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PROBABILISTIC ISOCHRONE ANALYSIS IN MILITARY GROUND MOVEMENT: MULTI-METHOD SYNERGY FOR ADAPTIVE MODELS OF THE FUTURE

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ABSTRACT

Timely and accurate prediction of adversarial unit movements is a critical capability in military operations, yet traditional methods often lack the granularity or adaptability to deal with sparse, uncertain data. This paper presents a probabilistic isochrone (PI) framework to estimate future positions of military units based on sparse reconnaissance reports. The approach constructs a continuous probability density function of movement distances and derives gradient prediction areas. Validation is conducted using real-world data from the 2022 Russian invasion of Ukraine, evaluating both the inclusion of actual future positions within the predicted rings and the root mean-squared error of our method. Results show that the method yields reliable spatial uncertainty bounds and offers interpretable predictive insights. This PI approach complements existing isochrone mapping and adversarial modeling systems and demonstrates a novel fusion of simulation, spatial analytics, and uncertainty quantification in military decision support. Future work will integrate simulation to enhance predictive fidelity.

1 INTRODUCTION

The method introduced here, referred to as the Probabilistic Isochrone (PI) approach, centers on computing a probability distribution over travel distances from historical sightings of individual units. By applying Weighted Kernel Density Estimation (WKDE) with exponential decay, we generate a smoothed and time-sensitive Probability Density Function of Distance (PDF-D) for each unit. This distribution is then used to compute a spatial ring-shaped prediction area, which captures 95% of likely future locations. Compared to traditional isochrone methods that assume deterministic speeds or fixed travel radii, the PI approach offers a statistically grounded and empirically validated uncertainty band, with higher confidence and interpretability.

To validate our approach, we apply it to the UAWarDataset, which contains geo-tagged movement reports from the early phases of the 2022 Russian invasion of Ukraine (Huwiler and Schlottmann 2025). We evaluate prediction performance using two complementary metrics: (1) the inclusion rate of actual unit positions within the 95% probabilistic ring, and (2) the Root Mean Squared Error (RMSE) between the predicted travel distance (mean of PDF-D) and the actual subsequent movement. These metrics offer both geometric and numeric insight into predictive quality. Visualizations of individual unit forecasts and aggregate RMSE distributions demonstrate the method's robustness, adaptability, and practical utility for command-level decision support.

2 RELATED WORK

Isochrones—spatial contours representing regions reachable within a fixed time or cost—have been widely applied across both civilian and military domains. While originally used for logistics and transportation planning, their use has expanded into predictive analytics, evacuation modeling, and accessibility assessments. This section reviews isochrone-based approaches across three key themes: (1) civilian evacuation and emergency planning, (2) accessibility modeling, and (3) military mobility and adversarial prediction, highlighting how the proposed PI framework extends this body of work.

2.1 Isochrone-Based Triggers for Civilian Evacuation

A prominent civilian use of isochrones lies in wildfire evacuation planning. Cova et al. (2005) introduced the concept of evacuation trigger buffers derived from fire spread models and Geographic Information Systems (GIS), where the intersection of a fire front with a trigger perimeter prompts evacuation. Later frameworks like PERIL Mitchell et al. (2023) and WUIVAC built on this by coupling fire spread simulation (e.g., FARSITE) with estimates of evacuation time (WRSET) to define non-uniform trigger zones around communities. These approaches reflect an early form of probabilistic reasoning, where safety margins ("safety factors") buffer uncertainties in terrain, fuel conditions, or human behavior. While deterministic in shape, the trigger zones implicitly reflect time-based probabilistic risk. Unlike our method, however, these approaches do not construct predictive distributions over likely outcomes; instead, they focus on rule-based spatial delineation of threat thresholds.

