Human-Machine Conversations to Support Mission-Oriented Information Provision

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ABSTRACT

Mission-oriented sensor networks present challenging problems in terms of human-machine collaboration. Human users need to task the network to help them achieve mission objectives, while humans (sometimes the same individuals) are also sources of mission-critical information. We propose a natural language-based *conversational* approach to supporting human-machine working in mission-oriented sensor networks. We present a model for human-machine and machine-machine interactions in a realistic mission context, and evaluate the model using an existing surveillance mission scenario. The model supports the flow of conversations from full natural language to a form of Controlled Natural Language (CNL) amenable to machine processing and automated reasoning, including high-level information fusion tasks. We introduce a mechanism for presenting the gist of verbose CNL expressions in a more convenient form for human users. We show how the conversational interactions supported by the model include requests for expansions and explanations of machine-processed information.

Categories and Subject Descriptors

H.5 [**Information Interfaces And Presentation**]: User Interfaces—*Natural language*

Keywords

mission-oriented sensor networks; conversational interface; controlled natural language

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1. INTRODUCTION

A mission-oriented sensor network (MOSN) must support high-level tasking of network resources in terms of mission objectives, and enable exploitation of soft (human) sources in addition to physical sensing assets. These requirements involve human-machine interaction: users need to be able to request information from the network, while also being sources of information. MOSNs have the potential to empower individuals in the field who, prior to the widespread provision of mobile information and communication platforms, have not traditionally been able to benefit from the best-available actionable information [2]. MOSN technology is becoming increasingly service-oriented, offering a range of capabilities from the identification of relevant sources, to the automatic generation of queries and sensor tasking requests, to the composition and invocation of useful information-processing services, to the selection of appropriate dissemination mechanisms which take into account the capabilities of an end-user's (mobile) device. Many of the technical elements required for MOSNs are discussed in [8].

In this paper we address the need for human-machine interaction in MOSNs by proposing a natural language-based *conversational* approach aimed at making it easier and more convenient for users in the field to access mission-supporting services. We introduce a model for human-machine and machine-machine interactions that includes support for: (1) requests for information, (2) provision of information, and (3) human-machine reasoning and information fusion. The approach is underpinned by the use of *controlled natural language* (CNL) to provide an information representation that is easily machine processable (with low complexity and no ambiguity) while also being human-readable [11]. A CNL is a subset of a natural language (NL), commonly English, with restricted syntax and vocabulary. For our purposes, using a CNL facilitates clearer communication between human and system, and also enables the system to act directly on the information without the need to transform to/from another technical representation, supporting human-machine reasoning and information fusion [10] in the MOSN context. Several controlled natural languages exist; we selected a form of Controlled English known as ITA Controlled English (CE) [5] for compatibility with related research efforts. A brief guide to CE syntax and modelling is given in the appendix. An example statement in CE syntax is shown below; this identifies an individual known to be a high-value target (HVT):

```
there is a person named p670467 that
  is known as 'John Smith' and
  is a high value target.
```

While it is possible for (trained) humans to communicate directly in CNL, for convenience we aim to enable conversations that flow from natural language to CNL and back again, through an exchange of messages we call *cards*. Section 2 summarises the kinds of interactions we aim to support, with examples. Section 3 describes our conversation model in terms of the primitive kinds of interaction and valid sequences. Section 4 demonstrates how the model can be used to support realistic exchanges in a MOSN context, using a scenario from previously-published work. Finally, Section 5 provides discussion and concludes the paper.

2. HUMAN-MACHINE CONVERSATIONS

We focus on supporting three main kinds of interaction:[1]

***human→machine* interactions** where the purpose of the interaction is to mediate between NL and CE forms of human-provided content. The human initiates an interaction in NL and the machine feeds back CE, prompting the human to refine the CE and agree an unambiguous CE form of the content. Example: a soldier on patrol reports a suspicious vehicle at a location by means of a text message from their mobile device; the software agent on their device asks them to confirm their message in CE format ("Did you mean. . . ?"). Note that the human's content could be a question or statements, and the confirmed form will correspondingly be a CE query ("is it true that the vehicle X is a threat?") or facts ("the vehicle X is a threat").

