Multirobot autonomous landmine detection using distributed multisensor information aggregation

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Motivation

- Humanitarian demining efforts are lagging: high casualty rate
- Autonomous detection of landmines using robots offers a safe, reliable and economic alternative
- Existing research: Develop a single robot that is capable of detecting landmines
  - Focus more on mechanical construction, sensors, etc.

Our Approach: COMRADES

- **CO**operative **M**ulti-**R**obot **A**utonomous **DE**tection **S**ystem for Landmines
- Use multiple, relatively inexpensive robots with different types of landmine detection sensors to detect landmines cooperatively

1. How to coordinate these robots to perform landmine detection-related tasks efficiently
2. How to fuse the information from different robots to increase the detection accuracy of the landmines

Information Aggregation for Landmine Detection

- Combine information from different types of sensors and make a decision about the object's type
- Previous research:
  - Dempster-Shafer theory - based on belief functions,
  - Distributed Data Fusion - use Kalman filter ,
  - Fuzzy logic - model uncertainty,
  - Rule-based fusion - use decision rules,
  - Voting techniques - sensor voting
- But they mainly focus on the static view of multi-sensor landmine detection

Research Problem

Dynamic aspect of multi-sensor landmine detection

- Given an initial signature perceived by a certain type of sensor from a potential landmine,
- what is an appropriate set of sensors (robots) to deploy additionally
- so that the landmine is detected with higher accuracy?

Challenges:

- Sensor inaccuracies - noise, self-interested
- Environment conditions - temperature, ground composition, etc.
- Domain knowledge - suitable sensor type

Our Solution

- Multi-agent market-based information aggregation mechanism
  - Prediction market for decision making
  - A mechanism, payment function, that incentivizes sensors to submit truthful reports
  - An aggregation function based on the payment function

Prediction Market

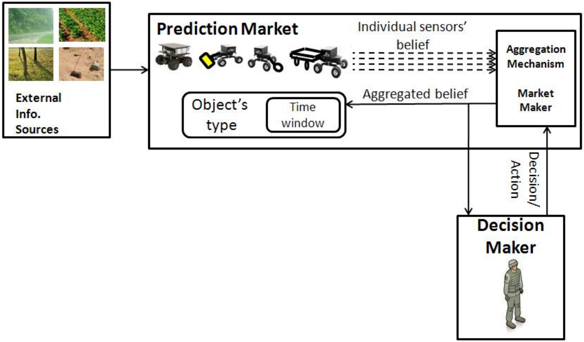
A Prediction market is

a market-based mechanism used to

- combine the opinions(beliefs) on a future event from different people and
- forecast the possible outcome of the event based on the aggregated opinion

Multi-robot sensor fusion is analogous to the information aggregation in the prediction market

Decision Making using Prediction Market



- Sensors have beliefs about the object's type
- A decision maker makes multiple (improved) decisions over the object's time window
- The object type is independent of the decision maker or the market

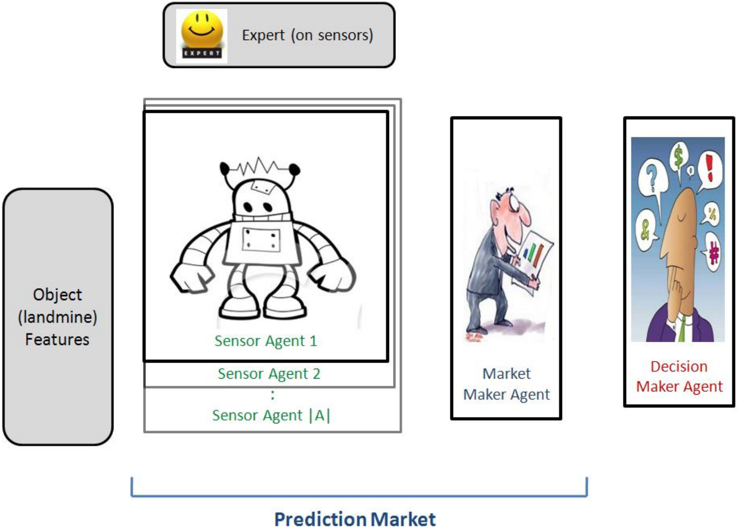
Problem Setting

- Environment with buried objects
- A set of robots, each with one sensor, is deployed into the environment
- Different robots have different sensor types (MD, GPR, IR)
- When one robot detects an object, an object's type identification *time window* starts
- Each sensor has a software agent associated with it

