Predicting Locations of Interest with Biased Lévy Flights

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Abstract - *We apply the metaphor of crime hotspot analysis to combat mission locations/areas of interest by investigating the utility to the combat mission planner of a novel algorithm using biased Lévy flights and cellular automata for identifying hotspots in space-time. These hotspots represent locations of interest for mission planners to direct their efforts. We apply our research to the insurgency in Afghanistan and report on our initial results.*

Keywords: cellular automata, Lévy flights, locations of interest

1 Introduction

The U.S. military continues to improve the battlespace awareness of their mission planners through enhanced identification of locations/areas of interest over large areas. This capability will come through batch/stream processing of diverse spatially referenced data sources (environmental, social, cultural), automated feature extraction, data normalization, space-time pattern recognition, and visualization.

This research addresses this goal through a biologically inspired cellular automaton model of human search for attractive locations based on biased Lévy flights. We use output from this model to generate heat maps of locations of interest from the blue or red mission planner perspective. These heat maps identify locations with a high confidence of enemy activity.

The inspiration for our approach comes from work done by scientists at UCLA in crime mapping [1][2]. They model the space-time evolution of crime hotspots using cellular automata models. Their initial work modeled the criminal behavior using a biased random walk. Subsequent research modified criminal behavior to allow criminals to move significant distances before narrowing their search for a target using Lévy flights. We also take inspiration from the application of crime analysis to insurgency and counterinsurgency [3].

We believe that this approach generalizes well to situations where people must select a location over some great distance from a number of alternatives with attractiveness that can change over time. A cellular automaton model with Lévy flights seems especially appropriate for the needs of U.S. military mission planners because it can model the temporal evolution of locations/areas of interest over large gridded areas from the perspective of either the blue or red perspective. Furthermore, linking technologies for domestic law enforcement crime mapping with military mission planning creates opportunities for cross-fertilization and commercialization. When applied to the right data, these tools and GIS offer a number of space-time analysis functions that could benefit combat mission planners.

Geographic information systems (GIS) can easily convert spatially referenced data to raster (grid) format, as well as georectify and reproject raster data products to a common grid size and geographic coordinate system. The raster data format supports the representation of environmental data (e.g. elevation, air quality, land use), demographic data (e.g. population, religion, language, ethnicity), places (e.g. hospitals, schools, air fields), and space-time events (e.g. IEDs, protests). Vector data, collected either from points (e.g. space-time events, point measurements), lines (e.g. roads, rivers), or areas (e.g. census data) can also convert easily a raster format. Thus, a cellular automaton model of human search over large areas very easily lends itself to fusing data from diverse spatially referenced sources.

Our research makes a number of significant benefits and contributions. First, it addresses the need of the U.S. military to identify temporally evolving locations/areas of interest over large areas to enhance battlespace awareness to improve mission planning and execution. Second, it generalizes the idea of crime mapping to military applications involving location/area of interest identification. Finally, our approach has a theoretical foundation in a biologically inspired model of spatial search for attractive locations and contributes to the scientific literature regarding the applicability of this model to biological behavior patterns.

2 Background

We apply the metaphor of crime hotspot analysis to combat mission locations/areas of interest by investigating the utility to the combat mission planner of a novel algorithm for identifying hotspots in space-time. Others have used crime analysis in the context of insurgency and counterinsurgency [3].

The original algorithm that forms the basis of our research describes a two-dimensional cellular automaton of criminals moving through space to commit crimes. The model incorporates the attraction of the location to the criminal, prior crimes at the location, and nearby criminal activity. The model assumes criminal movement resembles Lévy flights. Lévy flights describe movement that involves occasional long distance travel along with local random travel. Lévy flights appear to describe both human and animal movement [2]. This pattern of movement could also describe combat situations where blue or red units travel a great distance then search for a local target. Similarly, red units may travel a long way to a safe haven where they feel free to move around safely. The research presented here represents our efforts to test this hypothesis.

We make the following assumptions for identifying locations of interest for adversary activity.

