The International Technology Alliance
in
Network and Information Sciences

Agile Assignment of Sensing Assets to Mission Tasks in a Coalition Context

Alun Preece
Cardiff University, UK

IBM, Yorktown Heights
June 2015

MINISTRY OF DEFENCE

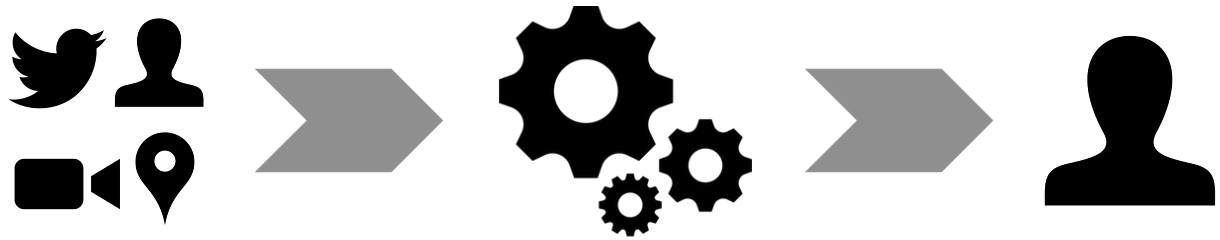
Context

Big Data / Data to Decisions

Eight Great Technologies

Policy Exchange

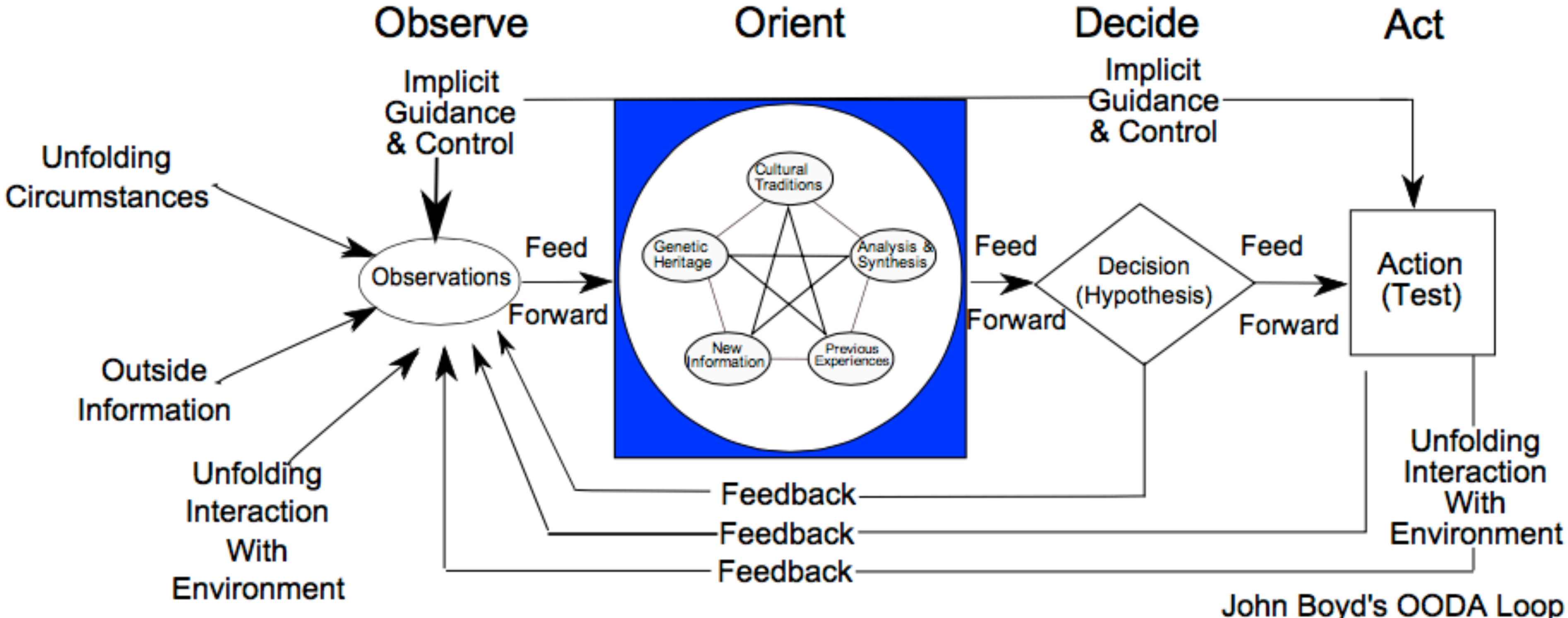
We face a data deluge. The next generation of scientific discovery and innovation will be data-driven as previously unrecognised patterns are discovered by analysing massive and mixed data sets.



The priority S&T investment areas in the FY13-17 Program Objective Memorandum are:

(1) **Data to Decisions** – science and applications to reduce the cycle time and manpower requirements for analysis and use of large data sets.

OODA Loop



http://en.wikipedia.org/wiki/OODA_loop

Forward & backward chains

fwd

Data-to-decision: an agent needs to make a decision based on actionable information from data sources

back

Decision-to-data: an agent needs to determine what data sources will help them achieve their hypothetical decision

Backward chain: decision to data

Rapidly construct pipelines by working backwards from an intended decision (hypothesis or query) and identifying useful analysis services and underlying data

Example – Fukushima 2011: urgent requirement arose to monitor radiation leaks leading to rapid deployment of networked Geiger counters

Approach:
Sensor Assignment to Missions

Sensor Assignment to Missions (SAM)

"Decision-to-data"

- Make best use of scarce sensing assets by considering all ways to achieve an ISR task

  "Locate high value targets in an area"

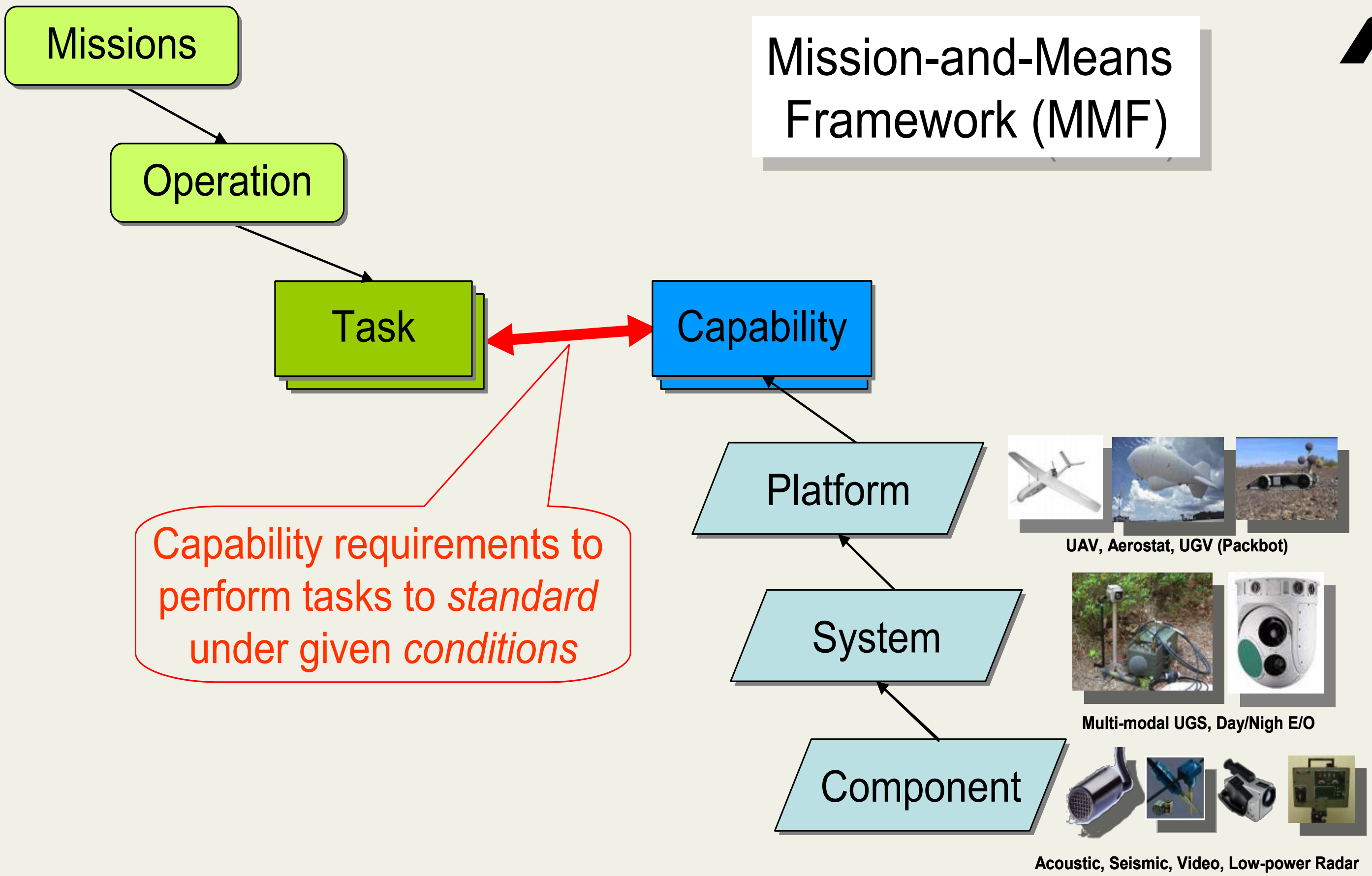
  - imagery, acoustic, seismic….
- Help users utilise all suitable and available assets across the coalition – without requiring them to have sensing expertise
- Be agile in the face of changing task requirements and available assets

Users are decision makers in the network or at the edge of the network

Knowledge-based approaches

- **Sensor Web Enablement Sensor Planning Service** (Open Geospatial Consortium)
- **OntoSensor** (U Memphis/ Purdue)
- **Semantic Sensor Network WG** (W3C)