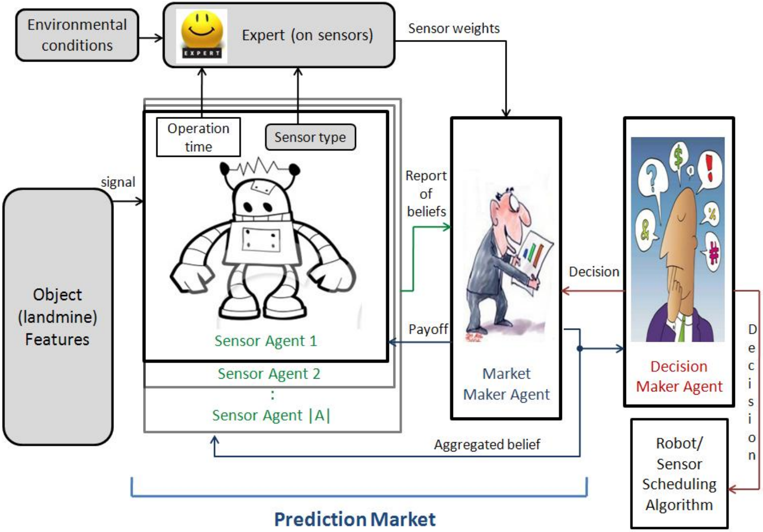
Question:

- Given an initial set of reports about features of the buried object,
- what is the suitable set (number and type) of sensors to deploy,
- so that the fused information reduces the uncertainty in determining the object's type

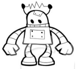
Problem Setting



Problem Setting



Sensor Agent



- Updates its belief based on the observation signals and the past aggregated belief
- Decides to submit truthful or non-truthful report based on utility-maximization
- Gets virtual reward for its report
- When the object time window ends, gets final reward

Market Maker Agent

- Calculates immediate reward to each sensor agent based on the value of its report and its cost of making its report
- Calculates final reward to each sensor agent at the end of the object's time window
  - based on the goodness of the sensor agent's last report
  - and the goodness of the decisions made by the decision maker agent's decisions

Market Maker Agent

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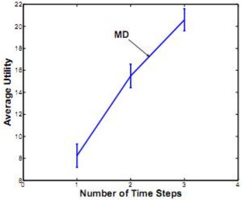
  - and the goodness of the decisions made by the decision maker agent's decisions
- **Payment function** is sensor agent's total received reward
- The payment function incentivizes truthful revelation
- Aggregated belief is computed throughout the object's time window
  - generalized inverse of the average payment function

Simulation Results

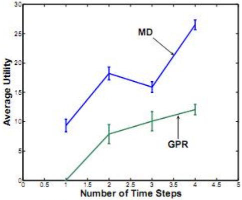
- Three types of sensors: MD, GPR, IR
- Max number of sensors - 10
- Max number of decisions - 14
- Object types:
  - mine,
  - metallic object(non-mine),
  - non-metallic object(non-mine)
- Features:
  - metallic content,
  - object's area,
  - object's depth,
  - sensor's position
- Object's identification window - 10 time steps