***machine→human* interactions** where the purpose of the interaction is to inform a human or ask them for information. While it is possible to use CE for this purpose, it is often more convenient to present the gist of full CE in a more compact form, for which templates can be used. Example: the information broker agent sends a brief "gist" report to a human analyst indicating the vehicle is associated with a known high-value target. Commonly, a human receiving a gist report will ask for it to be expanded so they can see the full (CE) information behind it; they may also wish to obtain explanations (CE rationale) for some or all of that information. In addition to CE content, communications may have other kinds of linked content, for example imagery or a reference to a document.

***machine→machine* interactions** where the purpose of the interaction is to exchange information between software agents. The conversation is carried out through an exchange of CE content. Example: the CE from the soldier in the above example is communicated to an information broker agent that then asks a database agent for further information on the vehicle. While there is normally no human involved in these exchanges, using CE as a uniform information representation avoids communication problems — the meaning of human-provided information is not changed by some translation process to a different formal language — while also making it easier for humans to audit the exchanges when necessary. Also, on occasion, it will be useful to copy selected messages to a human for information.

[1]While not our main focus, *human→human* interactions are also supported via exchange of NL or CE messages.

To summarise, our main requirements are to support the following kinds of conversational interactions:
— NL to CE query or CE facts (a 'confirm' interaction)
— CE query to CE facts (an 'ask-tell' interaction)
— exchange of CE facts (a 'tell' interaction)
— gist CE to full CE (an 'expand' interaction)
— CE to CE rationale (a 'why' interaction)

In the following section, we formalise these kinds of conversational interactions by identifying a set of conversational primitives and valid interaction sequences.

3. CONTROLLED ENGLISH CONVERSATION CARDS (CE-CARDS)

We conceptualise a conversation as a series of *cards* exchanged between agents, including humans and software services. Each card contains text, which can be natural (NL) or controlled (CE) language. To support human-machine conversation we allow three kinds of card content: fully-natural language, formal Controlled English, and a form of template-based CE that provides the gist of complex sets of CE sentences for brevity and easier human-readability. Drawing upon software agent research, a conversation unfolds through a series of primitive *communicative acts*; for example, queries, assertions, or requests [3, 4]. The key difference in our work is that we need communicative acts to support not only machine→machine communication, but also human→machine and machine→human.

3.1 CE-Cards Model

Based on our requirements, we model several sub-types of card, shown in Figure 1 and given in CE form in the appendix. The three direct sub-types of card — `CE card`, `NL card` and `gist card` — provide important context for their content because it is not possible to unambiguously determine whether a piece of text is NL, CE, or gist by parsing it. For example, compare the NL sentence "there is a person named John" with the CE statement "there is a person named p1234 that is known as John". If the parser interprets 'John' as an identifier then the first sentence could be misinterpreted as CE. (Note however that it is possible to determine that a string is *not* CE if it fails to parse as CE, in which case it could be NL or a gist.)

We define the following sub-types of CE card, each corresponding to a particular communicative act:

`ask card` that contains a CE query;

`tell card` that contains CE statements other than queries (e.g. facts or rationale);

`confirm card` that contains CE content derived from the content of a preceding NL card;

`expand card` that requests the formal CE form of the content of a preceding gist card;

`why card` that requests an explanation (CE rationale) for the content of a preceding ask or tell card.

