Representing simulated patterns of life using standards-based, discoverable specifications

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ABSTRACT

Representing the movement and other behaviors of large numbers of human inhabitants in a geo-typical fashion within an area of interest provides a way to enhance the realism of a simulation exercise scenario. It also establishes a baseline against which an analyst may make comparisons of behavior to support conclusions of intent, based on departures from the baseline. This capability can be used in simulations in both training and experimental scenarios where close contact with a local noncombatant population is expected.

We describe a data model that includes the information needed to characterize a set of signatures attributable to a local population, and that does so in a way that lends itself to discovery using automatic or interactive means. This latter aspect of discoverability is important given the rapidly increasing universe of network-accessible, searchable data, and the broad set of distinguishable population groups that military forces may interact with.

The model also includes parameters governing the population's inclination to be forthcoming with information during engagements with military forces within the area of interest. This inclination may be affected positively or negatively by behaviors of the occupying forces, and has implications with respect to the efforts that are required to establish meaningful relations between groups. This allows a unit commander (in a training setting) or an analyst (in an experimental setting) to estimate the return on investment of committing resources to attempt to align a local population more closely with military objectives.

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PATTERNS OF LIFE IN THE AREA OF OPERATIONS

In this paper we suggest techniques for the efficient representation of data needed to model patterns of life. These are important because actual data sets descriptive of indigenous behaviors are scarce and often less than comprehensive; therefore a means of adjusting from a baseline data set to achieve a mission-capable data set is needed. Additionally we propose a solution to the problem of determining definite locations of simulated individuals, which is an operationally challenging, and computationally expensive activity.

With increasing regularity, ground forces operate in areas where sufficient infrastructure exists to support the persistent presence of noncombatants. This is by no means a new phenomenon; for example, the Vietnam conflict saw substantial interaction between military forces and noncombatants. It has been observed that difficulties in conducting military operations may be correlated as being proportional to the density and proximity of noncombatants (Glenn, 1996). Such difficulties may be direct, such as harboring or otherwise assisting insurgent forces; indirect, such as impeding the mobility of military forces attempting to traverse a congested area; or coerced, such as Saddam Hussein's use of civilians as "human shields" during Operation Desert Storm (although strangely, some individuals traveled to the theater of conflict intending to place themselves in harm's way to protest the war) (DoD, 2016).

The nomenclature "patterns of life" has origins in the discipline of sociology, but the relevance of the term quickly made it useful in military contexts (Flynn, Juergens, and Cantrell, 2008). (Cross, 2012) described requirements for patterns of life effects to support training simulations as ethnocentric noncombatant and opposing force behaviors that are adaptable, unpredictable, believable, culturally and linguistically accurate, and consistent with scenario roles. He also stressed that such capabilities must be easily used.

From a simulation perspective, there are two primary use cases of interest:

- Producing observable patterns of movement and other behaviors that are realistic, reliable, and repeatable among non-military populations. These patterns, or interruptions of the same, serve as intelligence indicators to analysts or commanders and their staffs operating within the area and elsewhere.
- Modeling interactions between military forces and the non-military population of the area, and the effects of those interactions on the population's willingness to divulge information of intelligence value.

With these use cases in mind then, several observable effects must be simulated:

- Movement and the absence of movement to points of interest (going to places of worship, marketplace, school, work; ships arriving or leaving port; aircraft the same)
- Activities and the absence of activities at points of interest (speech of different kinds, sporting events, looting, rioting, explosions, weapons fire, erection of barricades)
- Transfer of information from non-military population to military forces as the result of person-to-person engagement in conversation, interviews, and interrogation.

As (Levesque, 2010) pointed out, the ability to represent patterns of life in simulation is important from a training perspective due to the high cost of conducting such training with live actors, and the prevalence of such interactions in the contemporary operational environment. (Flynn et al, 2008), (Flynn et al, 2010) and (Atwood, 2015) emphasized that detection and analysis of patterns of life are essential to any operation in close concert with noncombatants or an unconventional enemy. Likewise (Kaminsky, 2011) indicated the importance of intelligence, surveillance, and reconnaissance (ISR) as a means to observe patterns of life, and their close relation to counterinsurgency operations. It follows from these observations that the ability for simulations to portray such behaviors could be considered in some applications to be equally as important as the representation of kinetic effects.

