An Artificially Intelligent Battleship Player Utilizing Adaptive Firing and Placement Strategies

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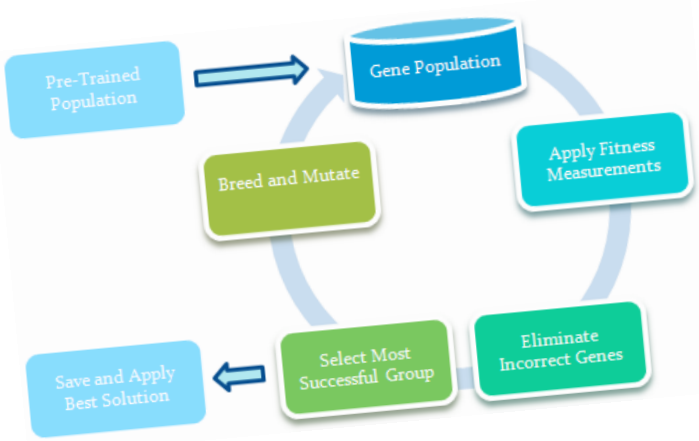

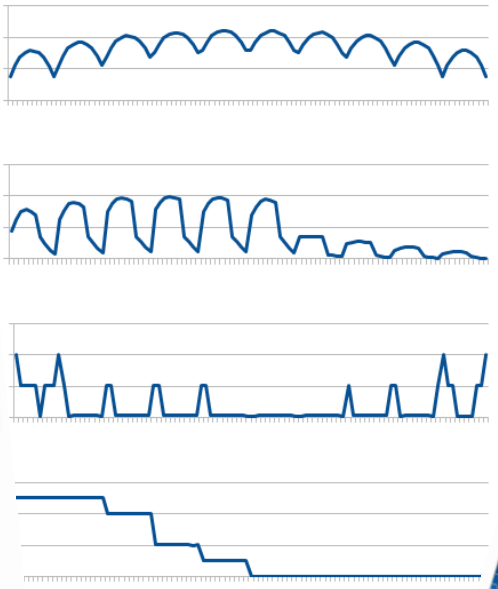

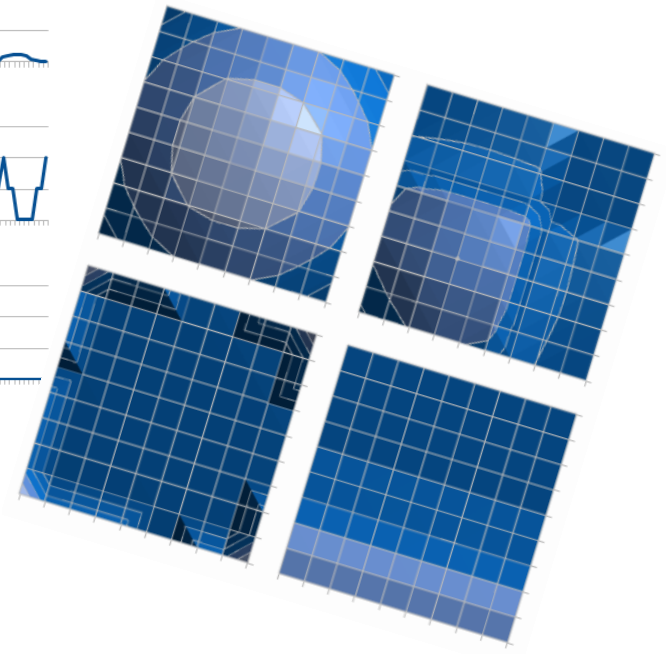

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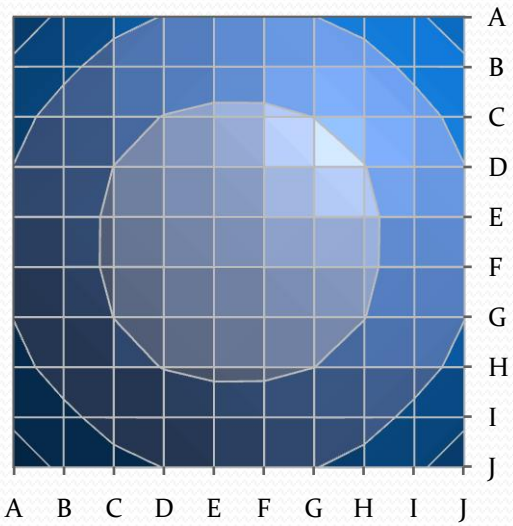
Solution Representation

- Divided to three components that have different AI approaches for solution searching:
  - **Ship placement** – Sequential Monte Carlo Method for enemy shot pattern recognition
  - **Targeting** – Genetic algorithm to track enemy ship placement via pattern recognition
  - **Sinking strategy** – Genetic programming to optimized sinking logic

