IEEE WCCI 2020
IEEE World Congress on Computational Intelligence
Virtual Conference – July 19-24, 2020

Training Data Set Assessment for Decision-Making in a Multiagent Landmine Detection Platform

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Introduction

Land Mines
Unexploited ordance
(UXO)

Militar

Specific shapes and materials (metal, TNT)
Specific targets (humans or vehicles)

Hand made
Improvised Explosive Devices
(IEDs)

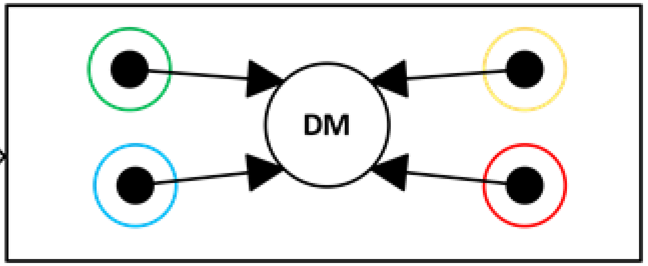
No specifications (shape, materials, targets)
Cheap and easy to make
Easy to deploy

Sensing land
& Detection

Complex task
No one sensor or method
low rate of failure

Obstacles
Variation of temperature
Variation of humidity
Type of ground
Type of land mines

Artificial Intelligence (AI)



Aggregate heterogeneous pieces of information

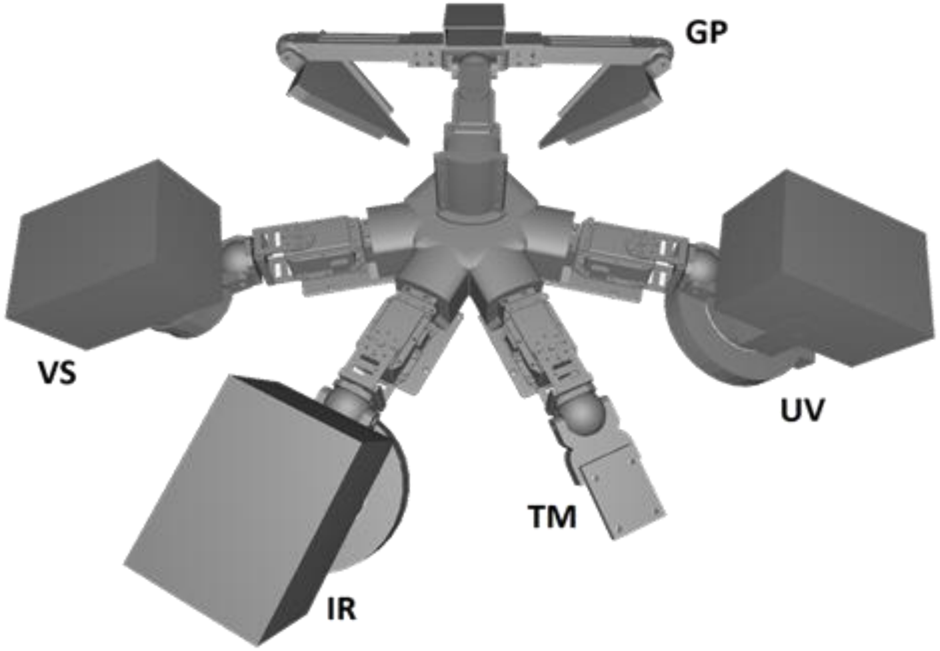
DM: Decision-making

Current research

- Land mine detection:
  - Dog units (Risky for operators and animals) [1]
  - Increase accuracy (e.g. Lower false- positive rate) [2]
  - Robotic platforms (e.g. UAV) [3, 4]
- It is needed a higher degree of integration between hardware and software (i.e. Robotic, sensors, AI algorithms).
- Our proposal integrates:
  - **Software:** A Cooperative and distributes decision-making system (CoD2M).
  - **Hardware:** Multi-agent Perception System (MAPS).
- ***This piece of research presents the assessment of the training and validation data distribution***

Our system

- **Hardware:** 5 heterogeneous agents
  - Sensors
    - VS: Visual spectrum sensor
    - IR: Near Infrared camera
    - UV: Near Ultraviolet Camera
    - GP: light GPR (Ground Penetrating Radar)
    - TM: a beam thermal sensor
  - Each sensor has a single board computer (SBC)
- **Software:** Distributed among agents
  - Each agent makes its decisions
    - The next acquisition position sensor (α).
    - A decision about the nature of a detected buried object, it's an IED or non-IED according to local information. Local decision-making (β).
    - A decision about the nature of a detected buried object, it's an IED or non-IED with the support received from the other agents. Cooperative decision-making (Ω).