The notion of a "pattern" of life suggests that there should be some discernible characteristics or actions that are repeated (or exhibited) over time, and are thus susceptible to detection. As applied to groups of individuals, these characteristics are referred to as *archetypes* (Schatz et al, 2012). In particular, we use this term to describe a sequence of movements or activities engaged in by a subset of the simulated population within a region. Participation by simulated individuals in one or more archetypes forms an equivalence class whose membership function is the set of entities belonging to an identifiable group. These equivalence classes may be hierarchical in nature (e.g. sects within a religious grouping), or not. The union of all such equivalence classes with the subset of individuals belonging to no equivalence class induces a partitioning of the simulated entities within a region of interest.

DEPARTMENT OF DEFENSE DISCOVERY METADATA SPECIFICATION (DDMS)

The Department of Defense Net-centric Data Strategy (DoD, 2003) established a number of goals regarding the visibility, accessibility, and management of data within the enterprise. Within that framework, the Department of Defense Discovery Metadata Specification (DDMS) directly supports achievement of these goals by establishing a standard for describing discoverable data. The term "metadata" is usually defined as "data related to, or about other data." The DDMS provides a structured way to consistently describe aspects of data sets in order to satisfy the goals of the DoD strategy.

The characteristic of visibility is one of the most significant goals of the strategy. As part of data-enabled problem solving, knowledge that data exists that is relevant to the issue at hand is by itself enormously valuable. The ubiquitous proliferation of network-hosted data resources is but one aspect of making such data available. In order to be useful, raw data must generally be augmented with metadata that allows it to be discoverable. The relevance of data to a particular problem typically must be inferred, and in some cases must be accomplished by an iterative process. To even the most casual Internet user, the technique of using a search engine to discover information is likely a familiar workflow. However well known, this unconstrained approach is suboptimal in the sense that the universe of data sources within which it searches has no agreed-to method for describing its contents. Indeed, much of the data searchable in this way has no associated metadata at all, and in those instances where metadata can be inferred (e.g. from file names, document headings, message subjects, and so on), the descriptive power of such inferences may be modest. By specifying a standard, the DDMS simultaneously makes possible much more powerful inference of relevance, as well as maximizing the probability that any particular search will be fruitful.

For example, consider a network-accessible data source consisting of a single file. Assuming that it is not redirected, the uniform resource locator (URL) for the file itself could contain metadata clues; a human could discern such clues within the structure of the string https://data.org/remoteSensed/lidar/florida/88191.jpg, such as the fact that this file is likely a JPG-encoded representation of digital elevations taken of some area within the state of Florida. But this inference depends upon convention and the power of human cognition to draw that conclusion. Alternatively, a DDMS-enabled description would leave no room for doubt:

```
<ddms:resource xmlns:ddms="urn:us:mil:ces:metadata:ddms:5">
   <ddms:metacardInfo>
      <ddms:identifier ddms:qualifier="TVC-15" ddms:value="15" />
      <ddms:publisher>
         <ddms:organization ddms:acronym="OSI">
            <ddms:name>Ono-Sendai</ddms:name>
            <ddms:email>david@ono-sendai.com</ddms:email>
         </ddms:organization>
      </ddms:publisher>
   </ddms:metacardInfo>
   <ddms:identifier ddms:qualifier="TVC-15" ddms:value="15" />
```

```
   <ddms:title>LIDAR data for Orlando, FL</ddms:title>
   <ddms:creator>
      <ddms:organization ddms:acronym="OSI">
         <ddms:name>Ono-Sendai</ddms:name>
      </ddms:organization>
   </ddms:creator>
   <ddms:subjectCoverage>
      <ddms:keyword ddms:value="lidar” />
   </ddms:subjectCoverage>
</ddms:resource>
```


Although it may appear verbose to a human reader, this description provides invaluable structured information that may be used to identify the file for discovery by automatic systems. The addition of point of contact information can likewise be invaluable to further refine the relevance of the associated data, although naturally this requires human interaction.