1. Define locations of interest as locations with high probability of adversary activity.

2. Adversaries looking for targets exhibit a type of foraging behavior.

3. Look for opportunities locally, but will travel large distances.

4. Existing activity attracts more participants, analogous to the broken windows effect for crime.

2.1 Lévy Flights and Biased Lévy Flights

Lévy flights appear as short distance movements with occasionally long distance movements. The movements represent Brownian motion with an inverse power law distribution. The probability density function of the flight distance l_j of move j has the form $P(l_j) = l^{-\mu}$ and $1 < \mu \leq 3$. Lévy flights enable optimal search for predators in environments with sparse clusters of prey beyond the range of their senses [4]. This of course generalizes to other search environment with sparse clusters of unknown goal states.

Scientists believe at least 14 species of open-ocean predatory fish exhibit foraging behavior described by Lévy flights [4]. Researches have also observed honey bees searching for their hive using a pattern of movement described by Lévy flights. The honey bees move quickly in one direction then search for landmarks indicating the direction of their hive [5].

A biased Lévy flight adjusts the direction of Brownian motion toward more attractive locations. This adaptation of the original Lévy flight model essentially extends the sensory awareness of the searcher beyond immediate neighboring sites. Scientists have also proposed Lévy flights as a way to describe criminals searching for an opportunity to commit a crime [2].

2.2 Cellular Automaton Model

A Lévy flight represents a random walk with a step size having a power law distribution. A biased Lévy flight adjusts the direction of motion toward more attractive location [2]. We now present the equations that describe the formation of hotspots [1][2].

We begin by defining the attraction $A_k(t)$ of location k as

$$A_k(t) = A_0 + B_k(t) \tag{1}$$

Self-excitation term $B_k(t)$ represents the attraction location k has given previous success at the location.

$$B_k(t+\delta t) = \left[(1-\eta) B_k(t) + \frac{\eta}{z} \sum_{s'} \right. \tag{2}$$

where the parameter δt indicates the time interval, $\hat{\eta}$ the strength of the self-excitation, ω the decay rate of the dynamic attraction, θ a proportionality constant, z the number of neighbor locations, and s a neighbor of location k. The variable $N_k(t)$ indicates the mean number of agents at location k.

We incorporate Lévy flights into the model through the relative weight W of an agent moving from i to k. The parameter μ represents the power law exponent for the Lévy flight and l the grid spacing.

$$W_{i\to k} = \frac{A_k}{l^{\mu}|i-k|^{\mu}} \tag{3}$$

We use W to compute the transition probability q of an agent moving from i to k by

$$q_{i\to k} = \frac{W_{i\to k}}{\sum_{j\neq i} W_{i\to j}} \tag{4}$$

The average number of agents at site k $N_k(t)$, with new agents recruited with rate Γ becomes

$$N_k(t+\delta t) = \sum_{i\neq k} N_i(t)\left(1 - A_i(t\right. \tag{5}$$

Finally, we assume the probability $p_k(t)$ of an event at site k occurs according to the standard Poisson process

$$p_k(t) = 1 - e^{-A_k(t)\delta t} \tag{6}$$

3 Data and Methods

This section describes our data and relevant details of our implementation of our cellular automaton model of biased Lévy flight for battlespace awareness. We use GRASS GIS [6] to create and manage the raster maps and R [7] to implement the cellular automaton model, run the simulations, and perform the analysis. We use Quantum GIS [8] to create the maps.

3.1 Data

Our first data set consists of total coalition casualties for the time period 2001 to 2011 [9]. We use this data to measure the performance of our model. Figure 1 shows vector data of total casualties of coalition forces in Afghanistan by province from 2001-2011.

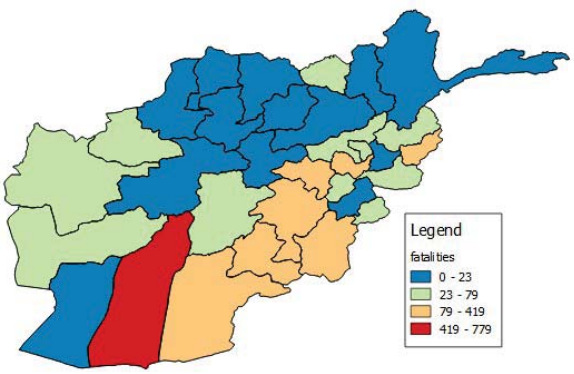

Figure 1. Total coalition casualties, 2001-2011 [9].