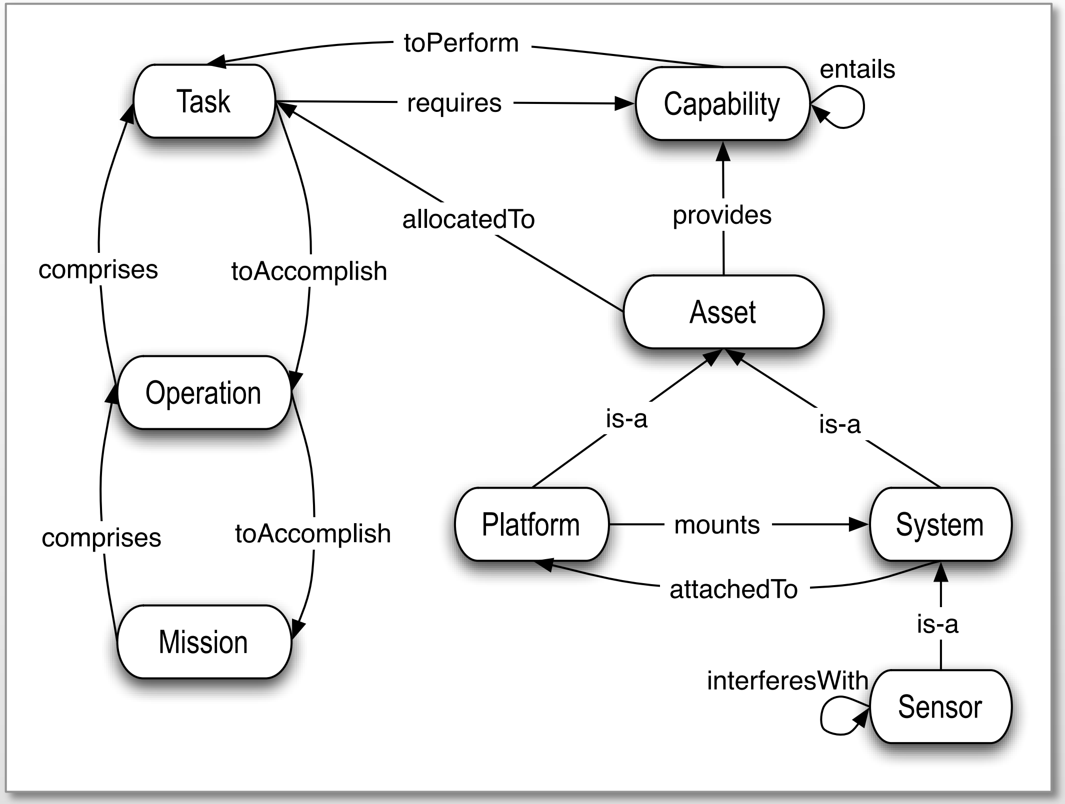
Tasking of ISR Assets - MMF



- Link tasks derived from missions to assets derived from capabilities
- Assign specific assets given state of sensors, ongoing missions, mission priorities
- Accommodate energy constraints and time dynamics, such as missions starting and ending, and deployment delays

Building on the Military Missions & Means Framework (MMF)

Formalised MMF as a collection of ontologies defined using Web Ontology Language (OWL), for machine-processability



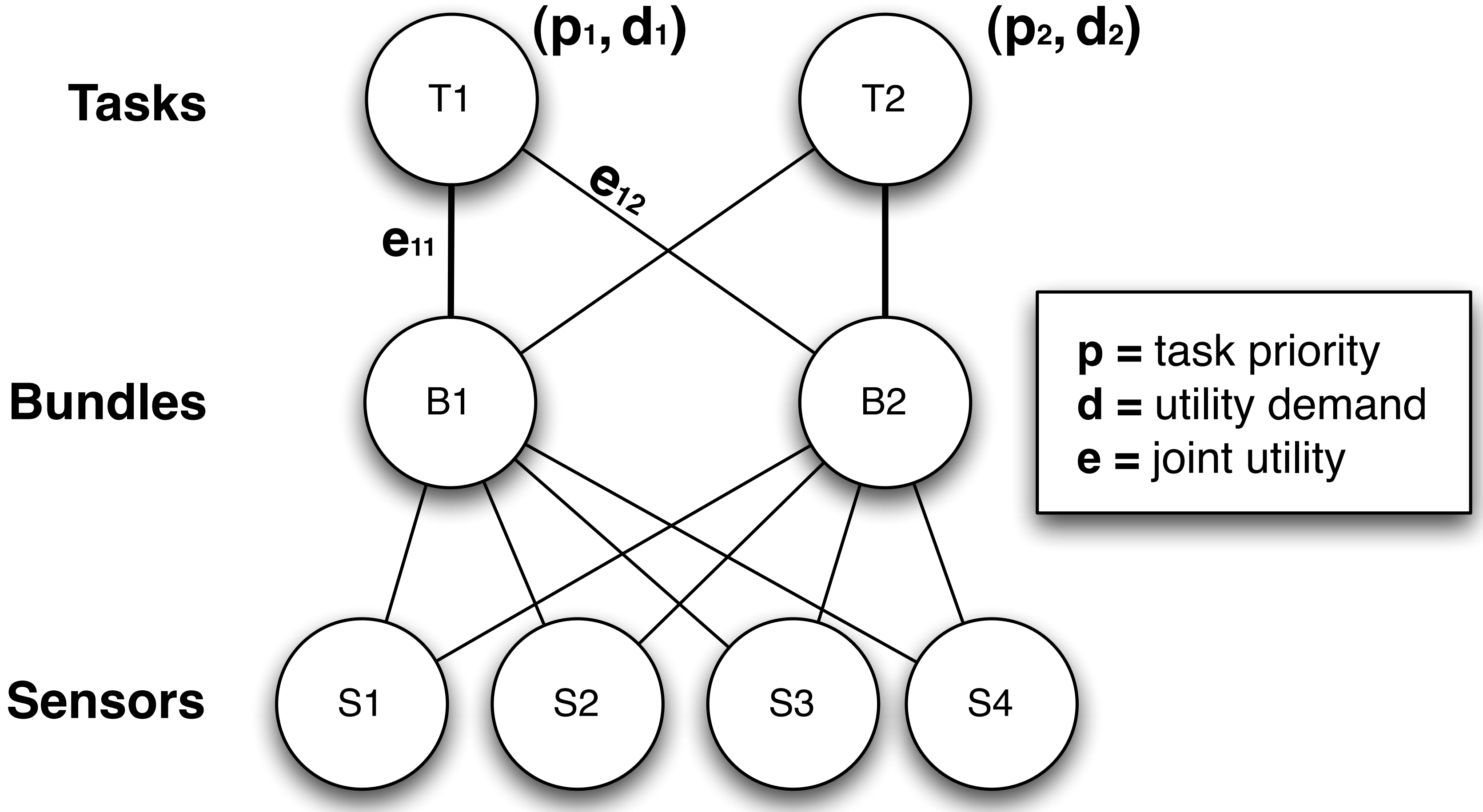
Extensible models

- Asset ontology based on OntoSensor
- Task ontology originally based on Joint Universal Task List
- MMF connects these:
  - tasks **require** capabilitites
  - assets **provide** capabilities

NIIRS-based approach

- Tasks are characterised by the data needed to achieve them
  - type of (imagery) data (visual, IR, radar, multispectral)
  - “quality” rating 0 to 9
- Assets are rated in terms of the data they can provide

Multi-sensor task allocation (Cardiff, CUNY, PSU)



Task-asset matching procedure

Definitions

- **Task type (TT):** a NIIRS interpretation task that characterises the given task, and requires a given NIIRS rating
- **Bundle type (BT):** a combination of platform and sensor(s) that provides a given NIIRS rating
- **Utility function (UF):** a means of assessing how effective a particular BT instance is likely to be in achieving a particular TT instance
- **KB Table (KBT):** a pregenerated set of triples of the form (TT, BT, UF) capturing all applicable BT/UF pairs for a given TT

1. **A user creates a task from which the system derives the corresponding TT.**
2. **The system retrieves all KBT entries (TT, BT, UF) for the given TT.**
3. **The system determines all possible *bundle instances* that conform to all retrieved BTs and uses the corresponding UFs to derive a utility for each.**
4. **A distributed allocation protocol attempts to assign a bundle instance, maximising overall utility in the face of multiple competing tasks.**

Vignette

A variety of applicable sensor systems are available

A user wishes to localize SUVs crossing a desert

Open middleware makes sensor systems available as services on the network

Tasks

- Tasks are triples consisting of:
  - operation (defined in an appropriate task ontology)
  - area-of-interest (point or region)
  - time (instant or period)
- For example, using our NIIRS-based* task ontology, an operation is a pair:
  - operator (one of: detect, identify, distinguish)
  - operand (one or more entity classes)

*National Image Interpretability Rating Scale

A knowledge-based approach

- Qualitative knowledge
  - ontology-based descriptions, rules

  defines what types of sensor (bundle) are appropriate for which task types
  - examples: vehicle identification can be done visually (“grade 4”) or acoustically (“grade 2”)
- Quantitative knowledge
  - joint utility models (functions)

  determines the value of a set of sensors
  - examples: cumulative detection probability; 2D-localization