DATA ENCODING

We describe a preliminary specification that is by no means comprehensive, but sufficient to minimally stimulate the intended use cases mentioned above (supporting pattern analysis, and encouraging engagement with a local population to facilitate intelligence-gathering). Compliant instances of the specification use the Extensible Markup Language (XML), which makes them amenable to automatic generation and analysis, and therefore suitable for use in applications requiring a formal description, such as the approach described by (Coffman 2004). Some of the more important functional elements within the schema include:

- Population change rates: birth, death, infant mortality (by gender)
- Given names (by gender)
- Cooperation
- Initial locations
- One or more archetype definitions:
  - Gender frequencies
  - Age distribution mean and variance
  - One or more activity type definitions:
    - Activity name (e.g. “Attend religious services”)
    - Recurrence
    - Start time
    - Duration
    - Venue type

These elements are populated as appropriate to encode the characteristics of the population of interest. These definitions are then used by the target simulation to create instantiations of actors representing the population.

Spatial distribution and locality

The choice of XML as the preferred format for representing the specification has important advantages. These include human readability; the availability of numerous applications for viewing, editing, and transformation; and widely supported libraries for software-controlled reading, parsing, and writing (Freire and Benedikt, 2004). But these advantages are also partially offset by an oft-mentioned disadvantage of the XML format, namely that the size of XML-encoded files can be large (Sakr, 2009). We address this issue at its source by seeking representations of patterns of life specifications that are pre-compressed, in the sense that they require relatively small numbers of parameters.

As part of scenario generation, thoughtful selection of the locations where activities take place can be one of the more time-consuming activities in creating a simulation scenario involving patterns of life. In order to support automatic identification of activity locations, the values used to populate the venue type field are actually feature categories. These may be mapped by the target simulation to a variety of different features supported in the terrain database that may be considered as candidates in selecting the actual place where a particular type of activity takes place. For example, the venue type “domicile” could be mapped to several different types of structures, such as single-story home, multi-story home, and others.

The initial locations of simulated entities and their associated patterns of life are essential to the simulation scenario, and therefore to the specification. Because the numbers of entities within an area may be large, it is important to consider factors related to the size of the specification, and its impact on simulation performance. There are two issues to address:

1. The need to support applications where a particular distribution is important to the achievement of a training or experimental objective, but no such distribution is known to exist, or is otherwise unavailable.
2. The ability to reproduce the characteristics of some geo-specific distribution of noncombatants.

For the first issue, a purely artificial distribution of locations may be used, provided that it meets the event-specific requirements. But this is not to say that the distribution of locations is completely random. Rather, given their inherently gregarious nature, human societies tend to congregate, resulting in a distribution of locations that tend to clump together (Boldrini and Passarella, 2010). Therefore, a model capable of reproducing this tendency for individual locations to be attracted to one another produces a more believable simulated result.

We employ an inhomogeneous Poisson cluster process (Gabriel, 2013) for this purpose. Briefly, this is a process that generates points in space such that their distance from one another is a function of a parameter called the *intensity*. Being inhomogeneous, the intensity is not constant; instead, it is an exponential function of the location within space. Figure 1 shows two realizations of this process:

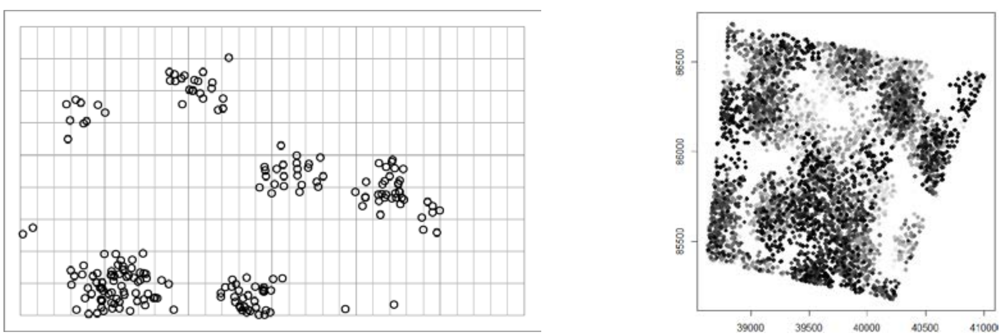

Figure 1 Two realizations of the Poisson cluster process. One is fit to an artificial unit volume (left), and the other constrained to a geo-specific area (right). The units are degrees latitude and longitude (× 10^4).