Equation 1 of our model specifies an initial attraction A_0 for each cell in the cellular automaton. Large population centers would seem to have more high value targets for insurgents and therefore locations near these centers would have more attraction. Figure 2 below shows the largest cities in Afghanistan.

Figure 2. Largest cities in Afghanistan.

The largest cities represent parts of the region most influenced by the outside world and represent centers of government control, even if it does not always extend far from the city. Thus, smaller settlements away from the largest cities may serve as attractive destinations for attackers because they can serve as local bases of operation. Figure 3 shows vector point data of settlements in Afghanistan.

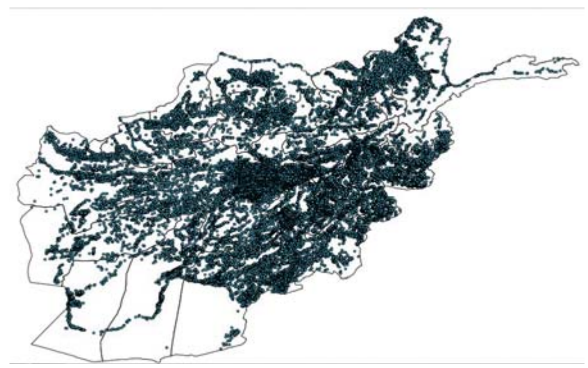

Figure 3. Settlements in Afghanistan [10].

Activities of the Taliban insurgency in Afghanistan before 2011 appear to have focus in part on areas suitable for poppy cultivation. The Taliban used heroin sales to finance their other activities. Land suitable for cultivation of poppies has a strategic importance to the insurgency so it makes sense for them to prefer targets in these areas because they serve a dual purpose of attacking US allied forces and gaining land for funding more attacks. Insurgence would target areas where they could grow poppies and not necessarily where farmers currently grow poppies. We account for this by using soil data and identifying areas having sandy loam soil, which best suits poppy cultivation (Figure 4) [11].

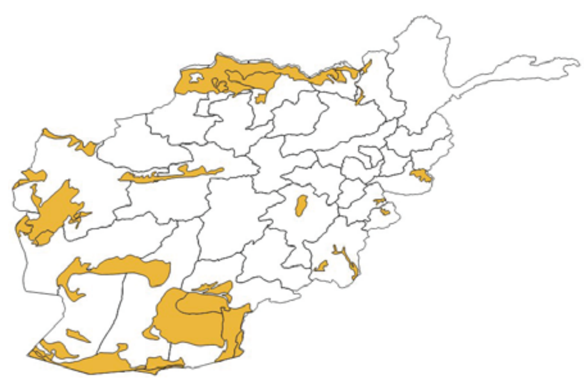

Figure 4. Soils suitable for poppy cultivation [12].

3.2 Methods

The cellular automaton evolves according the following algorithm:

1. Use GIS map algebra to create a raster grid of initial attraction $A_k(0)$ in each cell k from select raster data layers.

2. Initialize self-excitation $B_k(0)$ with estimates from past history. Assume zero.

3. Initialize average number of agents $N_k(0)$ by estimates from past history. See below.

4. Evolve the system (1)-(5) for some time period or to a steady state.

Lastly, we create a heat map of the probability values $p_k(t)$ to show locations/areas of interest.

We create a rasterized density map of population (Figure 5) from the largest cities (Figure 2).

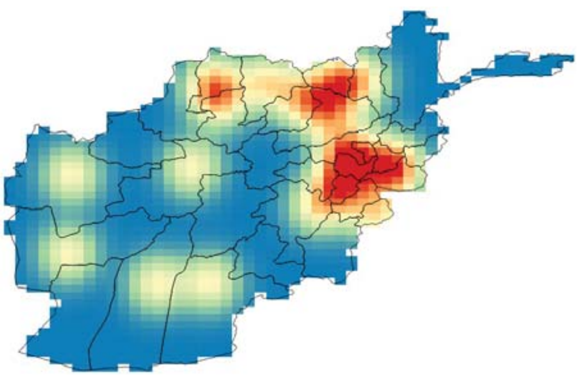

Figure 5. Population density from the largest cities in Afghanistan.