Other models, such as EVITA (Kiranoudis et al. 2014) and recent stochastic trigger models (Ramirez et al. 2019), introduced machine learning and Monte Carlo simulation to account for wind variability and fuel moisture uncertainty—highlighting the importance of probabilistic modeling in dynamic environments. These methods primarily focus on environmental threats and population clearance times. In contrast, our work centers on adversarial movement under sparse observation, a fundamentally different problem that benefits from similar isochrone reasoning.

2.2 Isochrones for Emergency and Healthcare Accessibility

Isochrones are also widely employed in health services and transportation planning. For example, Zhao and Zhou (2024) use cumulative opportunity isochrone analysis to assess emergency medical service (EMS) accessibility across Beijing's central districts. Their analysis emphasizes travel-time-based isochrone coverage during different traffic conditions, evaluating how facility placement impacts response equity. Similarly, Sheu (2024) highlights the importance of incorporating behavioral dynamics in evacuation planning, especially during disaster-triggered congestion. These works leverage isochrone-based modeling for evaluating infrastructure performance under time constraints, focusing on coverage and access equity rather than prediction.

From a methodological perspective, many urban applications use deterministic routing with traffic sensitivity (e.g., Amap, Mapbox) to generate isochrone contours. Some, like the radial-ray method (Zhao and Zhou 2024), employ dynamic traffic models to generate high-resolution temporal isochrones. Our method, while also based on empirical travel data (unit movement reports), departs by predicting probabilistic distances, not locations, enabling the construction of confidence-based spatial contours around origin points.

2.3 Isochrone Modeling in Military and Adversarial Contexts

Military uses of isochrones traditionally emphasize deterministic mobility envelopes. Our prior work (Roman and Rose 2024) proposed an improved method for calculating ground movement isochrones by incorporating off-road travel and buffering road networks with diminishing travel budgets. That method enables tactical planners to visualize feasible engagement or resupply zones. However, that approach treats all locations within an isochrone as equally likely, lacking a probabilistic notion of movement preference.

The ValoRens project (Bitoun et al. 2023) introduces adversarial prediction using simulation and graph-based reasoning over points of interest. Their system integrates topography, behavior models, and destination inference to estimate likely enemy positions. However, it relies on structured inputs (operations orders, doctrinal rule sets, etc.) and extensive simulation, whereas our PI model extracts behavior directly from sparse, noisy observations—learning travel distance profiles empirically through WKDE.

More broadly, template-based threat assessment in man-in-the-loop systems, such as the approach proposed by Lorenz and Biermann (2004), emphasizes the importance of integrating reconnaissance observations with expert-in-the-loop reasoning to predict threat development. While effective, these systems rely heavily on expert-defined rules and complete situational awareness.

3 PROBLEM STATEMENT

Isochrone models, while widely used for visualizing movement envelopes, traditionally assume uniform likelihood within defined regions and fail to represent uncertainty or preference in adversarial travel patterns.

Research Gap: Existing military movement models typically lack the ability to handle data sparsity, temporal irregularity, and dynamic behavior. These models are either too rigid—depending on doctrinal templates—or too complex, requiring extensive simulation infrastructure and structured inputs (e.g., orders of battle, predefined destinations). As a result, they do not provide practical or probabilistically grounded uncertainty quantification. Moreover, classical isochrone models treat all locations within a contour as equally likely, ignoring behavioral variance in actual movement. There is a critical need for a lightweight, interpretable, and data-driven method that can quantify where an adversarial unit is likely to be, rather than where it can be.

Methodological Innovation: This study introduces the PI framework, a novel approach for estimating future adversarial positions under uncertainty using sparse observational data. The core innovation lies in leveraging WKDE with exponential decay to model a PDF-D. This allows the system to assign higher importance to more recent observations and compute a statistically grounded travel distance distribution. The model then uses this PDF-D to create ring-shaped probabilistic contours that enclose 95% of the predicted future positions, thereby constructing spatial uncertainty bounds.