Decision-making

Algorithms and methods

- Intelligent decision-making method (IDMM)
  - A feed forward artificial neural network (ffANN) constructed using neuro-evolution algorithm (NEAT). (α, β and Ω)
  - A fuzzy decision support system (FDSS) which integrates an evolutionary algorithm to a fuzzy system to obtain a set of fuzzy rules. (α and Ω)
- Aggregation (Ω)
  - Maximum
  - Average
  - Median
- Voting mode (Ω)

All source code is available online [5]

Performance metrics

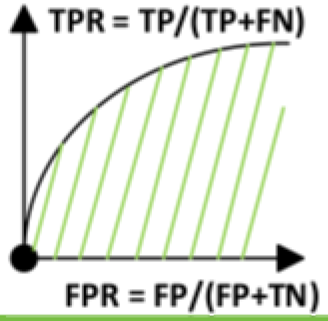
- Root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{S}\sum_{i=1}^{S}(x_i - \hat{x}_i)^2}$$

- Accuracy (ACC)

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}$$

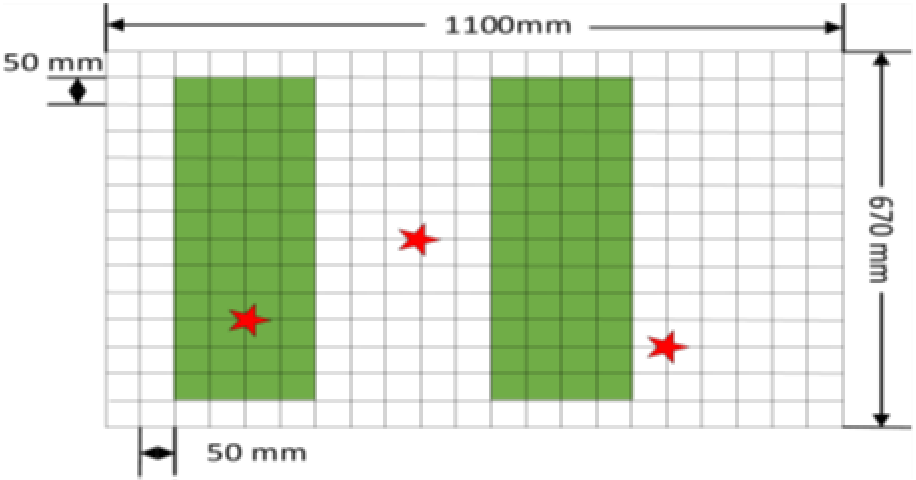
- Area under the ROC curve (AUC)



Experiment setup

- 3 IEDs are buried in the test terrain (Red stars). They are made with plastic bottles and PVC pipes
- Test terrain was kept intact of undesired debris (e.g. city garbage)
- Samples:
  - From two consecutive days.
  - Each day has a hundred of samples, from the same positions in the test terrain.
  - Day one has samples from morning hours on a dry day.
  - Day two has samples from afternoon hours and under drizzle conditions.

Test terrain:



- Distribution of samples:
  - C1 :
    Training data set = Samples from day one
    Validation data set = Samples from day two
  - C2 :
    Training data set = Samples from day two
    Validation data set = Samples from day one
  - C3 :
    Division from samples according to regions on the test terrain. For training (green area) and validation (white area).
    Samples from both days per each data set.

Performance evaluation

	C_1			C_2			C_3		
SEN	ACC	RMSE	AUC	ACC	RMSE	AUC	ACC	RMSE	AUC
VS	0,660	0,583	0,220	0,670	0,572	0,528	**0,763**	0,477	0,777
IR	**0,660**	0,582	0,783	0,340	0,808	**0,842**	0,722	**0,435**	0,809
UV	0,660	0,583	**0,825**	0,380	0,704	0,777	0,708	0,448	**0,866**
TM	0,340	0,537	0,510	**0,670**	**0,469**	0,512	0,375	0,560	0,499
GP	0,420	**0,494**	0,566	0,390	0,512	0,672	0,458	0,550	0,552

