

Predicting Opponent Squad Positions

CDR Kenneth Maroon, USN



Abstract

The Intelligence Preparation of the Battlespace (IPB) allows company commanders to grasp key aspects of the environment they are operating in, as well as the elements and objectives of the adversary they are facing. This project describes a process to represent IPB results as annotations to a navigation mesh and as position evaluation functions. These can then be used for scoring opposing force formations, based on objectives, tactics, and terrain data. Enemy formations that maximize our scoring function act as an educated prediction of enemy unit positions. These predictions can then support more robust automated planning and improved combat modeling.

Research Questions

Can we develop a method for predicting the location of enemy squad positions based on observed Units, expected enemy tactics/SOP/COAs, terrain, and environmental factors?

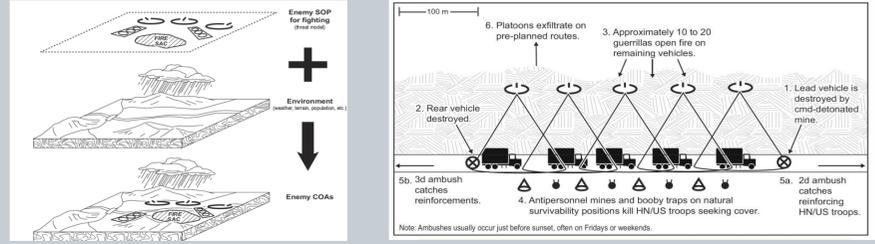


Fig 1.a, b
Enemy Situation Templates from the IPB. From U.S. Marine Corps, MCRP 3-10A.2.

Materials and methods

The prediction model is implemented in Wombat XXI, a Unity based representative Combat simulation developed by Byron Harder, similar to Combat XXI.

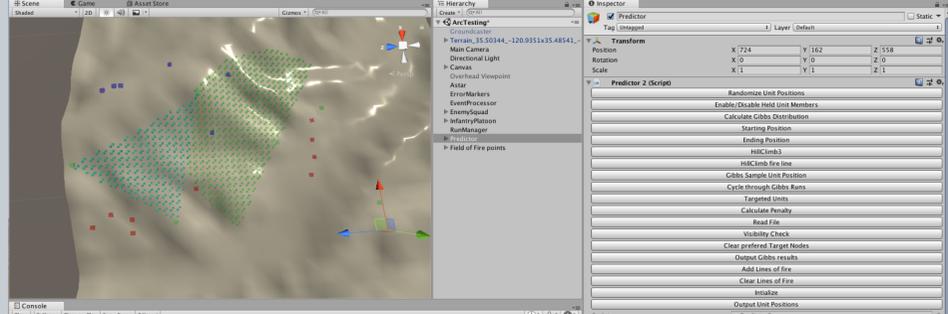


Fig 2.a
Wombat XXI was an ideal testing environment as it already allowed for real-world terrain, had an underlying navigation mesh/node structure, and force hierarchy implementation.

Testing Scenarios were built with Blue (friendly) and Red (enemy) entities. Each entity belonged to a Unit, which could contain more entities as well as sub-units. Each unit would have one entity designated as the unit leader. Units could be assigned a field of fire, or area of nodes, they were responsible for targeting. They could also be assigned specific nodes as preferred targets. Node to Node visibility was precalculated and used to determine entity detection as well as coverage of field of fire nodes. In Fig 2. a, Red units can be assigned fields of fire indicated by green and teal colored nodes.

Algorithm 1. The Formation Scoring algorithm

```

calculateTotalScore (unit)
  formationScore = 0
  for all entities in unit
    formationScore += calculateEntityScore (entity)
  for all subunits in unit
    formationScore += calculateTotalScore (subunit)
  return formationScore

calculateEntityScore (entity)
  entityPositionScore = 0
  for all preferredTargets assigned to entity
    entityPositionScore += preferredTarget's node targetability
  for all FoF nodes assigned to entity
    entityPositionScore += node targetability
    if (distance to unit leader > max distance to leader range)
      entityPositionScore -= outside range to leader penalty
    if (distance to other entities > max cohesion range)
      entityPositionScore -= cohesion penalty
    if (distance to other entities < min dispersion range)
      entityPositionScore -= dispersion penalty
    if (entity's node is targetable by opponent)
      entityPositionScore -= targetability penalty
  return entityPositionScore
    
```

The Formation Scoring Algorithm. Entities try to maximize their targetability (coverage) of preferred targets and fields of fire while minimizing their penalty for being out of position with regards to their unit leader and other unit members. Targetability and Penalty scoring weights can be adjusted to reflect different unit priorities.

The set of all XYZ positions for each entity in a Unit that maximizes the scoring function is the formation prediction.

To find maximizing formations, entities are randomly placed in designated areas of the map and use hill climbing to find optimal positions.

Entity Detection is simulated by holding the detected entity's (or entities) position(s) constant. Undetected unit members will then hill climb to nodes that maximize formation score given the observed unit(s).

Results

In developing our hill climbing algorithm we ran an experiment, testing it over 1000 runs. The formation scoring function weights were kept the same, but random starting entity positions were selected for each run. The hill climbing method increased formation scores by 251% on average, while decreasing the relative standard deviation of scores. Full results are shown in Table 1.

Table 1. Hill Climbing method performance test results.

	Starting Score	Ending Score	Change %
μ	12.320	38.414	251
σ	4.483	7.757	146
σ/μ	0.364	0.202	-55

Example Scenario

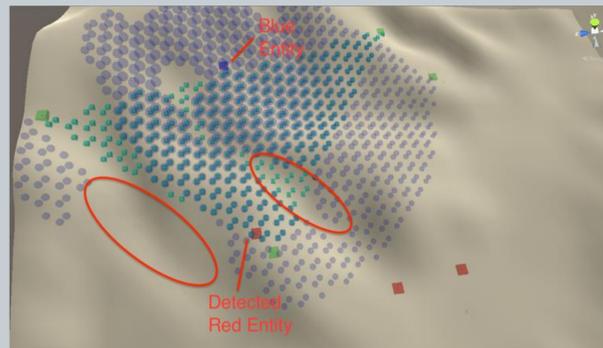


Fig 3.a
A red unit is detected by a blue entity. Two other red entities are undetectable by the blue entity. Note how terrain features produce gaps in blue's detection area (indicated by blue spheres). These gaps are marked by the red ovals.

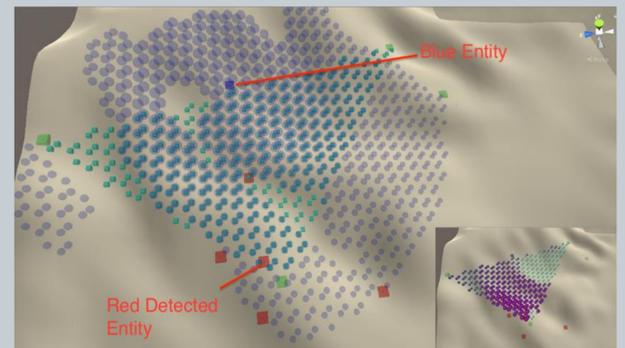


Fig 4.a
The highest scoring prediction formation. Red units are predicted to be located in the gaps and edges of blue's detection area. This formation maintains red unit spacing and maximizes targetability of the field of fire (coverage shown bottom right).

Conclusion

We have shown a method for building formation scoring functions and tested it in a prototype combat simulation. We plan further testing of more complex scoring functions. Including different tactics and accounting for lines of fire. We would also like to investigate other techniques for maximizing formation score.

References

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Contact Details and Thesis Advisor

kjmaroon1@nps.edu
Advisor: Chris Darken