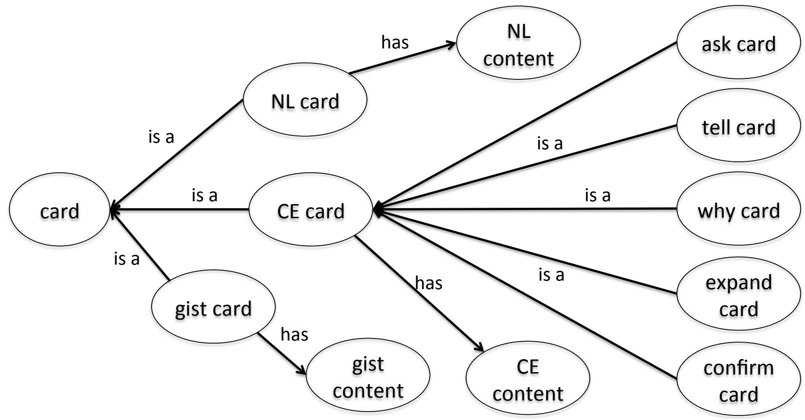

Figure 1: Graphical view of the CE-Cards model

An `expand card` marks a transition from gist content to full CE; the content is able to specify CE entities that the sender wishes the expansion to focus on. For example, consider the following exchange:

`gist`: "the red SUV is a threat"
`expand`: "red SUV"
`tell`: "there is a vehicle named v12345 that has 'red SUV' as description and has XYZ456 as registration and…"

Here, the agent issuing the `expand card` doesn't want an expansion of "threat", just the details of the SUV.

A `why card` marks a transition from CE facts to CE rationale; the content of a why card is able to specify CE entities that the sender wishes the explanation to focus on. For example:

`tell`: "there is a vehicle named v12345 that is a threat and is located at central junction and…"
`why`: "v12345 is a threat"
`tell`: "v12345 is owned by HVT John Smith and…"

Here, the sender of the `why card` wants an explanation of the threat as opposed to, say, the vehicle's location.

An example instance of a card in CE syntax is shown below.

```
there is a tell card named '#2b' that
  is from the agent tasker and
  is to the agent broker and
  is in reply to the card '#2a' and
  has content the CE content
    'there is an HVT sighting named h00453 that
      has the vehicle v01253 as target vehicle and
      has the person p670467 as hvt candidate'.
```

This is a `tell card` from an agent called `tasker` to another agent called `broker`, reporting a high value target sighting. The card is a response to a previous card: all cards have unique identifiers, allowing conversation "threads" to be identified. The example shows the use of various card *attributes*, defined formally as CE relationships in the appendix. Every card `is from` some individual human or software agent. A card `is to` either an individual agent or a named group (e.g. a team in the MOSN context); a card can be to multiple recipients. In addition to the attributes shown here, every card has a timestamp (the UTC for when the card was sent, from the sender's point-of-view) and may optionally have one or more linked resources, for example an associated image, video or audio stream, or document.

3.2 CE-Cards Conversation Policies

A *conversation* is a sequence of cards exchanged between two or more agents, with causal relationships between each pair of consecutive cards in the sequence (usually denoted by the identifier of the preceding card being used as the value of the succeeding card's `is in reply to` attribute). Following [4], we define *conversational policies* as rules that describe permissible conversations between agents, specifying allowed sequences of cards and constraints on the attributes and content of individual cards depending on their place in a sequence. Figure 2 sketches the set of sequence rules for the card types defined in our model. A full discussion of the constraints on card attributes and concepts accompanying this sequence is outside the scope of this paper, but examples are provided below and in Section 4.

In terms of our requirements for CE-Cards, the key interactions in the sequence in Figure 2 are as follows:

- The most basic form of conversation is an exchange consisting of an `ask card` a followed by a `tell card` t where t `is in reply to` a and the content of t is expected to be CE statements that satisfy the CE query in a.
- A conversation initiated by a human will typically begin with an `NL card` n to a software agent which will attempt to process the NL content of n into CE and respond with a `confirm` card c containing either a CE query or CE statements (depending on how the NL was interpreted), where c `is in reply to` n. There are now three permitted responses to c:
  - the originating human agent may accept (or edit) the CE content and, if it is a CE query, issue this content in an `ask card` a, where a `is in reply to` c;
  - the originating human agent may accept (or edit) the CE content and, if it consists of CE statements, issue this content in a `tell card` t, where t `is in reply to` c;
  - the originating human agent may not accept the content and issue a (modified) piece of NL content in a new `NL card` n', where n' `is in reply to` c.

