The user's requirements for SU place constraints on all levels of the JDL process, for example, prioritizing and valuing of particular kinds of data, objects, contexts and intents. Supporting these user refinement needs in an information fusion system for SU requires a means for the user to interact with elements of the system at both relatively high and low levels, requiring HCC, KRR and NLP.

The coalition operations information fusion environment is characterized by a high degree of dynamicity, needs for effective information and asset sharing, and constraints dictated by organisational and mission policies [6]. These features of the coalition environment require techniques from KRR and MAS in the context of an extended formulation of the SU problem, characterised in the next section as *coalition situational understanding* (CSU).

III. Mapping CSU Problem Attributes to CC Approaches

We identify a set of discrete attributes for the Coalition Situational Understanding (CSU) problem as follows.

Level of Understanding: In terms of the JDL fusion model [5], a CSU problem may address relatively high or relatively low levels of understanding, in terms of the kinds of semantic entities and relationships considered. For example, at the relatively low levels a CSU problem may be concerned with only the detection, identification and localization of objects such as vehicles or buildings (JDL levels 1 and 2). At higher levels, a CSU problem would be concerned with determining threats, intent, or anomalies (JD level 3). We denote this attribute of the CSU problem as $\mathcal{U}$; a CSU problem with a low level of understanding is denoted as $\mathcal{U}^{\mathcal{L}}$ and one with a high level of understanding as $\mathcal{U}^{\mathcal{H}}$. A CSU problem in which both levels of understanding are required is denoted as $\mathcal{U}^{\mathcal{HL}}$.

Temporal: As discussed in Section II, *understanding* is associated with *foresight*, requiring an ability to process in-

[1]This research was sponsored by the U.S. Army Research Laboratory and the UK Ministry of Defence under Agreement Number W911NF-16-3-0001. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the U.S. Army Research Laboratory, the U.S. Government, the UK Ministry of Defence or the UK Government. The U.S. and UK Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copy-right notation hereon.

[2]These approaches are listed alphabetically; no relative importance is implied.

CSU attribute				CC approaches
$\mathcal{U}$	Level of understanding	High	$\mathcal{U}^{\mathcal{H}}$ $\mathcal{U}^{\mathcal{H}}$	**KRR**
		Low	$\mathcal{U}^{\mathcal{L}}$ $\mathcal{U}^{\mathcal{L}}$	**VSP**
		High-to-Low	$\mathcal{U}^{\mathcal{HL}}$	**KRR, VSP**
$\mathcal{T}$	Temporal	Long	$\mathcal{T}^{\mathcal{L}}$	**KRR, ML, VSP**
		Short	$\mathcal{T}^{\mathcal{S}}$	**KRR, ML, VSP**
		Long-to-Short	$\mathcal{T}^{\mathcal{LS}}$	**KRR, ML, VSP**
$\mathcal{M}$	Multimodal Data	Hard	$\mathcal{M}^{\mathcal{H}}$	**ML, VSP**
		Soft	$\mathcal{M}^{\mathcal{S}}$	**ML, NLP**
		Hard & Soft	$\mathcal{M}^{\mathcal{LS}}$	**ML, NLP, VSP**
$\mathcal{D}$	Distributed	Coalition	$\mathcal{D}^{\mathcal{C}}$	**MAS**
		Heterogeneous	$\mathcal{D}^{\mathcal{H}}$	**KRR, MAS**
		Coalition & Heterogeneous	$\mathcal{D}^{\mathcal{CH}}$	**KRR, MAS**
$\mathcal{H}$	Human-in-the-Loop	Interpretable	$\mathcal{H}^{\mathcal{I}}$	**HCC, KRR**
		Tellable	$\mathcal{H}^{\mathcal{T}}$	**HCC, KRR, NLP**
		Interpretable & Tellable	$\mathcal{H}^{\mathcal{IT}}$	**HCC, KRR, NLP**

TABLE I
SUMMARY OF CSU PROBLEM ATTRIBUTES

formation temporally. We denote this attribute of the CSU problem as $\mathcal{T}$. We can distinguish between CSU problems that involve relatively short vs relatively long time-scales, denoted by $\mathcal{T}^{\mathcal{L}}$ and $\mathcal{T}^{\mathcal{S}}$ respectively. The latter would be characterized by foresight involving events in the very near future, requiring fine-grained consideration of time (hours, minutes, seconds, or less), while the latter would involve foresight of events in the more distant future, allowing a coarser granularity of time (hours, days, weeks, etc). A problem requiring consideration of time at both scales would be denoted $\mathcal{T}^{\mathcal{LS}}$.

Multimodal Data: Where a CSU problem involves the processing and fusion of multimodal data we denote this attribute as $\mathcal{M}$. As described in Section II, the data may be a product of physical sensors, so-called *hard* data, or originate from humans in the form of (usually textual) *soft* data. Where a CSU problem involves multimodal hard data alone — for example, imagery and acoustic data — we denote it as $\mathcal{M}^{\mathcal{H}}$. Where a CSU problem involves multimodal soft data alone — for example, combining mainstream media with social media reports — we denote this as $\mathcal{M}^{\mathcal{S}}$. Where a CSU problem involves fusion of hard and soft data we denote this as $\mathcal{M}^{\mathcal{HS}}$.

Distributed: As described in Section II, the CSU problem is distributed in nature, partly due to the structure of a coalition. Usually, each coalition partner will have data sources and processing resources, together with constraints on how those data and resources can be shared with other partners. Moreover, these distributed resources (data and processes) will be distributed between the centre and the edge of the network. We denote the distributed attribute of the CSU problem as $\mathcal{D}$ and the aspect of distribution that arises from the of the coalition as $\mathcal{D}^{\mathcal{C}}$. A second aspect of the CSU problem that makes it distributed in nature arises when different approaches are required to process the data. For example, hard and soft data will generally require different analytic techniques, as where the CSU problem is characterized above as $\mathcal{M}^{\mathcal{HS}}$. In other cases, it may be advantageous or required to process data of the same modality using a variety of techniques. In either case, when a CSU problem involves heterogeneous processing methods, we denote this as $\mathcal{D}^{\mathcal{H}}$. In the case where a CSU problem is distributed both due to coalition structure and heterogeneity, we denote this as $\mathcal{D}^{\mathcal{CH}}$.

Human-in-the-Loop: The final attribute represents the extent to which the human is in the loop of a CSU problem. As discussed in Section II, the human user typically has a number of interaction points with an information fusion system, generally in terms of setting requirements and preferences at the various JDL levels, denoted by $\mathcal{H}$. Specifically, where the human provides input to the CSU problem in terms that change the representation and reasoning of the corresponding CSU system — for example, by providing key information currently unknown to the CSU system — we denote this as $\mathcal{H}^{\mathcal{T}}$ and refer to the CSU system as *tellable* by humans. In cases where the CSU system cannot be a "black box" but must be in some senses transparent to users — for example, able to generate explanations for its output, we denote this as $\mathcal{H}^{\mathcal{I}}$ and refer to the CSU system as *interpretable* by humans. Finally, where a CSU problem requires both interpretability and provision of key human input, we denote this as $\mathcal{H}^{\mathcal{IT}}$.

Table I summarizes the attributes described above and shows the primary relevant CC approaches required to handle each attribute in a CSU system. The full version of this paper will analyse these in detail.

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