Simulation Results

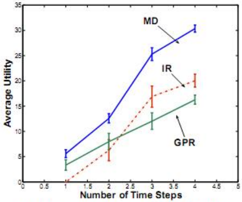
Varying the number of sensors



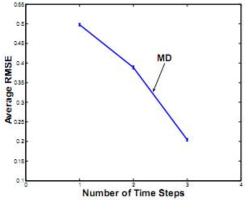
5 MD sensors

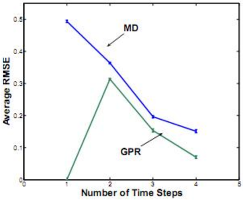


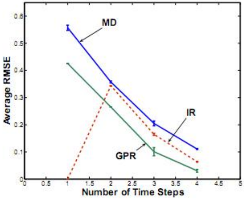
5 MD and 1 GPR sensor



2 MD, 2 IR, and 2 GPR sensors

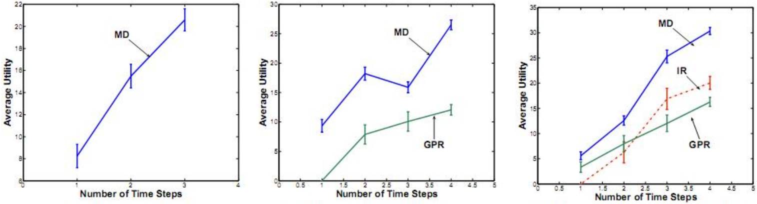




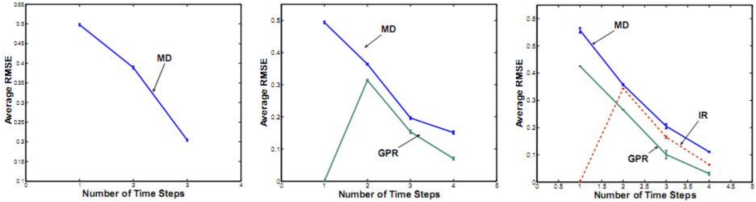


Simulation Results

Varying the number of sensors



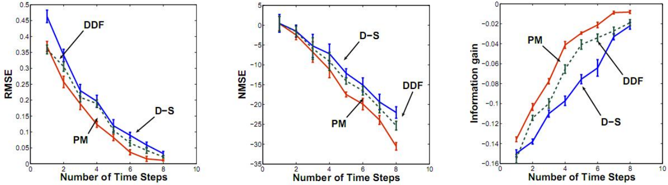
5 MD sensors | 5 MD and 1 GPR sensor | 2 MD, 2 IR, and 2 GPR sensors

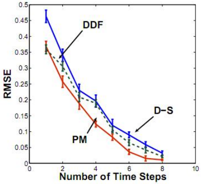


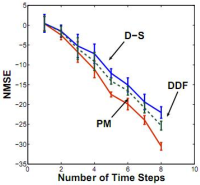
- When there are diverse sensors available (vs. only one type)
  - Sensors get higher utility
  - Root Mean Square Error (RMSE) is lower
  - Accuracy of detecting object's type is higher

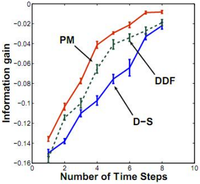
- For comparison we use two well-known techniques for information fusion
- Dempster-Shafer theory for landmine classification (by Bloch and Milisavljevic)
    - Two-level approach based on belief functions
    - At the first level, the detected object is classified according to its metal content
    - At the second level the chosen level of metal content is further analyzed to classify the object as a landmine or a friendly object
- Distributed Data Fusion (by Manyika, Durrant-Whyte)
    - Sensor measurements are refined over successive observations
    - Uses temporal Bayesian inference-based information filter

Simulation Results
Comparison









- Root mean square error (RMSE) using our prediction market-based(PM) technique is $5-8\%$ less on average than Distributed Data Fusion(DDF) and Dempster-Shafer(D-S) techniques respectively
- Normed mean square error (NMSE) using PM technique is $18-23\%$ less on average than DDF and D-S techniques respectively
- Information gain for PM technique is $12-17\%$ more than DDF and D-S techniques respectively

Other experiments we have conducted show that:

- Prediction market-based(PM) strategy deploys a total of $6-8$ sensors and detects the object type with at least 95% accuracy in $6-7$ time steps
- Distributed Data Fusion (DDF) strategy deploys a total of $7-9$ sensors and detects the object type with at least 95% accuracy in $7-8$ time steps

Conclusion and Future Work

In this work we have:

- Described a sensor information aggregation technique using a multi-agent prediction market
- Developed a payment function used by the market maker to incentivize truthful revelation by each sensor agent

In the future we plan to:

- Integrate the decision making problem with the problem of scheduling robots
- Investigate the problem of minimizing the time to detect an object in addition to the accuracy of detection
- Experiments with real robots

References

1. I. Bloch, N. Milisavljevic, "Sensor Fusion in Anti-Personnel Mine Detection Using a Two-Level Belief Function Model," IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews 33(2), pp. 269283, 2003.
2. Y. Chen, I. Kash, "Information Elicitation for Decision Making," in AAMAS 2011, pp. 175182, 2011.
3. R. Hanson. Logarithmic Market scoring rules for Modular Combinatorial Information Aggregation. *Journal of Prediction Markets*, 1(1):3-15, 2007.
4. J. Manyika, H. Durrant-Whyte, Data fusion and sensor management, Prentice Hall, 1995.

Thank You!

Questions?

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