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 **Multi-Robot Autonomous DEtection System** 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
Info: 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
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
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
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 \textit{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

Motivation
Problem
Background
Market-based aggregation
Simulation Results
Conclusion

Object (landmine) Features

Sensor Agent 1
Sensor Agent 2
Sensor Agent |A|

Expert (on sensors)

Market Maker Agent

Prediction Market

Decision Maker Agent
Problem Setting

- Environmental conditions
- Expert (on sensors)
- Sensor weights
- Operation time
- Sensor type
- Report of beliefs
- Payoff
- Aggregated belief
- Object (landmine) Features
- Sensor Agent 1
- Sensor Agent 2
- Sensor Agent 3
- Market Maker Agent
- Decision Maker Agent
- Robot/Sensor Scheduling Algorithm
- Prediction Market
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

- Sensors get higher utility
- Root Mean Square Error (RMSE) is lower
- Accuracy of detecting object’s type is higher
Simulation Results
Varying the number of 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.
Simulation Results
Comparison

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- 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.
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


Thank You!

Questions?

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