Walkthrough

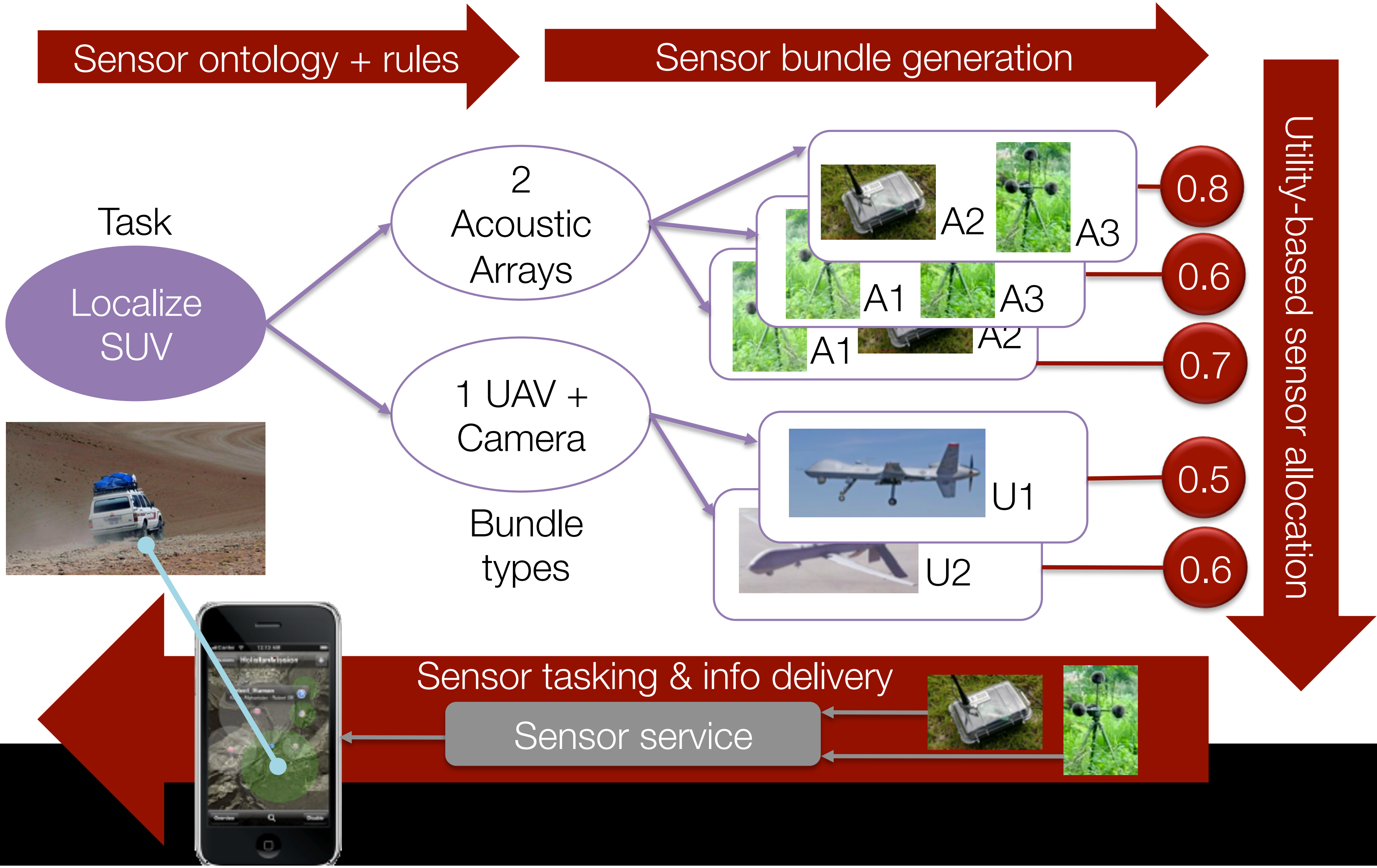
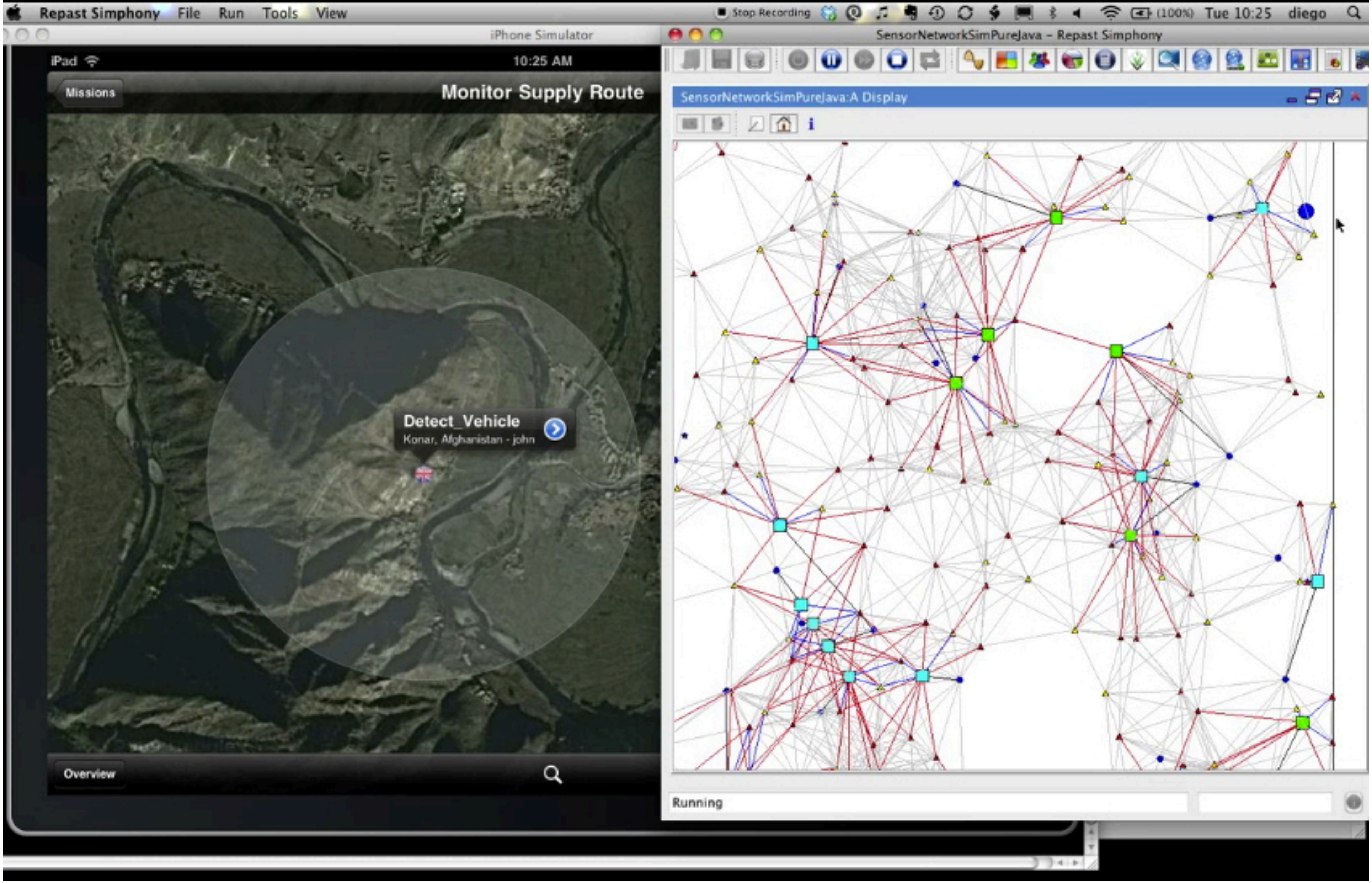
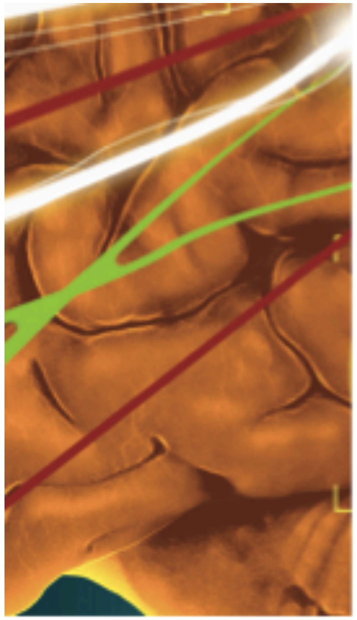


Illustration-of-concept app: iSAM





Agilely Assigning Sensing Assets to Mission Tasks in a Coalition Context

Alun Preece, *Cardiff University*

Tim Norman, *University of Aberdeen*

Geeth de Mel, *IBM TJ Watson Research Center*

Diego Pizzocaro, *Cardiff University*

Murat Sensoy, *Ozyegin University*

Tien Pham, *US Army Research Laboratory*

When managing intelligence, surveillance, and reconnaissance (ISR) operations in a coalition context, assigning available sensing assets to mission tasks can be challenging. The authors' approach to ISR asset assignment uses ontologies, allocation algorithms, and a service-oriented architecture.

In a coalition context, effectively using intelligence, surveillance, and reconnaissance (ISR) assets is a challenge.[1] Using sensor-provided data, there are multiple ways to achieve an ISR task. For example, the National Image Interpretability Rating Scales (NIIRS) framework characterizes different ISR tasks that end users can achieve using various types of visual sensing data (visible, radar, infrared, and multispectral).[2] ISR analysts, for instance, can't be expected to have a specialist's sensing knowledge; they must be able to state their information needs in terms of what they want (such as to track high-value targets in an area) rather than how the sensor data can satisfy those needs. Coalition partners must maintain control over how the assets they own are shared with other partners.[1] Therefore, absent a great deal of knowledge about sensing capabilities and coalition asset availability, identifying suitable ISR assets is difficult. Because ISR situations can evolve rapidly, the asset-provisioning infrastructure that supports ISR operations must be agile, responsive to changing user needs as well as the availability of relevant assets.

