Human-Machine Conversations to Support Coalition Missions with QoI Trade-Offs

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***Abstract*—Supporting coalition missions by means of networked information resources in a dynamic environment presents challenging problems, not least in terms of human-machine collaboration. Human users need to task the network to help them achieve mission objectives, while humans are also sources of mission-critical information. Information quality is highly variable, both due to the nature of the sources and the network capacity. We propose a natural language-based *conversational* approach to supporting human-machine working in a coalition mission context. 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 English (CE) amenable to machine processing and automated reasoning, including high-level information fusion tasks and QoI trade-offs, and the enforcement of policies for security and resource management. We introduce a mechanism for presenting the gist of verbose CE expressions in a more convenient form for human users, and show how the conversational interactions supported by the model include requests for expansions and explanations. We discuss how these mechanisms can support QoI trade-offs and enforcement of security and management policies.**

I. Introduction

Coalition mission support involves high-level tasking of network resources in terms of mission objectives, and enabling 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. Networked information resources 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 [1]. Coalition mission support 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 coalition mission support are discussed in [2]. Information quality in coalition mission support networks is highly variable, both due to the nature of the sources and the network capacity.

In this paper we address the need for human-machine interaction in coalition mission support 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.[1] 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 [3]. 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 [4] in the coalition mission support 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 II summarises the kinds of interactions we aim to support, with examples. Section III describes our conversation model in terms of the primitive kinds of interaction and valid sequences. Section IV demonstrates how the model can be used to support realistic exchanges in a coalition mission support context, using a scenario from previously-published work. Section V

[1]This paper is an extended version — created for the purpose of the ITA 2013 Fall Meeting, and not for wider publication — of the *MiSeNet'13* paper "Human-Machine Conversations to Support Mission-Oriented Information Provision". The vignette in Section IV has been extended and Section V has been added, along with some additional material in Section VI.

discusses how the conversational approach offers flexibility in dealing with trade-offs associated with information quality. Section VI provides discussion and implementation details, and Section refsec:conclusion concludes the paper.

II. Human-Machine Conversations

We focus on supporting three main kinds of interaction:[2]

***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.

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)

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

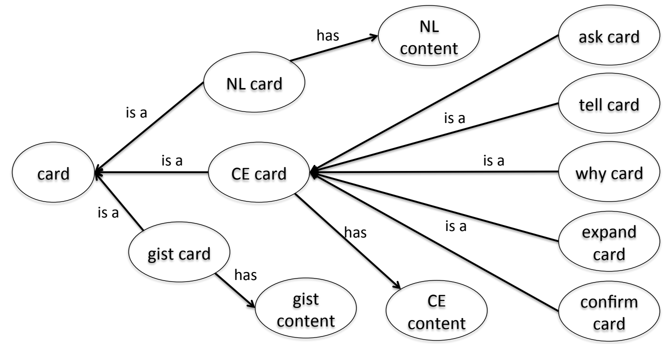

Fig. 1. Graphical view of the CE-Cards model

— 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.

III. 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 [6], [7]. 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.

A. 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.

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 coalition mission support 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.

B. 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 [7], 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 IV.

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.
- 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.