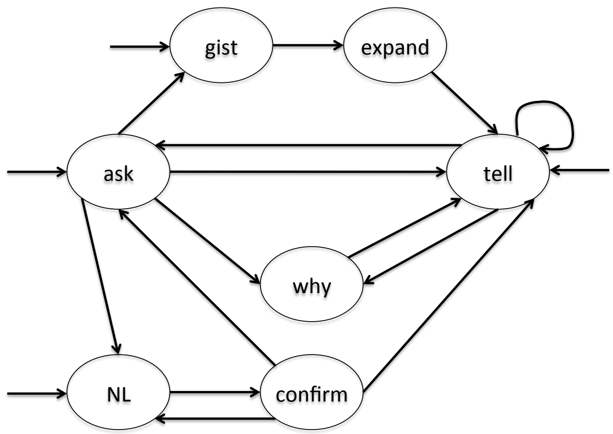

Figure 2: Conversation sequence rules for CE-Cards

- An agent may respond to an `ask card` with a template form of CE contained in a `gist card` g, to which the recipient may respond with an `expand card` e requesting the full CE form of the gist information. Now the recipient of e is excepted to respond with a `tell card` t the contents of which are expected to be the full CE form of the contents of g (e `is in reply to` g, t `is in reply to` e).
- An agent may respond to a `tell card` t with a `why card` requesting an explanation for the contents of t; the recipient of w is expected to respond with a `tell card` t', the contents of which are expected to be CE rationale for the contents of t (w `is in reply to` t, t' `is in reply to` w).

Conversation sequences are expected to begin with one of the following: an `ask card`, `tell card`, `gist card`, or `NL card`. More complex conversations can be constructed from the sub-sequences described above, and other permissible sequences. For example, following receipt of a `tell card` t, the recipient may issue a follow-up query in an `ask card` a, where a `is in reply to` t.

4. VIGNETTE AND ANALYSIS

We use a surveillance vignette from [10] to provide an illustrative walkthrough of the use of our conversational model in a mission context. We analyse the initial steps of the vignette in terms of human-machine, machine-human, and machine-machine interactions, involving four interacting agents:
— a human soldier (*patrol*)
— a human intelligence analyst (*analyst*)
— a software agent that mediates between humans and other agents (*broker*)
— a software agent that handles access to database and sensor resources (*tasker*)[2]

The interactions in the initial steps of the vignette are:

Step 1: The patrol reports a suspicious black saloon car, vehicle registration ABC123, moving south on North Road. The report is issued as a NL text message to the broker, which generates and confirms the CE form of the report with the patrol.

Step 2: The broker sends the patrol's report to the tasker, and a database query reveals that this vehicle is associated with a high value target, John Smith. This HVT sighting is communicated back to the broker.

Step 3: Based on its knowledge of mission priorities previously provided by the analyst, the broker issues a request to the tasker to track the location of the vehicle. An unmanned aerial vehicle (UAV) is assigned to this task.

Step 4: The UAV locates and tracks the black saloon as it heads south on North Road. The UAV reports that the vehicle stops near Central Junction. The analyst is alerted of this via the broker, and requests imagery from the UAV.

We now provide details of these conversational interactions using the CE-Cards model. Most of the following sequence of interactions is illustrated in Figure 3. For brevity we do not present exchanged cards in full CE syntax but instead use an abbreviated format as follows:

id.	*card type*	*sender→recipient*	`in reply to` *id.*
Content text			
Optional linked resource(s)			

Step 1: Human patrol sends text message

#1a	`NL`	*patrol→broker*	
Suspicious vehicle driving south: black saloon car with license plate ABC123			

#1b	`confirm`	*broker→patrol*	`in reply to` #1a
there is a vehicle named v01253 that has 'black saloon car' as description and has black as colour and has saloon as body type and has ABC123 as registration.			

Additional information about location, direction and reporting patrol is also generated but not shown here.

#1c	`tell`	*patrol→broker*	`in reply to` #1b
CE as in card #1b: patrol confirms no change needed			

Step 2: Machine stores confirmed extracted facts

#2a	`tell`	*broker→tasker*	
CE as in card #1b			

#2b	`tell`	*tasker→broker*	`in reply to` #2a
there is an HVT sighting named h00453 that has the vehicle v01253 as target vehicle and has the person p670467 as hvt candidate.			