Ship Placement

- Initial placement is based off of the inverse of the experimental random placement data *(See graph)*
- Save all enemy shots into density a map over time
- Apply Monte Carlo algorithm, and place ship to safety intelligently

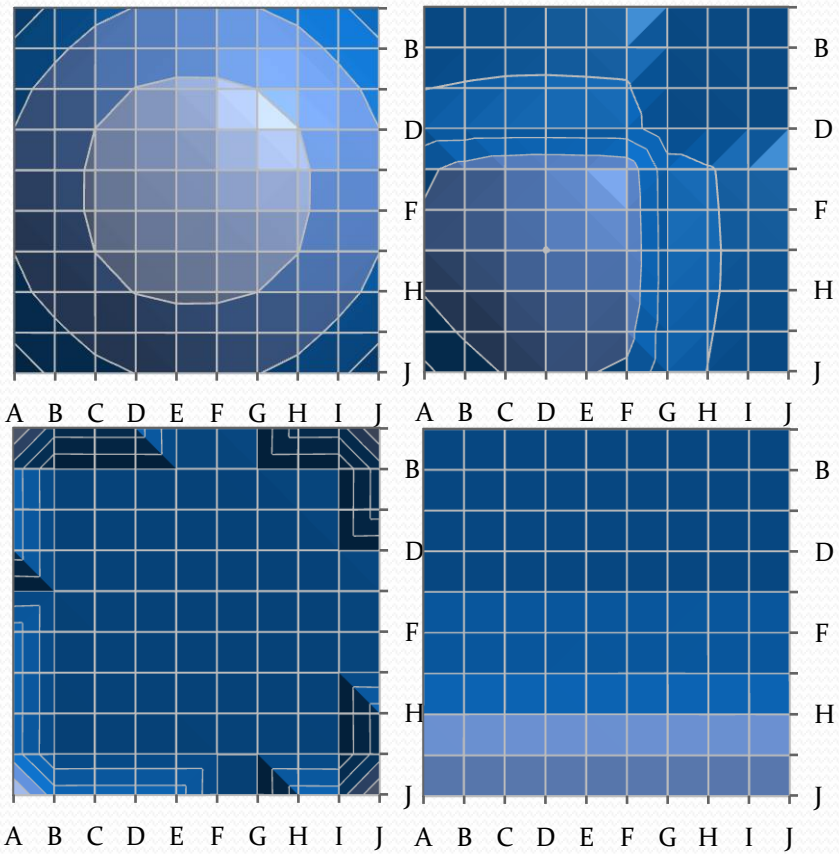


Inverse of random ship placement densities over 1,000,000 rounds

Ship Targeting & Shooting

- Uses a **genetic algorithm** for quick adaptation to enemy ship placement patterns / algorithm, even with random placement
- Defines a gene as five **harmonics** that are randomly chosen at first
- This harmonic represents a **probability distribution** of the likelyhood of enemy ship placement
- **Gene-mutation and cross-over** will converge the gene to a close-fit solution
- **Gene fitness** is done through a Fast Fourier Transformation