Similarly, we create a rasterized density map of settlements (Figure 6) from the distribution of settlements (Figure 3).

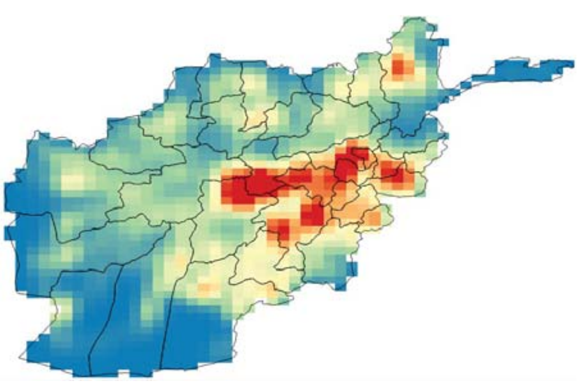

Figure 6. Settlement density.

In addition to the raster data in Figures 5-6, we also use the soil data (Figure 4) to estimate the initial attractiveness A_0. We will compute the attractiveness using map algebra in GRASS GIS to create single values for each raster cell from the three attraction sources.

Equations 2 and 5 require an estimate for the initial number of insurgents at each location. Here we make the assumption that insurgents recruited from less educated, less informed, and conservative populations found in settlements farther from large, urban centers. Furthermore, coalition forces had a more difficult time securing these areas because of large area and small, dispersed settlements [13]. Again, we apply map algebra in GRASS GIS to the population density and settlement density maps to estimate the initial density of insurgents.

4 Analysis

We hypothesize that biased Lévy flights represent a realistic model of anti-collation activity in regions like Afghanistan. Such regions exhibit sparse clusters of meaningful targets. Adversaries must travel long distance to these clusters, then search in a smaller local area for a viable target. A successful attack by one adversary will likely attract others to lend support.

Do biased Lévy flights offer a realistic predictive model for hotspots of insurgent or criminal activity? Since this model describes optimal motion for individual searchers, it seems we can quickly answer in the negative. Biased Lévy flights guide individuals to attractive locations. Knowing the initial attractiveness of each location means we already know the final distribution of activity.

However, this assumption fails to consider the initial distribution of searchers relative to these attractive locations and the distance decay governing how far they will travel to make an attack. Many might feel reluctant to travel too far from home. Nearer to home means familiarity, support, and refuge. Thus, attractive sites need not experience the largest incidences. As attacks increase in these nearer sites, the broken window effect may result in these areas becoming more attractive than they would otherwise. The initially most attractive locations for attacks may not experience the greater number naively expected because the attackers found opportunities nearer to themselves and their success drew others to them.

We perform three types of simulations and compare their performances in predicting total coalition casualties. The first simulation uses the attraction data computed from population density, settlement density, and soil type. This allows us to test whether we need a model of search at all to predict location of interest over large areas. In the second simulation, we test whether Brownian motion, involving only local search, can explain the observed distribution of coalition casualties. We test the performance of biased Lévy flights in our third simulation.

We will analyze the results of these three simulations in R to determine there ability to accurately predict total coalition casualties. Models from the three simulations do not need to accurately predict the actual casualty counts, but only the relative values of the provinces.

5 Conclusions

We will continue our investigation into the suitability of a cellular automata model of biased Lévy flights by performing simulations under various scenarios and analyzing the results compared to historical data of insurgency activity in Afghanistan. We also intend to acquire more accurate and varied data with higher spatial resolution, then calibrating our cellular automaton model for all years of data to measure predictiveness on real-world data.

We anticipate a renewed interest in algorithms like the one presented here for identifying locations of interest for adversaries search large areas for locations to attack. We expect IS forces in Syria and Iraq will eventually fragment, leaving the hardcore members to conduct more guerrilla-style attacks throughout the region. Modeling their movement as biased Lévy flights seems like a promising way to anticipate where they will strike next. The insight provided by our cellular automaton gives mission planners another piece of valuable evidence to use it deciding where to position allied assets and conduct operations.

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