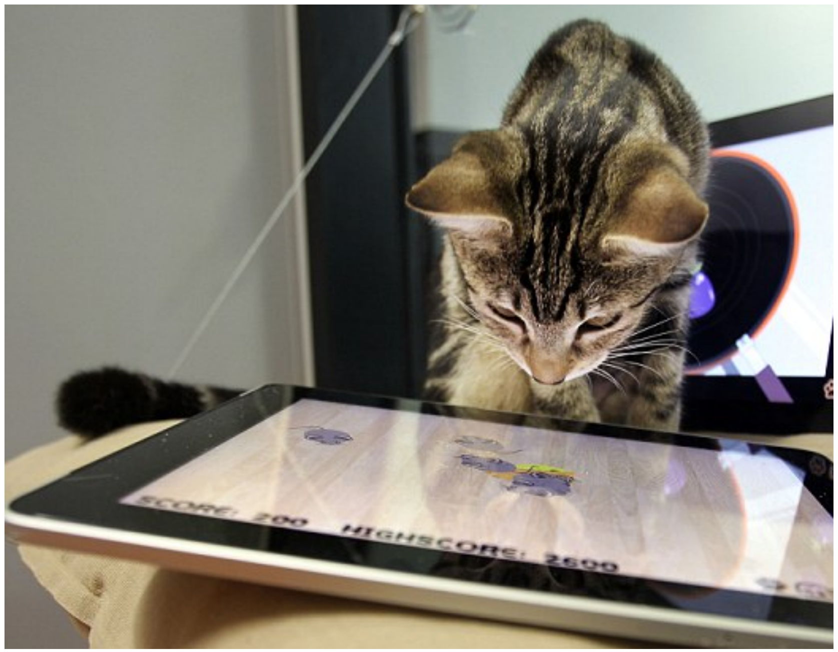
Any solution to this problem requires a common representation of tasks and assets that users can extend to new task or asset types. It must express tasks at a high level in terms of what the user wants. To match tasks to available assets, efficient mechanisms are needed that consider all possible means of satisfying the task. To solve this problem, several works have proposed using a knowledge base or mapping that relates

Preece, Norman, de Mel, Pizzocaro, Sensoy & Pham, Agilely Assigning Sensing Assets to Mission Tasks in a Coalition Context, *IEEE Intelligent Systems*, 2013

New approach:
Controlled English SAM

The priority S&T investment areas in the FY13-17 Program Objective Memorandum are:

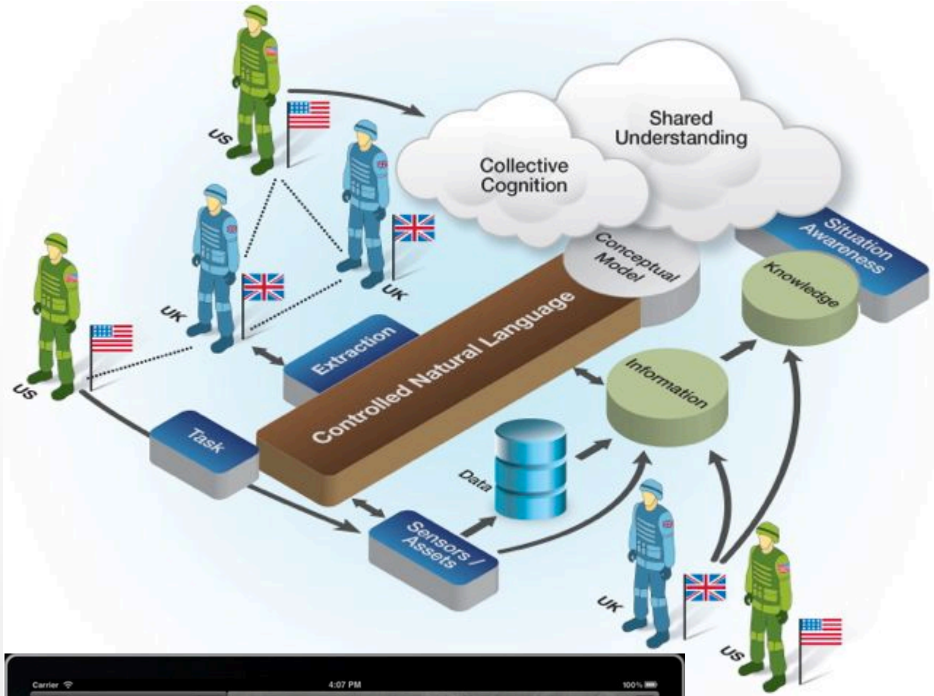
(1) **Data to Decisions** – science and applications to reduce the cycle time and manpower requirements for analysis and use of large data sets.



A new approach using Controlled Natural Language

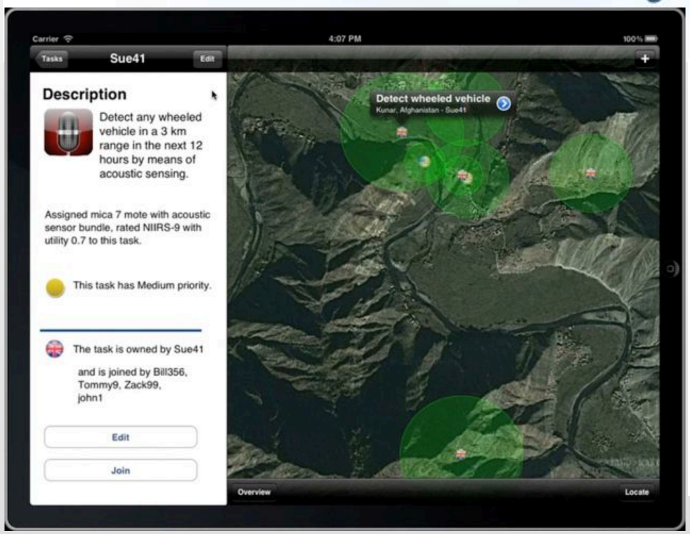
Controlled Natural Language

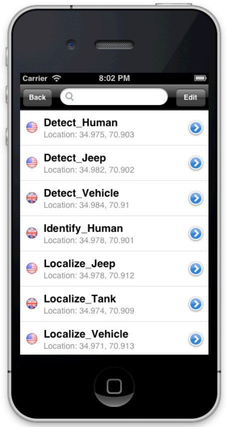
- A subset of a natural language with restricted syntax and vocabulary.
- Used to provide an information representation that is easily machine processable while also being human-readable.



Research questions

- Can our MMF-based knowledge base be expressed in CNL, with no loss of power to support automated asset-task matching?
- How can a CNL-based representation of tasks and their resourcing be used to create a human-understandable tool to promote task sharing among users?





Reformulating the ontology in ITA Controlled English

conceptualise a ~ capability ~ C.

conceptualise the mission M
~ comprises ~ the operation O.

conceptualise the operation O
~ comprises ~ the task T.

conceptualise the task T
~ requires ~ the capability C.

conceptualise the asset type A
~ is rated as ~ the NIIRS rating R and
~ provides ~ the capability C.

conceptualise a ~ system type ~ S that
is an asset type.

conceptualise a ~ sensor type ~ S that
is a system type.

conceptualise a ~ platform type ~ P that
is an asset type.

conceptualise the platform type P
~ mounts ~ the system type S.

conceptualise a ~ UAV ~ U that is a platform type.

conceptualise a ~ MALE UAV ~ M that is an UAV.

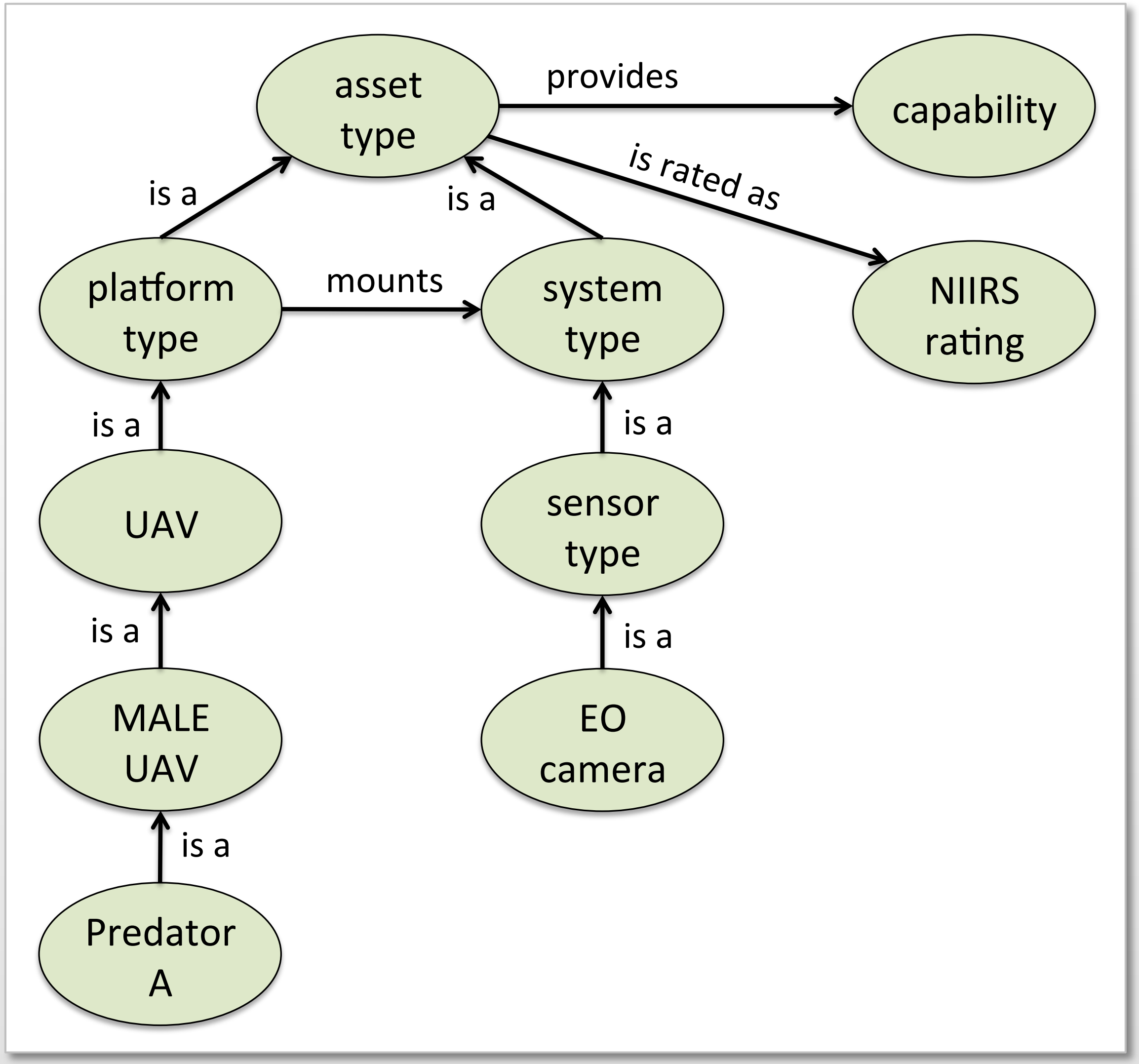
Note: MALE = Medium Altitude, Long Endurance.

conceptualise a ~ Predator A ~ P that is a MALE UAV.

conceptualise an ~ EO camera ~ E that is a sensor type.