Objectives and Anticipated Impact: The objective of the PI method is to provide a reliable, interpretable, and computationally efficient prediction mechanism for future enemy unit positions under uncertain and sparse reconnaissance conditions. By quantifying spatial uncertainty and enabling validation through real-world datasets (e.g., UAWarDataset), the method supports more informed military decisions. The approach is designed to integrate easily into Command and Control Information Systems, war games, and tactical simulations, offering an empirical and probabilistically justified enhancement over traditional isochrone and behavior-template models.

Key technical components include:

1. Exponential decay weighting to prioritize recent observations.
2. Distance normalization to derive daily average movement metrics.
3. Ring construction using 2.5% and 97.5% quantiles of the PDF-D to encapsulate likely movement areas.
4. Validation pipeline using RMSE and spatial containment of actual positions within the predicted ring.

Assumptions and Simplifications:

1. Given any isochrone area we assume the underlying unit can reach any point within that area within a fixed time frame at a fixed speed. In other words: the probability of the unit being within the area is 1.0.
2. The distribution of probability weights over that reachable area is not uniform. Units have a purpose, they try to reach a goal or leave the location where they have been spotted, etc.
3. Given the movement data of a unit we can compute a PDF-D.
4. The mean of the PDF-D is used as a point estimate for travel prediction.
5. PDF-D can be computed using standard mathematical methods like Kernel distribution estimations.
6. Using this PDF-D we can calculate the PI.
7. We simplify the gradient to a simple ring. The ring is used to describe the area where 95% of predictions are in.

8. We normalize the distribution function of the most likely travel distances to a daily time frame.

4 METHOD

The following method describes how we calculate the PI for one unit. In Appendix A we describe a Pseudo Code version of how our method is computed. Algorithm 1 shows the prediction for one unit, and algorithm 2 depicts the validation using the whole dataset.

The basic idea of our method is as follows:

To calculate the PI of any unit we need a PDF-D, which we get through WKDE out of sparse data.

WKDE requires us to calculate many distances between two geo-locations. Our proposed way to compute distances and isochrones uses a Graphhopper server (GH) (GraphHopper GmbH 2025) to compute the shortest road-bound distance. Our fallback is the Great Circle (GC) distance, serving as both, our fallback measurement and base truth, if the GH server cannot return a path. GC describes a simple straight line measurement between two points, accounting for earth curvature.

To validate our PI method, we make use of the UAWarDataset (latitude, longitude, unit name, and timestamps) from the Russian invasion of Ukraine in 2022. We evaluate each unit separately and derive two performance values:

1. We measure the error with the Root Mean-Squared Error (RMSE) between the predicted positions d_{pred} and the actual recon positions *groundTruthLoc* in the validation set as an estimation how far off we are with our prediction
2. We check, if we were able to correctly predict the ring area, where the unit moved to.

The final result of one experiment consists of the distribution of RMSE over the whole dataset and the percentage of how often the *groundTruthLoc* was in the predicted circle. Furthermore, we compare GH to GC distance measurement, since GC is our base truth.

4.1 Weighted Kernel Distribution Estimation - WKDE

Standard KDE assigns the same weight to every observation, meaning each data point contributes equally to the density estimate. In contrast, weighted KDE assigns specific weights w_i to each observation, allowing for a differential influence. This is used in this work to assign more weight to recent observations.

In standard KDE, we estimate the density $f(x)$ from a sample $\{x_1, x_2, \ldots, x_n\}$ using a kernel function $K(\cdot)$ and a bandwidth h as follows:

$$\hat{f}(x) = \frac{1}{n\,h} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right).$$

To give more recent observations a higher influence we incorporate weights, and modify the estimator to:

$$\hat{f}(x) = \frac{1}{h \sum_{i=1}^{n} w_i} \sum_{i=1}^{n} w_i\, K\left(\frac{x - x_i}{h}\right).$$

Here, each w_i represents the weight for observation x_i, and the normalization factor $\sum_{i=1}^{n} w_i$ ensures that the estimator still integrates to one.