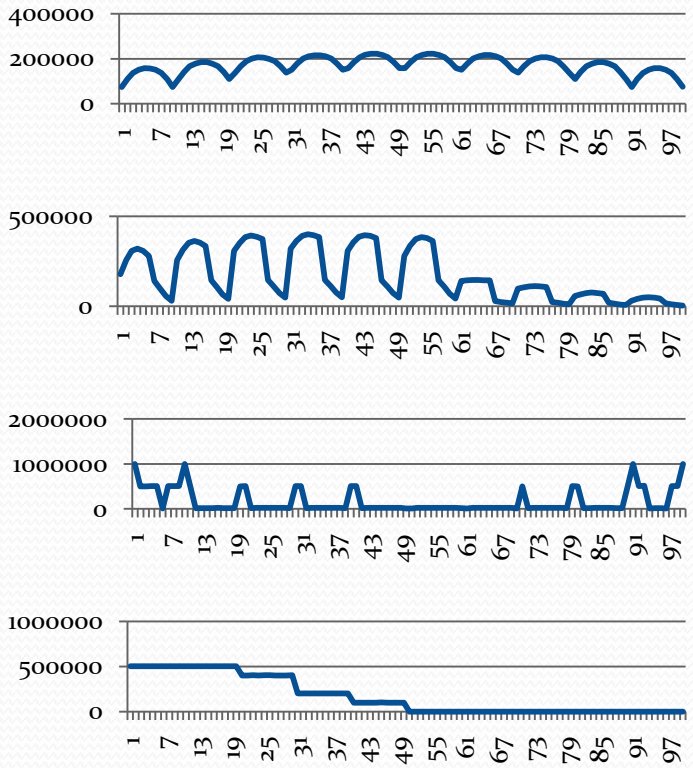
Ship Targeting & Shooting



Placement Density Maps

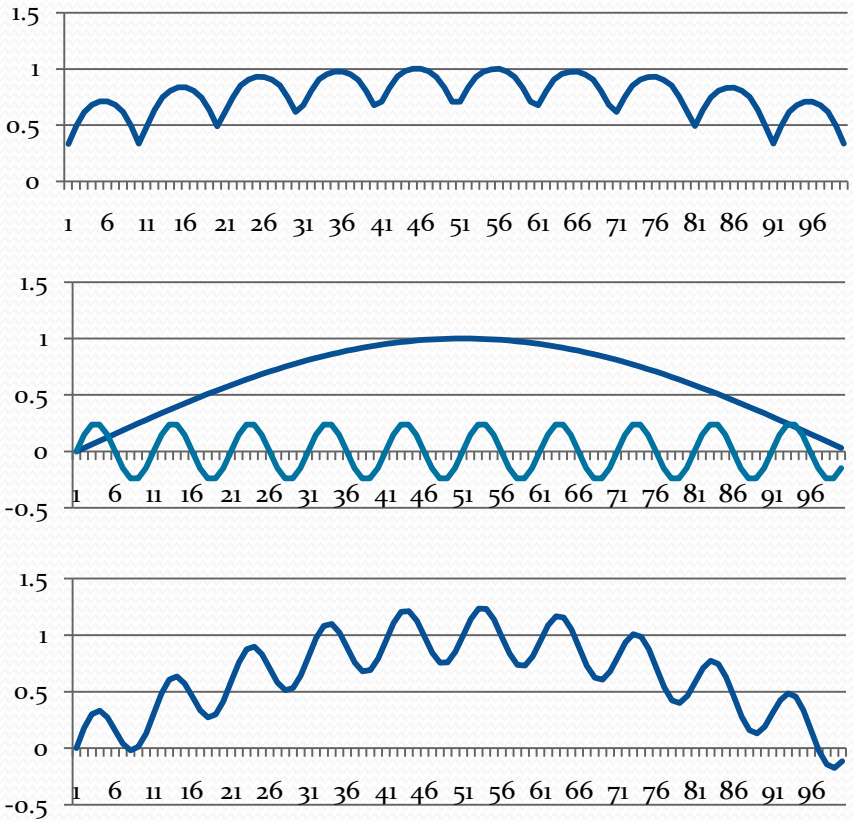
Different methods of ship placement over 1,000,000 rounds. Lighter color indicates higher density of ship placement. From top left, clockwise: Random, lower-left corner favored, bottom wall, one ship in each corner.

Ship Targeting & Shooting



Placement Density Linear Functions
Different methods of ship placement over 1,000,000 rounds; graphed as a linear function. From top to bottom: Random, lower-left corner favored, one ship in each corner, bottom wall. Same as the left maps.

Ship Targeting & Shooting



Sample Target Data and Gene Harmonics

***Top**: Linear function of the random ship placement density map.*

***Middle**: Harmonic gene with only two components.*

***Bottom**: Successful gene outcome, matching the top pattern.*

Ship Sinking

- Sinking based off of **genetic programming**
- A **state machine** is needed due to the complexity of sinking a ship: Targeting, locking, sinking
- Each **gene** is a series of operations paired with a register machine based on 16 defined instructions
- The **initial** gene pool is pre-trained against hard-coded logic but quickly changes per opponent

Ship Sinking

Register Machine

- **TargetPos**, The current target location, defaults to (0, 0)
- **TempPos**, Temporary position, defaults to (0, 0)
- **TargetDir**, The current target direction, defaults to North / up
- **TargetHit**, Boolean where true if the last shot was successful in hitting a ship
- **TempHit**, Temporary boolean flag for internal usage

Ship Sinking

Sample sinking logic:

1. **MoveFwd** // Keep walking through it
2. **Shoot** // Fire a shot
3. **IfMiss** // If we went past the end
4. **IfTrue** // And we have already sunk the other side..
5. **Jump** // Go back to seeking
6. **IfMiss** // If we went past the end
7. **OppDir** // Flip directions
8. **IfMiss** // Same logic as above
9. **LoadPos** // Load position into register

Implementation & Analysis

- In same-skill matches, the player to shoot first had a 10% greater chance of winning
- **Checker-board** patterning greatly improved ship-hit rate to 70% compared to full-board shooting
- AI ship placement successfully avoided random shooting and avoided intelligent learning methods
- Targeting & shooting performed well at pattern matching
- Ship sinking logic outperformed hard-coded solutions

Conclusion

- The use of **genetic algorithms** is both a valid approach to AI and an effective way at learning, pattern matching, and searching
- Genetic algorithms are especially promising for large-scale future applications due to the growth of **multi-core processors**; helpful in splitting fitness and breeding processing

Questions?

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