This statement is inferred CE that has been is created as a result of fusing the new information from the patrol with background information already held in a database.

The recipient (or a human in a later forensic operation) could ask "why" to this response, in which case the rationale could be returned (not shown in Figure 3):

#2c	`why`	*broker→tasker*	`in reply to` #2b
CE as in card #2b			

[2]Other configurations of the software agents are possible, for example splitting the *tasker* into multiple agents with responsibility for different kinds of resources; the aim here is to show machine-machine communication while keeping the scenario simple.

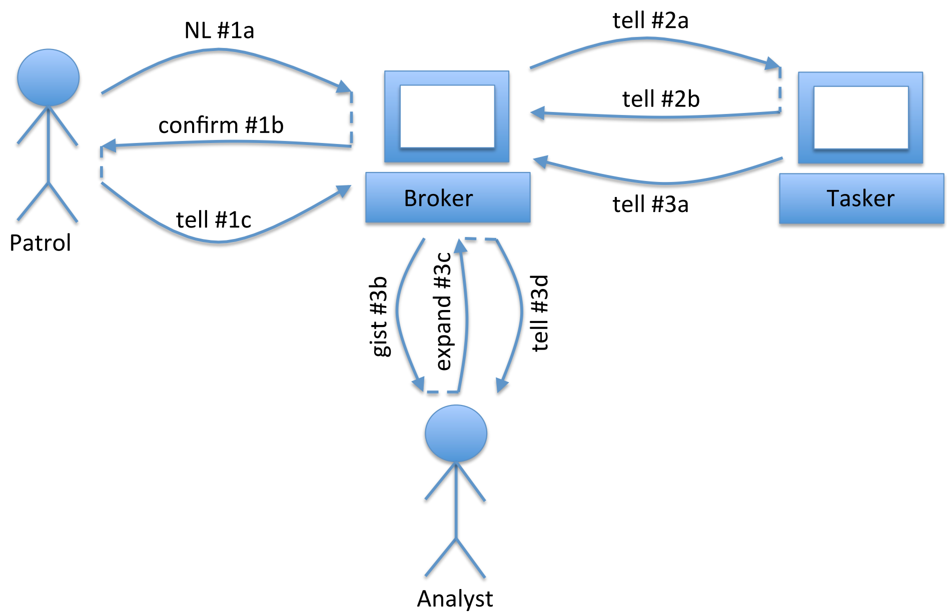

Figure 3: Interactions for steps 1–3 of the vignette

#2d	`tell`	*tasker→broker*	`in reply to #2c`

because
  there is a person named p670467 that
  is known as 'John Smith' and
  is a high value target and
  the person p670467 has ABC123
    as linked vehicle registration and
  there is a vehicle named v01253 that
  has ABC123 as registration.			

Step 3: Generation of sensing task to localize vehicle

A trigger is set in the system that will automatically create task instances whenever HVT sightings are reported.

#3a	`tell`	*tasker→broker*

there is a task named t327893 that
  requires the intelligence capability localize and
  is looking for the vehicle v01253 and
  operates in the spatial area 'North Road' and
  is ranked with the task priority high.		

A CE description of the new task may be posted to the analyst for their information.

#3b	`gist`	*broker→analyst*
A MALE UAV with EO camera has been tasked to localize a black saloon car (ABC123) with possible HVT John Smith in the North Road area.		

Assignments of sensing assets to tasks is done using the method described in [9], using a CE knowledge base of suitable sensor and platform types for a range of intelligence, surveillance, and reconnaissance tasks. The analyst could request an expansion of the above gist by means of an **`expand card`**; the expansion would be expressed in terms of the CE knowledge base, to justify that choice of asset (see Figure 3; messages not shown here for space reasons).