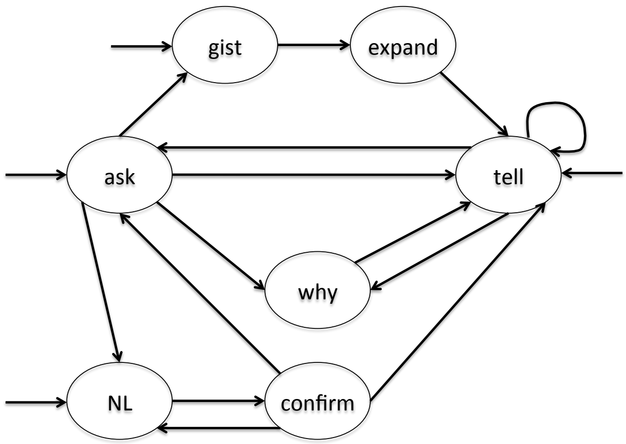

Fig. 2. Conversation sequence rules for CE-Cards

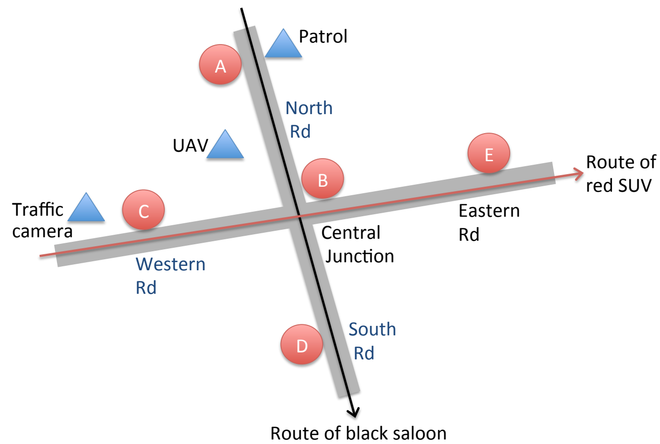

Fig. 3. A surveillance D2D vignette with hard and soft information fusion

IV. Vignette and Analysis

We adapt and extend a vignette from [4] which will be used in later sections to illustrate the use of our CNL-based approach to supporting D2D activities. An area of interest around the intersection of four roads is shown in Figure 3. The locations of various assets — sources of both hard and soft information — are marked by triangles. The passage of two vehicles causes a sequence of events, associated with labelled points on the map (A–E), to unfold as follows. 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*)[3]

1) The patrol on North Road (location A) reports a suspicious black saloon car, vehicle registration ABC123, moving south. 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
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.
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.
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 (location B). The analyst is alerted of this via the broker, and requests imagery from the UAV.
5) The imagery from the UAV shows that the black saloon has stopped by the roadside next to a red SUV. The analyst indicates that the red SUV is an object of interest. The two vehicles now depart the junction, the saloon heading south onto South Road, and the SUV heading east on Eastern Road.
6) The analyst's indication that the red SUV is now of interest causes a recent report to be retrieved from a camera system on Western Road (location C): a red SUV passed the camera recently; license plate recognition software determined that its registration is XYZ789. This identification is now associated with the SUV from Central Junction with a high degree of certainty, given the recency of the report and the fact that no other similar SUVs passed by.
7) As the saloon and SUV head south and east respectively, decisions need to be taken on whether and how to track their movements. The only available assets in the area are the UAV and a traffic camera system on Eastern Road. Both are capable of locating the vehicles, though the camera system can only do so in a limited area. In the event, the UAV is tasked to continue following the saloon in the South Road area (location D).
8) The camera system on Eastern Road (location E) is tasked to issue an alert on identifying a red SUV with license plate XYZ789. As this only covers part of the road, local law enforcement in the Eastern Road area are also alerted to look out for this vehicle.
9) Images of suspect John Smith and his known associates are automatically retrieved by database query and made available to patrols in the Eastern Road area with requests to confirm whether any of these individuals (including Smith) are driving the SUV. The quality of imagery made available takes into account available bandwidth to the patrol's mobile devices; metadata is provided to the patrols' devices allowing them to prioritise accessing

[3]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.

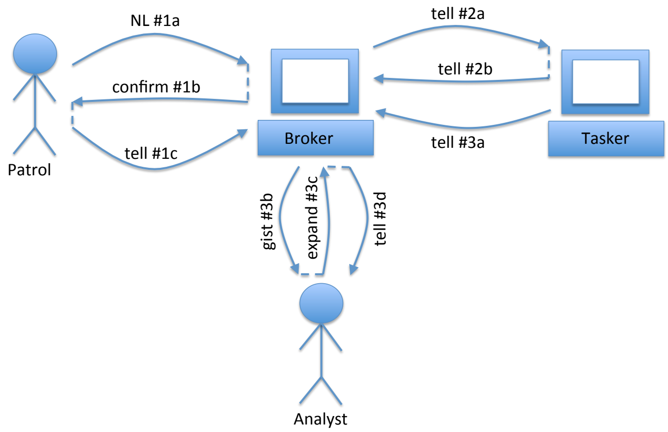

Fig. 4. Detailed interactions for steps 1–3 of the vignette

the images in order of priority based on the likelihood of each individual being the driver.