We are applying exponential decay, assigning weights so that more recent data are given higher importance. If the data are time-ordered, with time stamps $t_1, t_2, \ldots, t_n$ (where t_n is the most recent), a common choice is:

$$w_i = \exp\Big(-\lambda\left(t_n - t_i\right)\Big),$$

with $\lambda > 0$ controlling the rate of decay—the larger the λ, the faster the weight decreases for older observations.
An explanation of the components can be found in Appendix B. For a comprehensive treatment of the method, including various kernel functions, bandwidth selection, and extensions like weighted KDE, you may refer to Silverman (2018).

5 RESULTS

Figure 1 shows a typical prediction of our method. Our new PI method yields a prediction accuracy of 87% for the sparse dataset we used. The RMSE distribution for the same data in Figure 2 is significantly lopsided to the left.

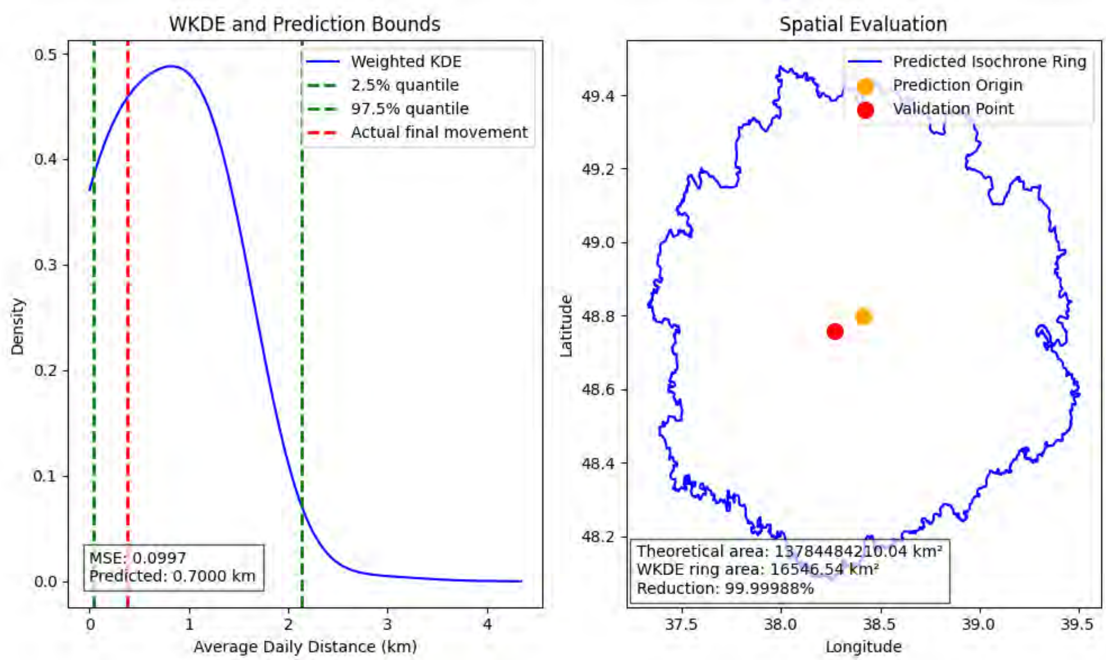

Figure 1: On the Left: The PDF-D with the ring diameters (green), we expect the real location (red) to be within. On the Right: a visualization of bespoke ring area. The lower bound is so close to zero, that the ring shape is not apparent.