Step 4: Tracking updates are reported to the analyst

Here, there are a number of possibilities depending on how closely the analyst wishes to follow the tracking of the black saloon. This would be handled by the analyst expressing preferences to the broker via ask cards. For simplicity, we assume the analyst wishes to be alerted when the vehicle stops at a location:

#4a	`gist`	*broker→analyst*
Vehicle ABC123 with possible HVT John Smith has stopped at location Central Junction.		
Link to map showing position of vehicle		

At this point the analyst may request imagery from the UAV:

#4c	`NL`	*analyst→broker*
Show me live imagery from the UAV.		

There will now be a confirmation conversation to determine that this is a CE query, and an **`ask`** card issued, to which the broker will respond with a **`tell`** card including a link to the imagery as a **`resource`** attribute. Details of these interactions are similar to Step 1.

5. DISCUSSION AND IMPLEMENTATION

The above analysis illustrates most of the sub-sequences in Figure 2, and shows that the CE-Cards model is sufficient to support interactions among human and software agents in an MOSN context. The model has been designed to be minimal in terms of our requirements to support conversational flows from natural (NL) to controlled (CE) language, and back. The seven main types of card can be grouped in terms of which parts of the flow they support: NL→CE (NL, confirm), CE→CE (ask, tell, why), CE→NL (gist, expand).

Research in agent communication languages (ACLs) [3, 4] viewed conversations as sequences of communicative acts, drawing on work in philosophical linguistics. The idea of *illocutionary acts* from speech act theory [1] was adopted as a basis for ACL messages having explicit "performatives" that classify messages as, for example, assertives (factual

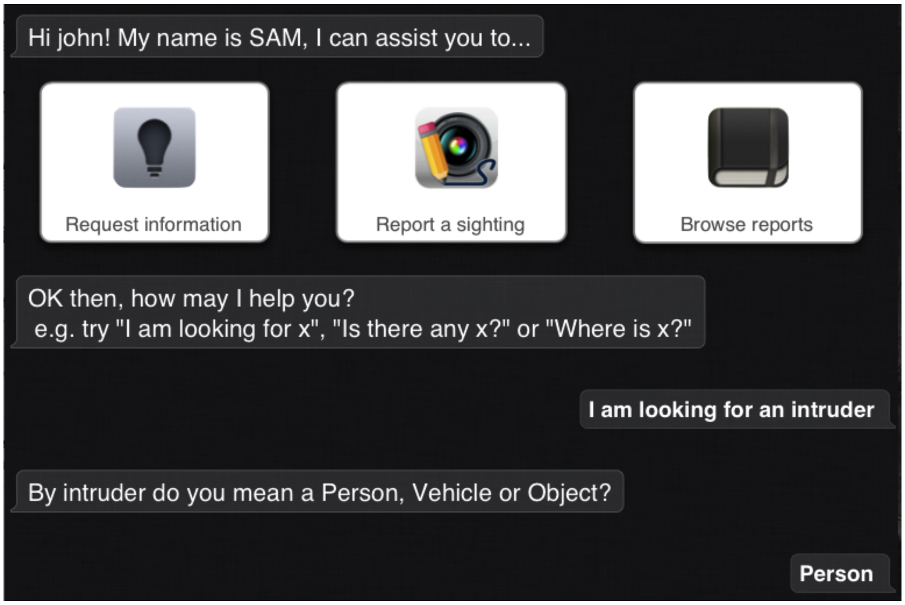

Figure 4: Conversational broker agent prototype

statements), directives (such as requests or commands), or commissives (that commit the sender to some future action).

Our model features speech act-style performatives only for CE→CE interactions (ask and why are directives, tell is an assertive), as these support machine-machine communication. However, because CE is machine-processable, in principle the receiver could determine the illocutionary act from the message content. This is already true for ask and tell (CE queries versus CE facts); there is currently no CE form for a "why" query but one could be added to the language. In our approach, NL and gist cards do not have explicit performatives because the illocutionary act is determined by the human sender or receiver. The purpose of the confirm card is to disambiguate the intended act to allow software agents to respond as expected; the purpose of a gist card is to make complex CE easier for a human to understand and determine the sender agent's intent (e.g. assertive or directive).