We now provide details of these conversational interactions using the CE-Cards model. Most of the following sequence of interactions is illustrated in Figure 4. 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 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 4):

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

#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 [8], 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 4; 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.

V. Handling Information Quality Issues

This section addresses a range of quality-of-information (QoI) issues that arise in the context of human-machine, machine-human, and machine-machine interactions, using illustrative examples from the vignette. In each case, we discuss how the conversational interaction mechanisms can handle QoI issues, support trade-offs, and enforce security and management policies where needed.

Example 1 — QoI from the patrol (step 1): If the patrol is a trained team then it is likely that the word "suspicious" has a codified meaning and can be directly mapped to some kind of certainty range. If the message is coming from an untrained team or social media then the subjective meaning of "suspicious" would need to be estimated and the certainty recorded. This could take into account things like past performance (if available, for example to account for teams that over-report suspicious things vs those that are historically accurate). Certainty could be recorded in terms of a numerical probability, or using a symbolic grading scheme[4]. All of these cases can be handled by the receiver of the message (the broker in our vignette) using rules that are essentially representations of conversational pragmatics [9].

Example 2 — policy-based confirmation to the patrol (step 1): In the conversational protocol, the purpose of the confirm response is to eliminate the possibility of errors in the NLP parsing of the incoming message. If the confirm message does not contain all of the information, and the correct information, then the receiving user has the opportunity to correct in their "tell" response. However, in some cases — due to policy — the recipient of the NL card may choose to withhold a (complete) confirmation. For example, the broker may have a policy rule that says to reply to any message from a less-trusted coalition partner with a simple acknowledgement of receipt rather than CE that may reveal something about how the partner intends to model and exploit the information. Of course, where there is no confirm/tell part of the conversation there is the possibility that the NLP was not accurate (another source of uncertainty) so this should be recorded, or the message should be routed for review to some internal user to achieve certainty of parsing accuracy (via a confirm/tell with them). Again, all of these cases can be handled using pragmatic rules.

Example 3 — quality of information retrieved from database (step 2): Here we may have uncertainty that the vehicle is associated with HVT John Smith (the information may be out of date or inaccurate). This form of uncertainty may be a different representation to that used in example 1, for instance a probability vs a symbolic rating, making combining the two a challenge. Subjective logic may play a role in addressing this issue. Additionally, CE rationale plus provenance information[5] offers a means of communicating the compounded result, and gist offers a way to make it easily-digestible while also being expandable to users on request (or during subsequent audit).

Example 4 — quality of information from camera on Western Road (step 6): Here, the accuracy of license plate recognition software needs to be associated the assertion that the registration of the SUV is XYZ789, and carried forward into subsequent linking of information about the SUV. A subsequent observation might confirm or contradict this one from the Western Road camera, leading to the construction of an argument/evidence graph. Moreover, assuming a human user makes the judgement that XYZ789 must be the corresponding plate due to the low number of vehicles of that type in that time period, in this case the certainty needs to be carried forward (and recorded with rationale) so that it can be fused with all the other uncertainties, many of which are system-generated, that arise in subsequent processing. This kind of interaction is well-suited to the use of explicit certainty on CE statements.

Example 5 — fusion of information (step 6): At this stage in the vignette there is uncertainty as to (a) whether John Smith or an associate is driving the SUV, (b) whether John Smith is even involved (examples 1 and 2), and (c) the registration of either vehicle (examples 1 and 4). All of these — potentially heterogeneous — uncertainty representation need to be aggregated. Once again, use of rationale, provenance, subjective logic, and gist (to convey summaries to a human user) can help. Note that we expect the fusion/understanding of all these sources of uncertainty to be fundamentally a human activity with support from the machine to make understanding/audit easier (through gist and rationale).