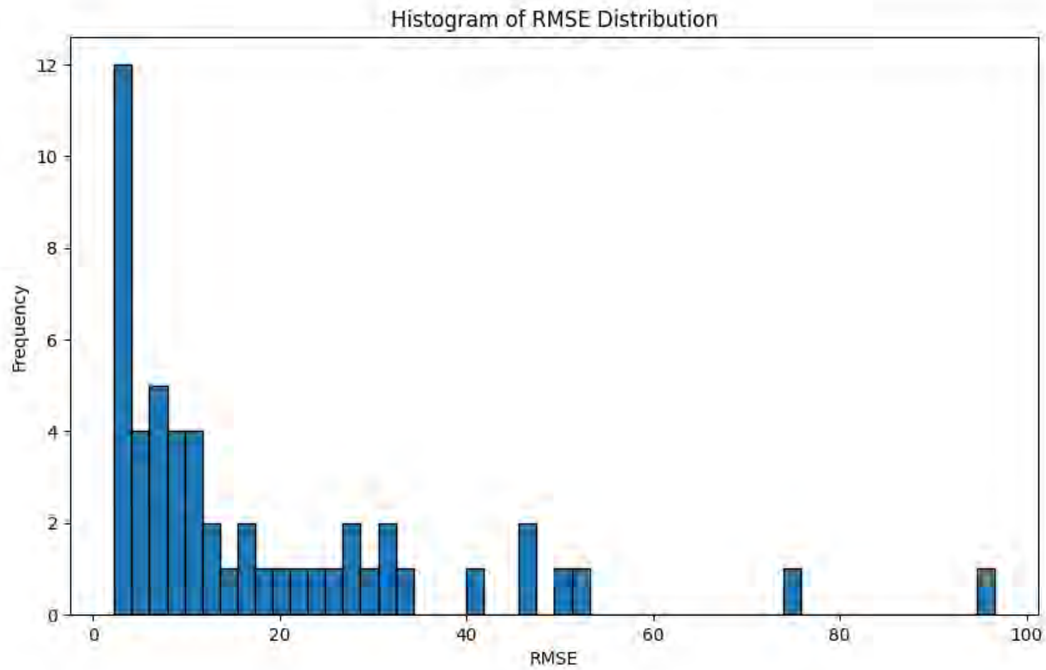

Figure 2: A left sided distribution of the RMSE. Data was collected over the whole dataset. Each unit that had valid data was evaluated according to our experimental design.

6 DISCUSSION

At first glance, the lopsided distribution of RMSE in Figure 2 indicates that our analysis tends to predict with small errors. Furthermore, the real world travel distance (the red dotted line in Figure 1) is within the 95% percentile 87% of the time. So, all in all quite promising numbers. But there are some caveats we are pondering on.

Distance Measurementsa and Pathing

Figure 3 shows that base truth distance measurement, in this case GC, seems to be better than using shortest road-bound path distance computed with our GH server. We assume two factors to be of significance in that regard.

First, for long time frames the isochrone area should closely resemble a circle, which should hold especially true in areas with well-established and dense road networks. This would imply that at a certain threshold time after reconnaissance, the prediction should switch from GH to GC to save resources.

Second, GH computes distances based on the traveling profile we give it, returning the shortest path it can find. But the server might not return a path, or the path is irrationally long. Basically, the GH based route prediction has a non-zero chance of returning bad pathing (e.g. a path that is unnecessarily long and winded, since a military unit could just take an off-raod shortcut instead), if the traveling profile is not well crafted enough.