Note: EO = Electro-optical.

Controlled English model and 'prototypical' instances



'Prototype' instances

there is an EO camera named '**EO camera sensor type**' that provides the capability 'visible sensing'.

there is a Predator A named '**Predator A platform type**' that mounts the sensor type 'EO camera sensor type' and is rated as the NIIRS rating 'visible NIIRS rating 6'.

Associating tasks with asset bundles

Model

conceptualise the task T
  ~ requires ~ the intelligence capability IC and
  ~ is looking for ~ the detectable thing DT and
  ~ operates in ~ the spatial area SA and
  ~ operates during ~ the time period TP and
  ~ is ranked with ~ the task priority PR.

conceptualise the assignment template AT
  ~ fulfills ~ the intelligence capability IC and
  ~ is looking for ~ the detectable thing DT and
  ~ can be satisfied by ~ the bundle type BT and
  ~ is ranked by ~ the utility function UF.

conceptualise the bundle type BT
  ~ is deployed on ~ the platform type P and
  ~ uses ~ the sensor type S.

Sample instances

there is a task named t1265 that
  requires the intelligence capability detect and
  is looking for the detectable thing
    'wheeled vehicle' and
  operates in the spatial area r942 and
  operates during the time period t1789 and
  is ranked with the task priority medium.

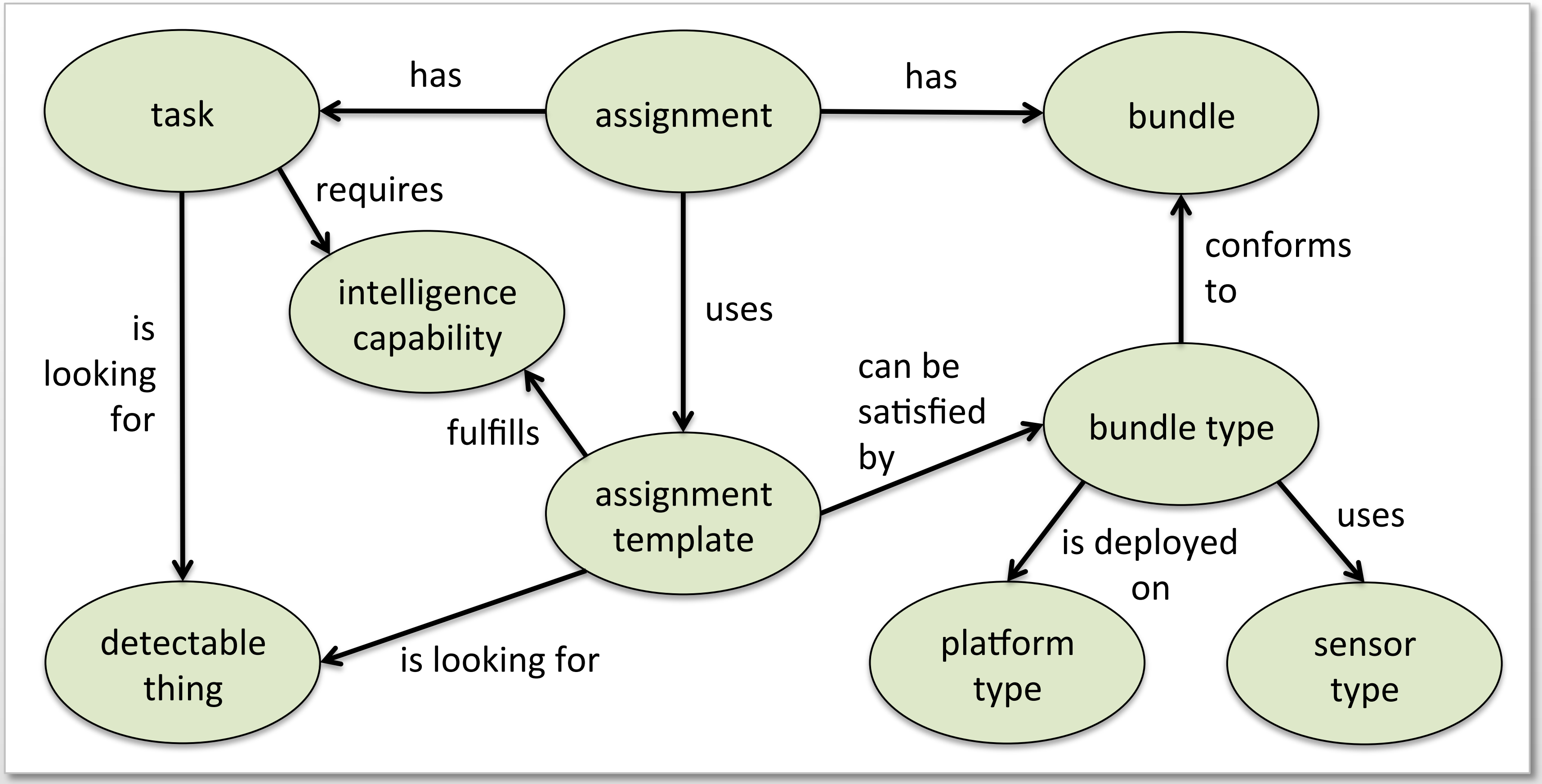
there is an assignment template named at349 that
  fulfills the intelligence capability identify and
  is looking for the detectable thing
    'wheeled vehicle' and
  can be satisfied by the bundle type bt312 and
  is ranked by the utility function CDP.

there is a bundle type named bt312 that
  is deployed on the platform type
    'Predator A platform type' and
  uses the sensor type 'EO camera sensor type'.

Task-assignment-bundle model

conceptualise an ~ assignment ~ A that
has the task T as ~ task ~ and
has the bundle B as ~ bundle ~ and
has the value US as ~ utility score ~.

conceptualise the assignment A
~ uses ~ the assignment template AT.



Associating assignments with users

Model

conceptualise a ~ user ~ U.

conceptualise a ~ coalition partner ~ CP.

conceptualise the assignment A
  ~ is provided by ~
    the coalition partner CP and
  ~ is owned by ~ the user UO and
  ~ is joined by ~ the user UJ.

Sample instances

there is an assignment named a43288 that
  has the task t1265 as task and
  has the bundle b17352 as bundle and
  has '0.7' as utility score and
  uses the assignment template at349.

there is a bundle named b17352 that
  conforms to the bundle type bt312.

the assignment a43288
  is provided by the country UK and
  is owned by the user Sue41 and
  is joined by the user Bill356 and
  is joined by the user Tommy9 and
  is joined by the user Zack99.