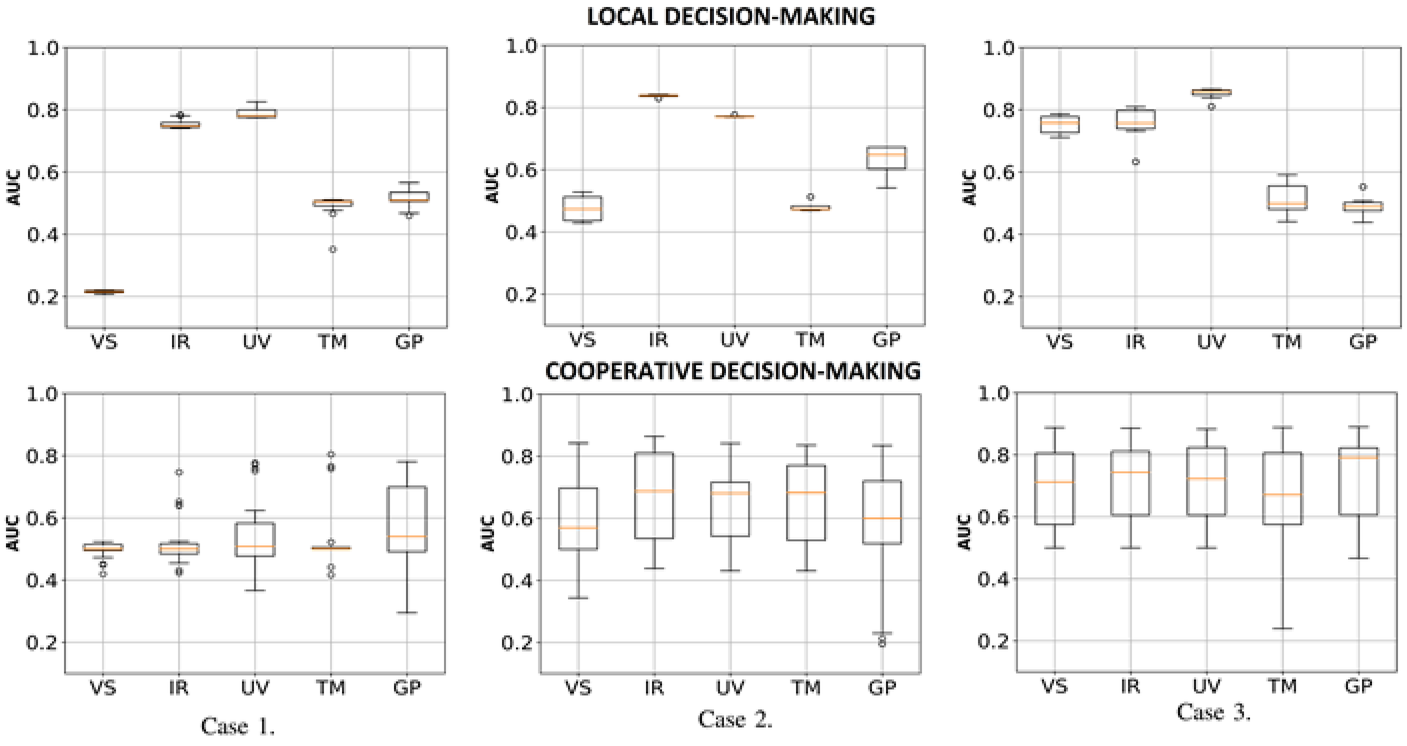
(a) Local decision-making (β)

	C_1			C_2			C_3		
SEN	ACC	RMSE	AUC	ACC	RMSE	AUC	ACC	RMSE	AUC
VS	0,660	0,499	0,522	0,670	0,491	0,500	0,639	0,463	0,757
IR	0,660	0,529	0,524	0,470	0,485	**0,716**	**0,777**	**0,427**	0,809
UV	**0,690**	**0,488**	0,759	0,670	0,490	0,500	0,625	0,437	0,815
TM	0,660	0,490	**0,804**	0,670	0,477	0,500	0,736	0,513	0,678
GP	0,660	0,547	0,780	**0,670**	**0,463**	0,610	0,638	0,422	**0,824**

(b) Cooperative decision-making (Ω)

TABLE IV: Metrics of the best accuracy result per sensor and per case for the validation data set

- The best metrics values ACC, RMSE and AUC values belong to C3, for local and cooperative decisions



Conclusion and future direction

- The distribution methodology of samples from the data set into training and validation is crucial when these samples are taken under the influence of varied external conditions. For our case, It is particularly critical.
- The validation results show the real performance of the models since they are tested with fresh data, it implies for our work that the C3 has the best performance.
- Intelligent decision-making models obtained from case 3 are less sensible to sensor noise produced by external parameters (e.g. sunlight and humidity), in contrast to, the models trained with similar environmental conditions (C1 and C2).
- An extension of this work is acquired more samples with other environmental conditions (e.g. terrain and vegetation) to consider IEDs as disseminated along to the world.

References

[1] P. A. Prada and M. C. Rodriguez, "Demining Dogs in Colombia - A Review of Operational Challenges, Chemical Perspectives, and Practical Implications," Sci. Justice, vol. 56, no. 4, pp. 269–277, 2016.

[2] J. Prado and L. Marques, "Reducing false-positives in multi-sensor dataset of landmines via sensor fusion regularization," in 2017 IEEE International Conference on Autonomous Robot Systems and Competitions, ICARSC 2017, 2017, pp. 204–209.

[3] J. Colorado, C. Devia, M. Perez, I. Mondragon, D. Mendez, and C. Parra, "Low-altitude autonomous drone navigation for landmine detection purposes," in 2017 International Conference on Unmanned Aircraft Systems (ICUAS), 2017, pp. 540–546.

[4] T. Dogaru, B. Phelan, and D. Liao, "Imaging of buried targets using UAV-based, ground penetrating, synthetic aperture radar," in Radar Sensor Technology XXIII, 2019, vol. 11003, pp. 18–35.

[5] J. Florez-Lozano, F. Caraffini, M. Gongora, and C. Parra, "CoD2M-MAPS Source Code." figshare, 2019.