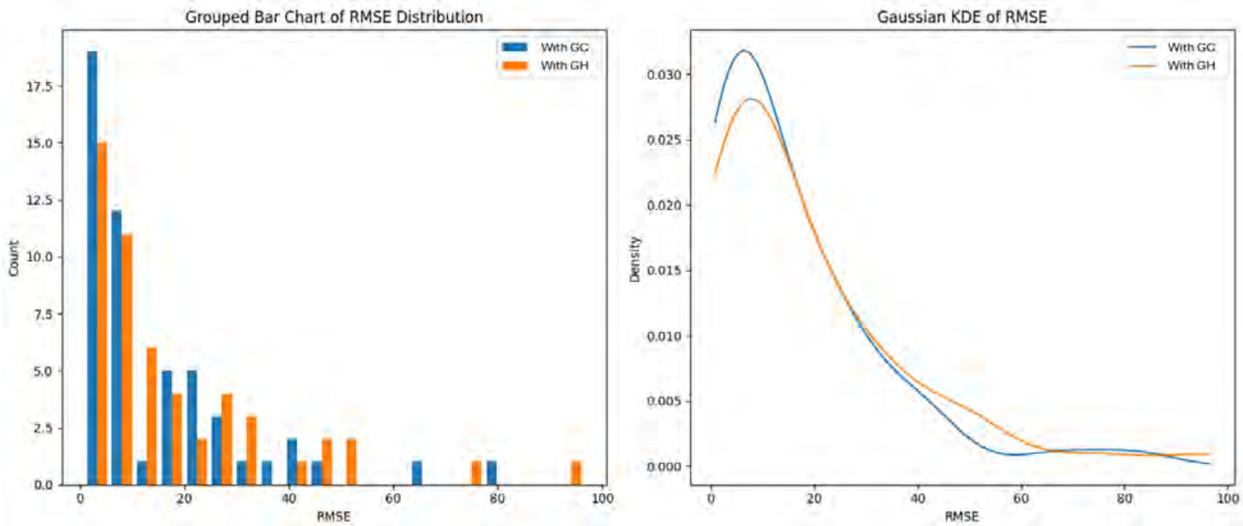

Figure 3: Dissimilarities of simple great circle to a isochrone based approach. Significant similarities and dissimilaritys are evident.

Dealing with Frugal and Sparse Data

The real world dataset we used shows time steps of at least three days between sightings and suffers from degrading data density over time. In an ideal case, we would have enough data to form a PDF-D for each time frame we want to predict, e.g. to predict the area the unit will be in in two hours, we would have to have enough data to form a PDF-D for two hours. And we would need another PDF-D for one hour, and one for three, and so on. However, when working with real world data, this is not possible; data is too frugal and sparse.

Figure 4 shows the degradation in the UAWar dataset. Which is expected; this specific dataset is open source intelligence (OSINT) and consists of civilian reports of troop sightings that have been posted to social media (Instagram, Reddit, etc.). A sighting, usually a picture and a geolocation, was then evaluated by experts or hobbyists to identify the unit. The ongoing war led to evacuations, which resulted in fewer reports from civilians. Simultaneously, OSINT shifted to standard military reconnaissance. Adding the fact that high-resolution movement data of military movements is usually confidential, we have no publishable way to validate our method with remotely good data sources.

Furthermore, isochrones are normally used in time frames of minutes to hours, well beneath one day. This fact lead to two concessions we had to make to still utilize the data we had for validation.

First, to get close to these time frames our method normalizes travel distance data to one day. Meaning, we divide the distance a unit traveled between sightings by the number of days between sightings. We do that to get as much data for the WKDE computation as possible, since our method needs the PDF-D to make predictions.

Second, because the PDF-D is a one-day probability, we have to scale it up if more than one day has passed since the last sighting. We multiply the 2.5%-97.5% quantile of the PDF-D to form the prediction ring by the number of days we want to predict. This infers a huge error since we scale the error with our prediction. So, the further time passes, the greater the error gets.

One would assume that to increase the prediction quality nonetheless, we should focus on the data-dense area of the dataset. But that leaves us with so few data points that any sort of prediction would equal a guessing game.

This leaves us two possible future routes to take: (1) use undigitalized open data on conflicts (e.g. WWII); (2) build a data-farming pipeline to generate data ourselves.