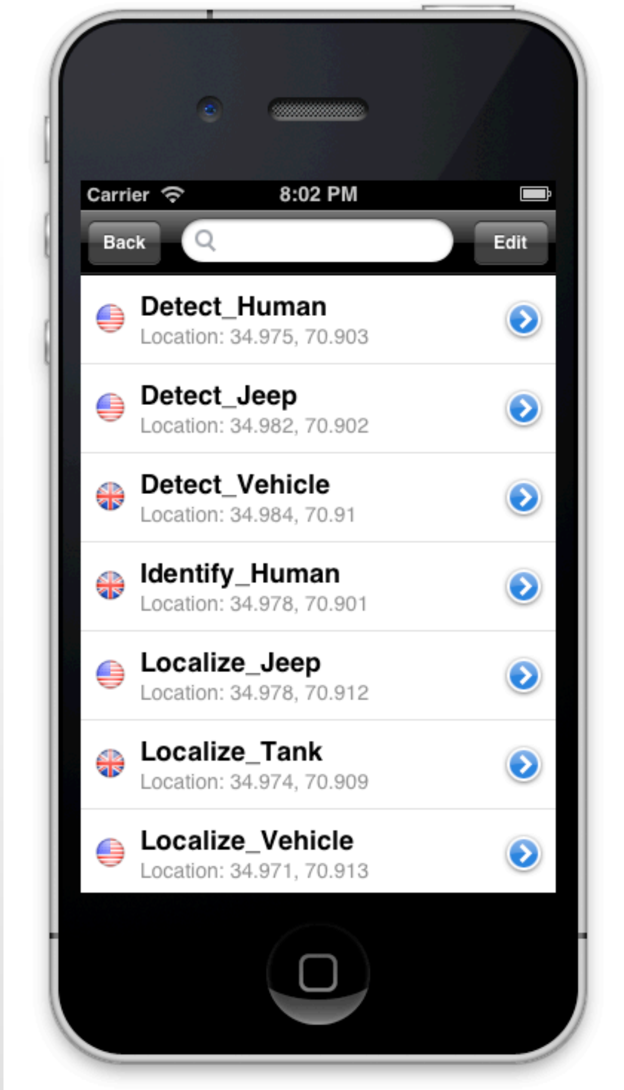
Concept illustration via mobile apps

Aims of original smartphone app

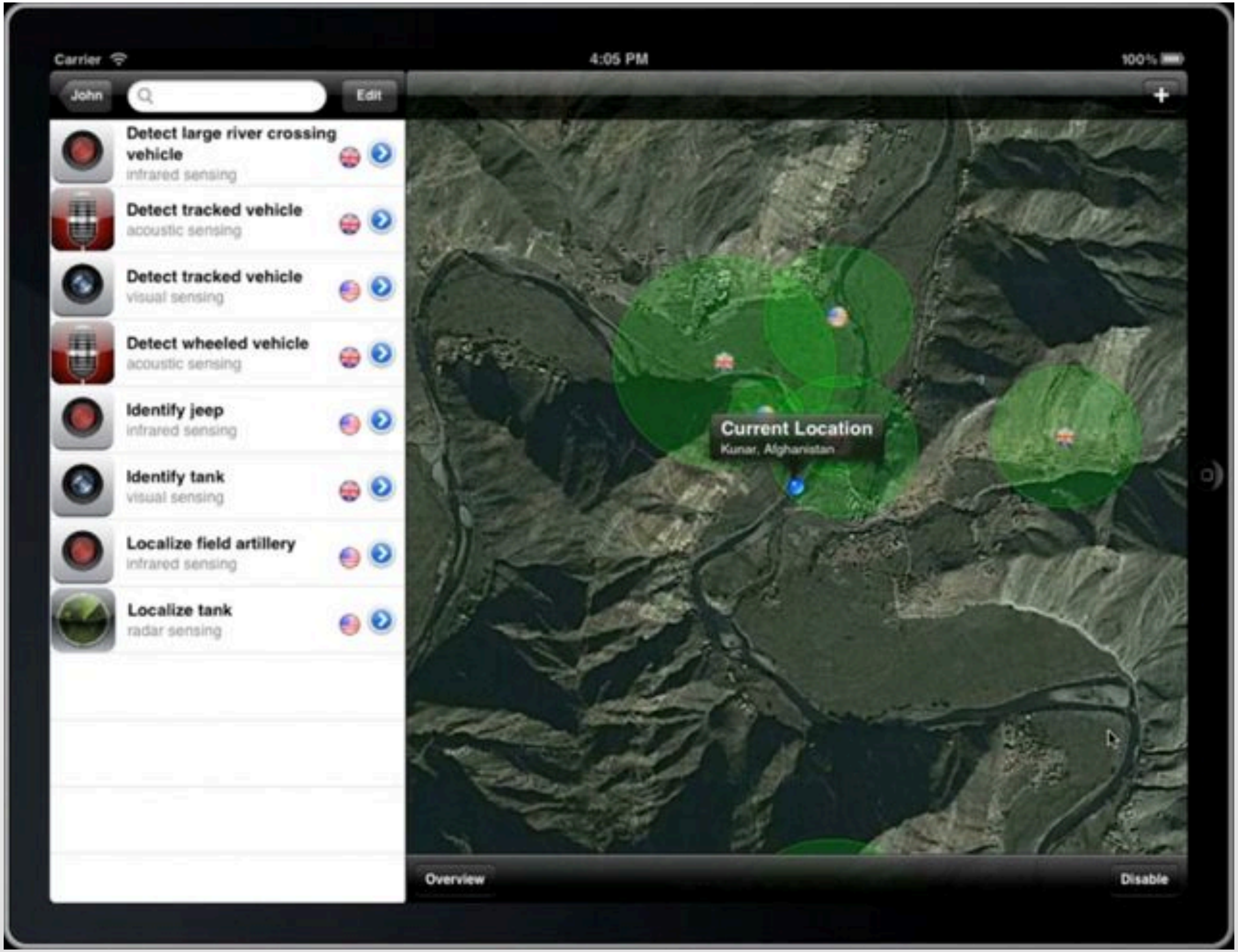
- Allow a user to create an ISR task in an area-of-interest, by means of a convenient user interface, and submit the task for asset assignment.
- Achieve separation between **what** information the user requires and **how** the information is obtained.

Aims of enhanced tablet app

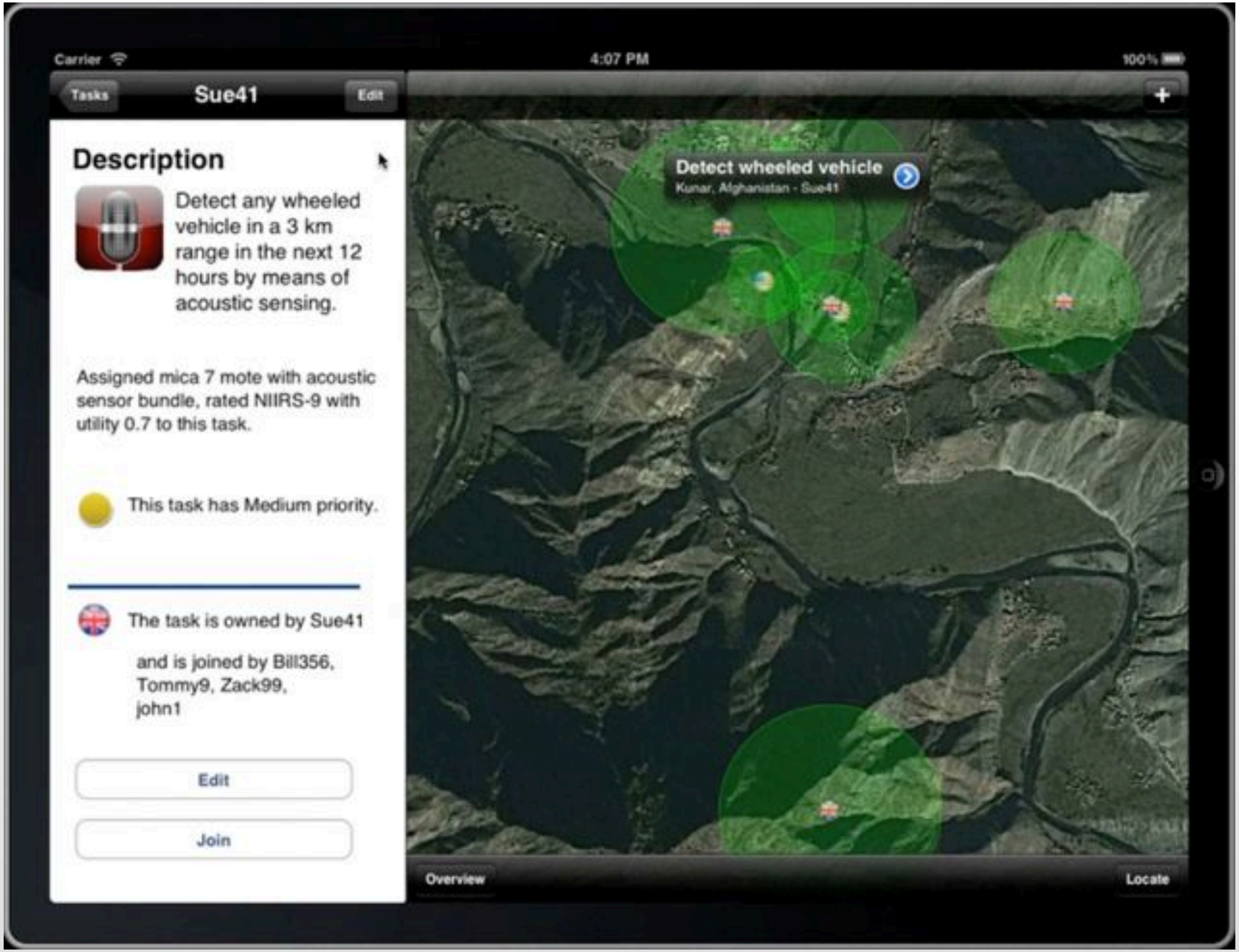
- Allow a user to view all tasks with assigned assets in an area of interest (subject to access policies).
- Allow the sharing of tasks among users (again, subject to access policies).



Tablet-based app: task panel



Tablet-based app: task assignment panel



Conversational D2D

Conversational D2D

The traditional data-to-decision pipeline can be re-thought peer-to-peer interactions between human and machine agents with different specialisms

- Data sources are becoming increasingly "smart" and communicative
- Increasing sophistication of mobile devices has freed decision-makers to operate in contexts much nearer to the tactical edge

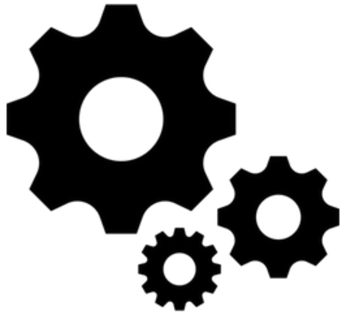
Human-machine conversations

Choice of an appropriate form for messages is a challenge:

- humans prefer natural language (NL) or images
- these forms are difficult for machines to process, leading to ambiguity and miscommunication

Compromise: controlled natural language (CNL)

there is a person named p1 that is known as 'John Smith' and is a high value target.

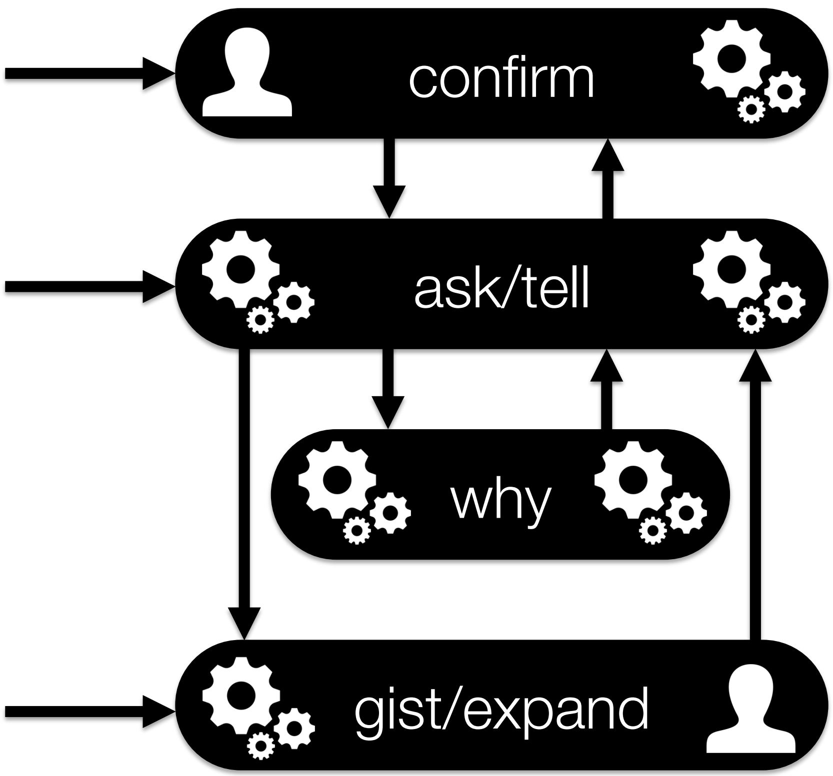


low complexity | no ambiguity

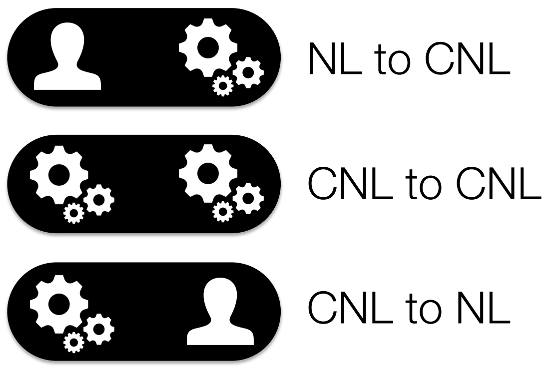
ITA Controlled English (CE)