Prototypes of the "broker" and "tasker" agents from the vignette have been implemented and evaluated informally by subject-matter experts from the US Army Research Laboratory and UK Ministry of Defence. The broker is implemented with a text-based interface on a tablet computer; a screenshot is shown in Figure 4. The way that the system "plays back" natural language as CE was highlighted as a particularly beneficial feature. Work is now underway to conduct more formal experiments with human subjects working in collaboration with software agents using NL, CE, and the template-based gist format. A speech-based interface is also under consideration, in conjunction with an eyeline-mounted display to feed back the gist form of CE (we would envisage full CE being directed to a user's handheld device).

The processing of NL cards to extract the information in a CE format builds upon ongoing research in information extraction using CE [12]. The main difference between that research and the usage in this context is the increased dependence on lexical descriptions for the concepts, relationships and attributes within the CE model to better enable the detectability of phrases and terms within NL statements and questions. The high-level approach taken is to first shallow-parse the NL text into component words and phrases and to seek these within the current set of available CE models available to the processing agent. If suitable matches are not detected using this simplistic approach then the NL sentence is sent off to the traditional NL processing using full lexical parsing of the sentence to determine whether this additional lexical knowledge can provide further accuracy. In all cases (including partial parses) the successfully extracted information from the NL sentence is converted to CE and returned to the user for review and correction in the response. An estimate of parsing coverage can also be included in the response if deemed useful by the consuming application.

The generation of gist messages is currently based mainly on the use of pre-defined templates for different parts of the CE model where simple variable substitution is used to populate the templates against the actual data for a given situation. The templates can be used individually or combined as fragments to form a larger summary when the relevant information spans multiple templates. CE statements regarding the mapping of these templates and the relative importance of concepts, relationships and attributes are defined in the language of the CE meta-model. This builds on a technique known as *linguistic transformation* [6] whereby the information required to undertake linguistic transformations such as summaries is communicated directly in the CE language. Future research may look to integrate more advanced summarisation algorithms into this CE-based environment to make the summary generation capability more closely matched to human readability and relevance expectations.

The tasker agent incorporates the results on previous work in resource allocation in MOSNs, where a knowledge-based system matches sensing assets to mission tasks [9]. Because this system is essentially performing the role of a "facilitator" in software agent research [4], a future possibility is to extend the CE-Cards model to support “brokerage” acts such as advertisements, subscriptions, or contracts.

6. CONCLUSION

This paper has introduced a model to support human-machine conversational interactions in a mission-oriented sensor network context, and shown how the model can be applied in practice. A key focus of our future work is developing these ideas in a coalition context. We are researching the effectiveness of CE policies for security and resource management [7] and will integrate that work into the conversational context, when information and assets are shared among different coalition partners with varying levels of trust, and conversations involve negotiations over access to resources.

7. ACKNOWLEDGMENTS

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APPENDIX

CE is used to define both models and instances. Model definitions take the form of concept definitions. CE `conceptualise` sentences are intended to define by concepts by example; that is, they provide generalised examples of how to say things about concepts, including relationships between them. A CE model may also include the definition of logical inference rules which are used to express further information about the concepts and relationships and how they are logically related. Concepts may be specialisations of other concepts (indicated by `is a` declarations). The following definitions cover the core CE-Cards model (Figure 1):

```
conceptualise a ~ card ~ C that
  has the timestamp T as ~ timestamp ~ and
  has the resource R as ~ resource ~.
conceptualise the card C
  ~ is from ~ the individual I and
  ~ is to ~ the agent A and
  ~ is in reply to ~ the card Q.
conceptualise a ~ CE card ~ C that
  is a card and
  has the CE content CO as ~ content ~.
conceptualise a ~ gist card ~ C that
  is a card and
  has the gist content CO as ~ content ~.
conceptualise an ~ NL card ~ C that
  is a card and
  has the NL content CO as ~ content ~.
conceptualise an ~ ask card ~ C that is a CE card.
conceptualise a ~ confirm card ~ C that is a CE card.
conceptualise a ~ expand card ~ C that is a CE card.
conceptualise a ~ tell card ~ C that is a CE card.
conceptualise a ~ why card ~ C that is a CE card.
```