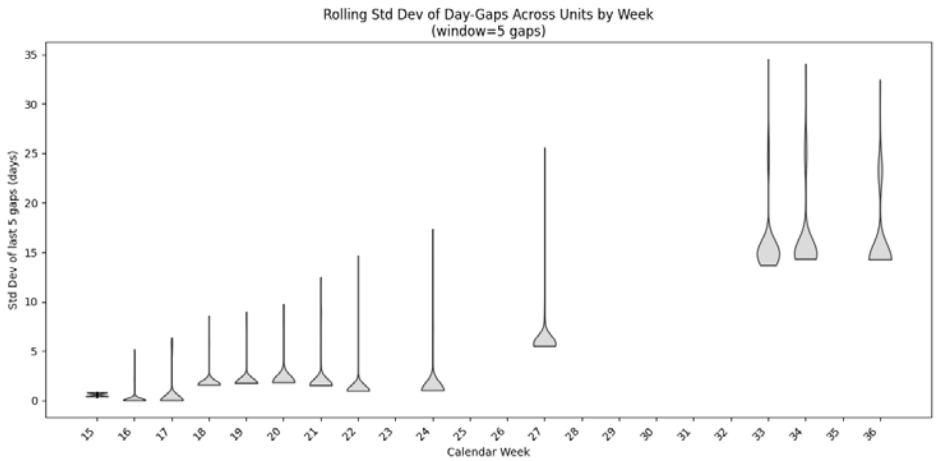

Figure 4: Violin plot of the standard deviation of days-gaps between sightings. Basically the frequency at which the UAWar dataset has records. Lower values indicate frequent sightings.

Gradients, Points and established Methods

The next issue lies in using a PDF and in extension WKDE as a basis to build the PI. The base concept of our method is to synthesize all the decision-making (i.e, all the military doctrines) down to a PDF we use to predict movement.

The fact that it still works 87% of the time with errors that tend to be small, may be taken as an argument for the viability of the core concept of our approach. Namely, using stochastic movement data and heuristics to predict unit movement as a PI. But KDE is not a probabilistic method per se, it yields points not gradients or areas, we simply forced it to do so. There are several established methods we want to evaluate: Bayesian inference, Kalman filters, or Kriging. Maybe a combination of different techniques would be most effective.

However, our results show that our approach has the potential to predict troop movements, but we will need to address key issues in future research and with further experimentation. Moreover, by building upon established libraries (OSMnx, NetworkX, GeoPandas, graphhopper, etc.), the method ensures reproducibility and ease of integration into existing decision-support systems.

Future Work

We will utilize agent-based combat simulation software to generate rich datasets we can validate our method against. If that software will be of-the-shelf or in-house has yet to be addressed. It has to be said that the formulation of agent based simulations of the granularity we need for this particular data generation task is extensive and highly involved. We would much rather use existing data or software.

On the other hand, we are working on using explainable AI methods that could potentially be used to digitalize data that is very rich and not confidential, namely WWII data. But, this digitization pipeline is in its infancy stadium.

Regarding the benefit of our method for tactical to operative level planning. We plan to develop an adversarial test environment. Two AI-agents compete in finding and hiding from each other. Experiment will be cathegorized by search method. For instance, a baseline could be a simple grid search around the last seen location. We will then compare the baseline to our method of prediction where an adversary could be.

We believe isochrones to be a very flexible tool for military planning. And, they play a big part in the thesis of this papers author. As such we are currently working on implementing similar prediction methods to less movable assets that are not in the direct frontline context this paper has addressed. For example, a supply depot will be stationed at several hours from the front lines, still reachable in a pinch but far enough to not get immediately found and destroyed. Furthermore, the location of that supply depot is highly impacted by logistical necessities.

Regarding different stochastic methods or combinations thereof to improve the WKDE to PDF-D approach. We have already researched the prediction accuracy of singular methods, but not yet the combination of several methods. The results of our preliminary research therein will be published at a later date.

7 CONCLUSION

In conclusion, our study has demonstrated that the PI framework represents a promising advancement in the predictive modeling of adversarial unit movements. By leveraging weighted kernel density estimation with exponential decay, our approach not only produces an interpretable probability density function of travel distances but also translates these insights into a practical ring-shaped spatial prediction area. Our validation results, indicating an 87% inclusion rate and favorable RMSE metrics despite inherent data sparsity, underscore the operational viability of the method.