Example 6: alerting patrols on Estern Road (step 9): To make available information on the suspected driver of the red SUV to patrols on Eastern Road we have to judge how high quality the imagery needs to be, taking into account available bandwidth to the patrols' devices. As well as deciding what information to prioritise for the patrols, there will be other considerations such as how many are likely to be possible in the right time frame. The order and set that may be of interest can be chosen by the user, but the machine can help with prioritising by fusing information from sources — including for example John Smith's background, and the focus of the current operation — and making that information available via rationale if the user seeks justification (for example, "Why Fred Jones?" "Because John Smith is a trafficker who lives in Hightown but Fred Jones is an associate who is also a trafficker and lives near North Road"). Pragmatic rules and mission policies can help make these choices.

VI. Discussion and Implementation

The analysis in Section IV illustrates most of the subsequences in Figure 2, and shows that the CE-Cards model is sufficient to support interactions among human and software agents in a coalition mission support 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) [6], [7] viewed conversations as sequences of communicative acts,

[4]For example, the "4×4", "5×5" and "6×6" schemes: http://4knowledge-za.blogspot.co.uk/2009/05/intelligence-grading-systems.html

[5]Rationale will record the sources of the CE and any inferences; additional information about the sources (who, what, where, when) is recorded as provenance, with the rationale effectively linking it all together.

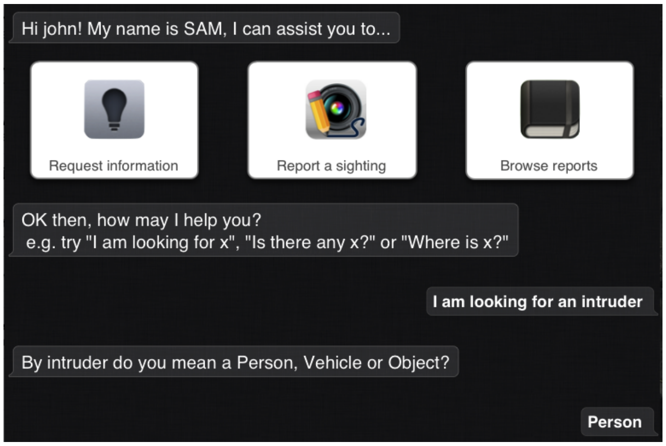

Fig. 5. Conversational broker agent prototype

drawing on work in philosophical linguistics. The idea of *illocutionary acts* from speech act theory [9] was adopted as a basis for ACL messages having explicit "performatives" that classify messages as, for example, assertives (factual 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 5. 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 [10]. 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 (if policy allows) and correction in the response.

One area for experimentation is the use of gist cards instead of CE confirm cards, especially in cases where policy dictates a "verbatim" CE version not be provided to the sender (as seen in example 2 in Section V). This would be especially useful when the receiver of the NL message does not wish to expose any inferred/extracted knowledge but does wish to acknowledge the receipt (e.g. "Thank you for your message"). Of course, this means that there is no formal confirmation by the sender of their intended meaning so, as discussed above, confirmation may need to be established by a (human) third party.

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* [11] 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. Another area for experimentation is the use of a graphical form for the gist, which might be especially useful in a form factor such as an eyeline-mounted display. The style/format (e.g. text or graphical gist) can be determined based on additional contextual factors such as the user, their role, the current operational tempo and the form factor of the device they are using.

The tasker agent incorporates the results on previous work in resource allocation in coalition mission support, where a knowledge-based system matches sensing assets to mission tasks [8]. Because this system is essentially performing the role of a "facilitator" in software agent research [7], a future possibility is to extend the CE-Cards model to support "brokerage" acts such as advertisements, subscriptions, or contracts.

VII. Conclusion

This paper has described 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, including consideration of policy and QoI issues. 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 [12] 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.

VIII. Acknowledgments

This research was sponsored by the US Army Research Laboratory and the UK Ministry of Defence and was accomplished under Agreement Number W911NF-06-3-0001. 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 US Army Research Laboratory, the US Government, the UK Ministry of Defence or the UK Government. The US and UK Governments are authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation hereon.

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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.
```