Conversational interactions

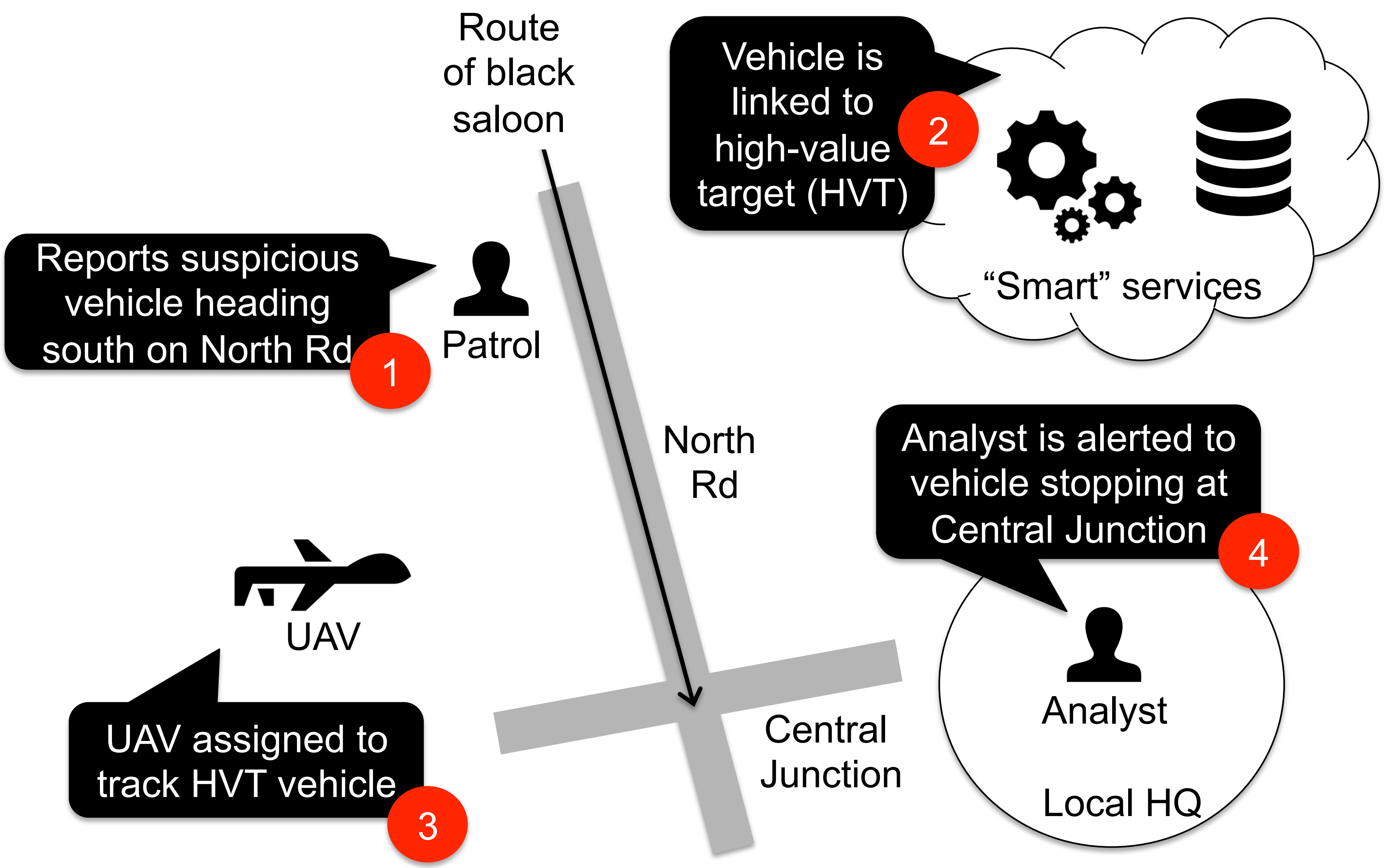
Aim: to enable conversational interactions that flow freely between natural language and CNL



Conversational protocol draws on research in agent communication languages and philosophical linguistics (speech acts)



Vignette



Route of black saloon
Vehicle is linked to high-value target (HVT)
2
"Smart" services
Reports suspicious vehicle heading south on North Rd
1
Patrol
North Rd
Analyst is alerted to vehicle stopping at Central Junction
4
Analyst
Local HQ
UAV
UAV assigned to track HVT vehicle
3
Central Junction

Use case: spot report

A **confirm interaction** is initiated by a NL message from a human patrol

Suspicious vehicle heading south: black saloon with license plate ABC123

```
there is a vehicle named v48 that
  has ABC123 as registration and
  has the colour black as colour and
  has the vehicle body type saloon as body type and
  is a moving thing.
 there is a moving thing named v48 that
  has the direction south as direction of travel.
```

The CNL form uses a model (also represented in CNL) that defines concepts and relationships. Terms may be negotiated in the conversation from the user's NL message to CNL (e.g. “license plate” vs “registration”)

Use case: information fusion

Following receipt of the user's confirmed CNL message, a fusion service infers the following CE:

there is a HVT sighting named HS_v48 that
has the vehicle v48 as target vehicle and
has the person p1 as HVT candidate.

In this way, a graph of interconnected facts is constructed.

An agent in receipt of this fact may wish to obtain the <u>rationale</u> for the information, by engaging in a **why interaction**, obtaining:

because there is a person named p1
that is known as ‘John Smith’ and is a high value target and
the person p1 has ABC123 as linked vehicle registration and
there is a vehicle named v48 that has ABC123 as registration.

Use case: sensor tasking

An agent may issue a tasking request via an **ask/tell interaction** with an agent responsible for ISR asset management (reported at SPIE DSS 2012):

there is a task named TS_HS_v48 that
requires the intelligence capability localize and
is looking for the detectable thing car and
is seeking instance the vehicle v48 and
operates in the spatial area 'North Road' and
is ranked with the task priority High.

NL messages (**gist/expand interactions**) may be used to notify humans of the asset assignment and task patrols to take action:

A MALE UAV with EO camera has been tasked to localize black saloon car (ABC123) with possible HVT John Smith in North Rd area.

Be on the lookout for a black saloon car (ABC123) with possible HVT in the North Road area.

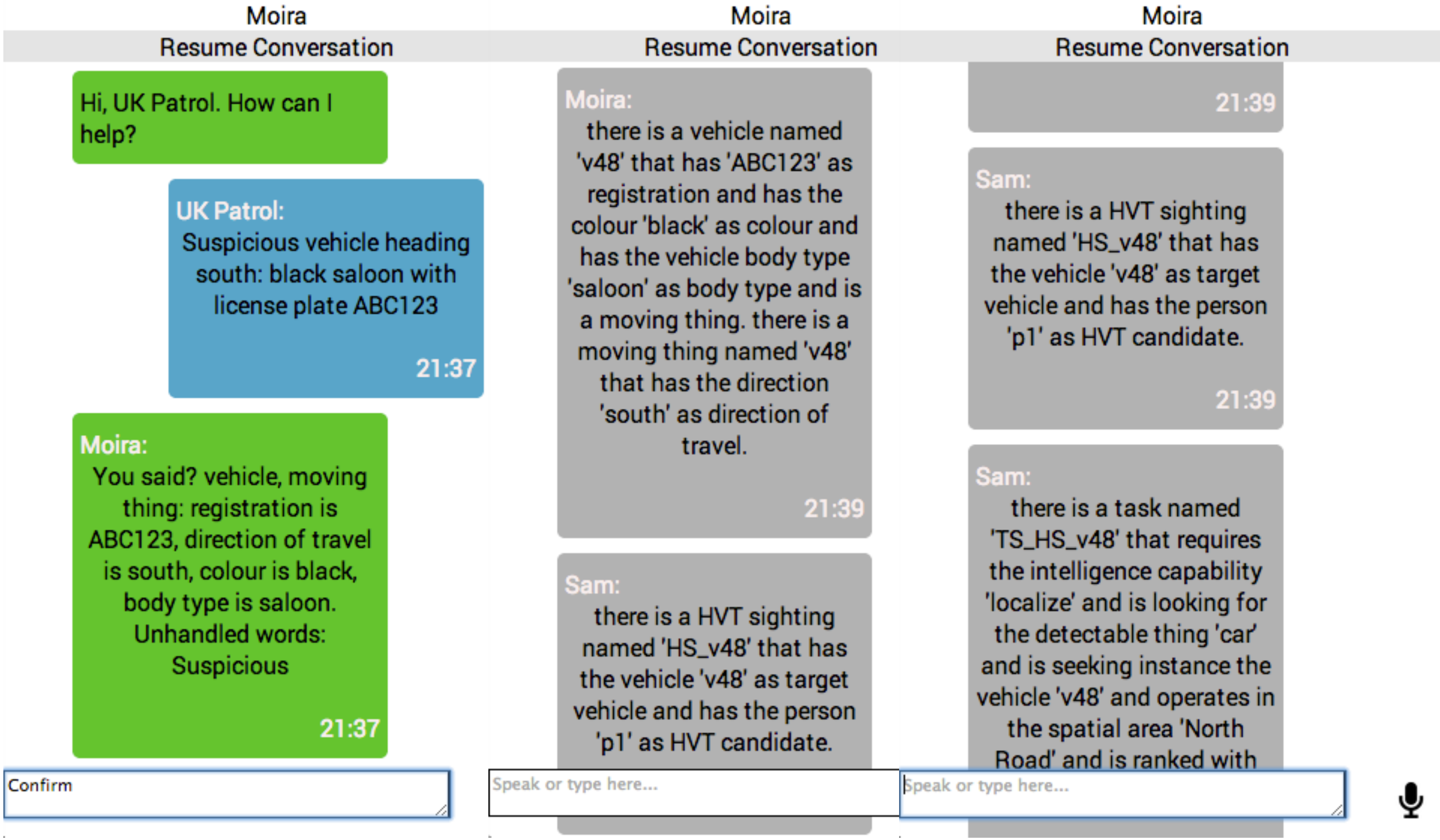
Prototype conversational agents

Two distinct agent functionalities have been identified as useful and reusable:

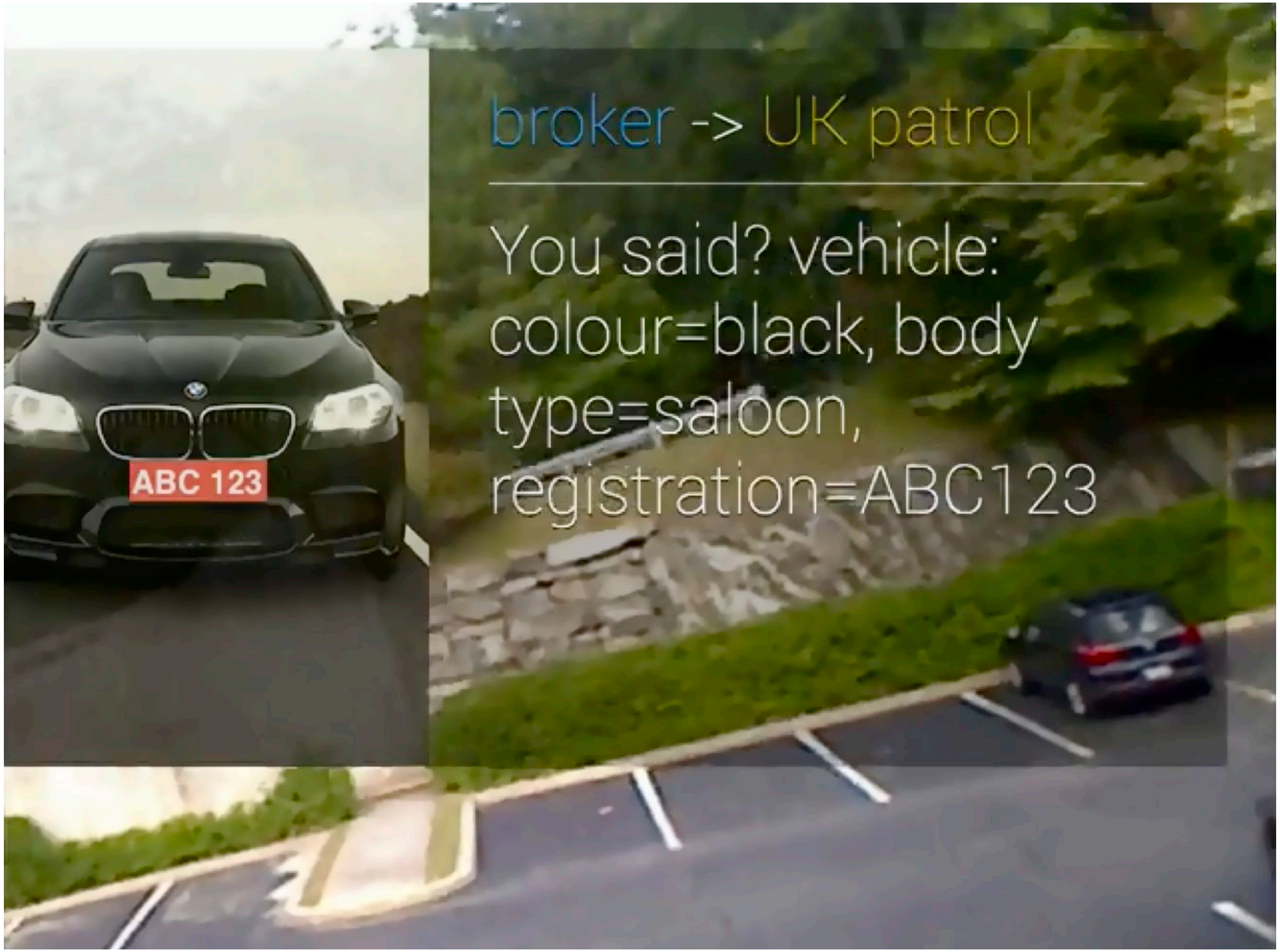
- Moira (Mobile Intelligence Reporting App): mediates interactions with human users
- Sam (Sensor Assignment to Missions): applies knowledge of tasks and ISR assets to match tasks to available sensing assets

Apps built on top of the ITA CE Store

An example conversation



Glass-style concept of use



Early experiments suggest a **gist** form of confirmatory message is highly suitable

The example shows a generated image and text from software agent to human

Preece, Braines, Pizzocaro, Parizas, Human-Machine Conversations to Support Mission-Oriented Information Provision, *ACM MC2R*, 2014

Human-Machine Conversations to Support Mission-Oriented Information Provision

Alun Preece
School of Computer Science and Informatics
Cardiff University
Cardiff, UK
A.D.Preece@cs.cf.ac.uk

Dave Braines
Emerging Technology Services
IBM United Kingdom Ltd
Hursley Park, Winchester, UK
dave_braines@uk.ibm.com

Diego Pizzocaro
School of Computer Science and Informatics
Cardiff University
Cardiff, UK
PizzocaroD@cardiff.ac.uk

Christos Parizas
School of Computer Science and Informatics
Cardiff University
Cardiff, UK
ParizasC@cardiff.ac.uk

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

MiSeNet'13, October 4, 2013, Miami, Florida, USA.

ACM 978-1-4503-2367-3/13/10 ...$15.00.
http://dx.doi.org/10.1145/2509338.2509342.

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

Wrapping-up

Experiments with human subjects

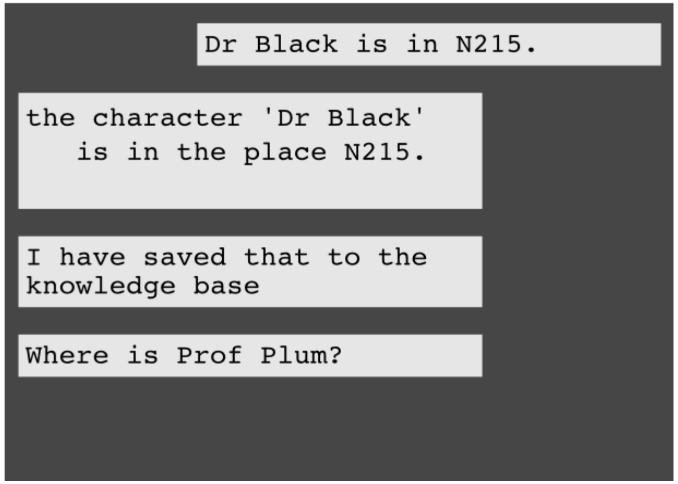
Main aims:

- to determine the degree to which we can rapidly build NL-CE apps
- to evaluate utility of the conversational protocol interactions
- to test Moira's robustness with untrained users

Experiment 1: 20 subjects viewed a series of scenes and described them in NL via a text-based interface

Experiment 2: ~40 subjects played a collaborative crowdsourcing game

There is two policemen are riding on a horse. The horses color are white and brown! They are riding in the same direction.

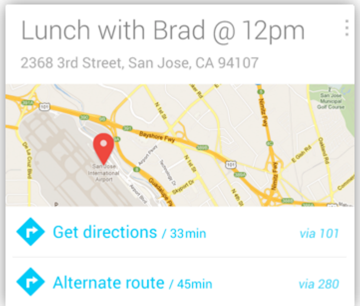


ZERO-OVERHEAD*

***Low training overhead** is key to provide **problem-focused info delivery**.

Personal mobile assistants help you navigate through apps content.

Google Now



CONTEXT AWARE
Location, time, search history

Apple Siri

NATURAL LANGUAGE
No training required

*D.J. Patil, "Building For The Enterprise — The Zero Overhead Principle", http://tcrn.ch/Y2o5n5 (accessed 10 Feb 2013).

“A Conversational Internet of Things” (Nick O’Leary, IBM UK)

A **confirm interaction** between a human and a thing:

The thermometer in the living room has moved to the dining room

the thermometer t1 is located in the room r2.

We can envisage conversations like this:

I will be late home tonight

the house will have a state of occupied at 1900.

confirmed

the room r1 has a temperature with minimum allowable value 20 after time 1900

THANKS TO

Amotz Bar-Noy

Konrad Borowiecki (PhD)

Dave Braines

Mario Gomez

Chris Gwilliams (PhD)

Tom La Porta

Matt Johnson

Geeth de Mel (PhD)

Gavin Pearson

Tien Pham

Diego Pizzocaro (PhD)

Hosam Rowaihy (PhD)

The International Technology Alliance in Network and Information Sciences

Thanks for listening!

Any questions?

IBM, Yorktown Heights
June 2015

MINISTRY OF DEFENCE