While acknowledging the challenges associated with temporal normalization, data sparsity, and distance measurement uncertainties, we view these as valuable avenues for further enhancement rather than insurmountable obstacles. Future work will focus on refining the normalization techniques, examining the integration of multiple stochastic methods, and incorporating higher frequency movement data to further improve predictive accuracy. Overall, this research lays a solid foundation for more nuanced and reliable decision support tools in military operations, and we remain optimistic about the potential for these refinements to substantially elevate the practical impact of the PI framework in real-world scenarios.

A OUR METHOD IN PSEUDO CODE

Algorithm 1 Simplified PI Computation Sequence

Require: Unit sighting data *unitData* (list of timestamped locations)
Ensure: Prediction area A, Predicted travel distance d_{pred}

```
procedure ComputePI(unitData)
    Sort unitData by date.
    Initialize list dailyDistances.
    if |unitData| < 2 then return Error: Insufficient data
    end if
    for all consecutive sightings (s_i, s_{i+1}) in unitData do
        Δt ← days_difference(date(s_{i+1}), date(s_i))
        if Δt > 0 then
            moveDist ← CalculateBestDistance(loc(s_i), loc(s_{i+1}))  ▷ Road dist, fallback G. Circ.
            if moveDist is valid then
                Add (moveDist/Δt) to dailyDistances  ▷ Normalize and store
            end if
        end if
    end for
    if dailyDistances is empty then return Error: No distances computed
    end if
    PDF-D ← ComputeWKDE(dailyDistances)  ▷ Get density of daily distances
    (q_low, q_high) ← 2.5% and 97.5% quantiles of PDF-D.
    lastLoc ← location of the last sighting.
    Compute Isochrones I_low, I_high for distances q_low, q_high from lastLoc.
    A ← I_high − I_low  ▷ Define 95% prediction ring area
    d_pred ← mean(PDF-D)  ▷ Predict mean travel distance
    GenerateVisualization(A, lastLoc)  ▷ Draw area and start point
    return A, d_pred
end procedure
```

Algorithm 2 Prediction Validation Sequence

Require: Full unit sighting data *unitData* (with enough points for training+test)

Ensure: Boolean *isInside* (True if actual location is in predicted area), Squared Error *SE* (between predicted and actual distance)

```
procedure VALIDATEPREDICTION(unitData)
    if |unitData| < 3 then                                    ▷ Need >=2 for PI train, 1 for test
        return Error: Insufficient data
    end if
    Split unitData: trainingData ← all points except the last one.
    groundTruthLoc ← the last point's location in unitData.
    lastTrainingLoc ← the last point's location in trainingData.
    (A, d_pred) ← COMPUTEPI(trainingData)        ▷ Prediction based on training data (Algorithm 1)
    if call failed or returned error then
        return Error: PI computation failed
    end if
    isInside ← Check if groundTruthLoc is within predicted area A.              ▷ Geometric check
    realDistance ← GC_DISTANCE(lastTrainingLoc, groundTruthLoc)        ▷ Actual distance moved
    if realDistance is invalid then
        return Error: Could not compute real distance
    end if
    RMSE_PDF ← GC_DISTANCE(d_pred, groundTruthLoc)
    return isInside, RMSE_PDF
end procedure
```

B EXPLANATION OF WKDE COMPONENTS

- **Kernel Function $K(\cdot)$:** A symmetric and usually unimodal function (e.g., Gaussian, Epanechnikov) that determines the contribution of each data point relative to its distance from the point x where the density is estimated.
- **Bandwidth h:** A smoothing parameter that controls the width of the kernel. A smaller h results in a more detailed (less smooth) density estimate, while a larger h produces a smoother estimate.
- **Weights w_i:** In this weighted version, each data point's contribution is scaled by w_i. With exponential decay, recent observations (with higher w_i) influence the density estimate more than older ones.
- **Normalization $\sum_{i=1}^{n} w_i$:** This ensures that the area under the density curve remains 1, maintaining the properties of a probability density function.

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