The symbols used to plot the locations of the Poisson process output in the figure above are greatly enlarged to enhance their visibility. In the right-hand image, the intensity of the grayscale represents affiliation of the corresponding point with a particular culturally significant group, such as a tribe. The geographic boundaries for the terrain used to produce this distribution correspond to a neighborhood in downtown Baghdad having sufficient cultural features (i.e. buildings of various types) to support a rich set of periodic behaviors.

Where explicit locations for individuals are at hand, an efficient representation is essential, since it generally would not be practical to convey information on a per-entity basis, and yet such information is ultimately needed to portray the characteristics of individuals in simulation. The use of a multiresolution *wavelet transform* is well suited to such an application, as it simultaneously encodes spatial and frequency (i.e. density) information. This feature greatly reduces the amount of space needed to encode the specification.

For a discrete signal $S[n]$, the discrete wavelet transform is determined by the coefficients c_k that satisfy:

$$S[n] = \sum_{k=0}^{\infty} c_k \varphi_k[n] \qquad \text{(Eq. 1)}$$

The wavelet functions φ_k have the characteristic of spanning the space containing the signal $S[n]$ (Daubechies, 1988). In the patterns of life case, that space is the two-dimensional universe of real numbers, $\mathbb{R}^2$. We use two dimensions instead of three, under the assumption that the elevation (z-axis) parameter may be assumed to correspond to the surface of the earth at the given (x, y) location.

Wavelet functions also have the characteristic that they are finite; that is, they are non-zero over intervals of finite length. It is this feature that imbues the wavelet representation with the capacity to encode information over a finite spatial extent. This produces a very efficient data footprint: the transform only needs to store information where it will be usable to reproduce the original signal (Mallat, 1989). In this way the wavelet representation is self-compressing, but for the patterns of life use case it is possible to be even more economical, if an exact reproduction of the input signal is not required. This is not infrequently the case, such as in simulation-enabled experiments or training where a purely hypothetical locale is employed.

Experiments using data from a Poisson process with the same parameters as the one used to generate Figure 1 showed that reductions of storage space on the order of 8:1 could be achieved while preserving greater than 80 percent of the original signal. Appropriate selection of the encoding for the wavelet coefficients needed to recreate the locations would reduce the size needed to describe the pattern even more. The specific characteristics of the pattern of life being simulated would be expected to influence performance of the encoding, as suggested by (Gurley et al, 2003).

Synthetic extrapolation

An interesting special case of the second issue mentioned above having particular relevance to patterns of life simulation arises when data describing the distribution of one or more characteristics of the population of interest is available, but is known to be out of date, or otherwise not precisely suitable to support the training or experimental objectives. This can arise when the original data, which may have come from a country study, intelligence or surveillance assets, or other sources, is either not recent, or does not align with the intended application. In such cases, a technique that we refer to as *synthetic extrapolation* may be used to determine the unknown parameters of the desired distribution from the existing one. This allows for construction of data sets that may be considered as templates for a family of synthetic patterns of life specifications.

For example, suppose that the probability of an individual's attendance at a certain village's weekly gathering is described originally as having a normal distribution with known mean and variance. Intelligence suggests that from time to time, the probability of attendance increases by some value ΔP. It has also been observed that this increased attendance seems to correlate with nefarious activities within the village. In order to represent the distribution of increased attendance given the baseline distribution, a method is needed to determine the corresponding change to the distribution variance.

An individual is considered to have "missed" the meeting if his arrival is outside its temporal span. We adopt the following notation:

- α: A random variable indicating the deviation of an individual's arrival after the scheduled start time.
- μ_α, σ_α: The mean and standard deviation of the distribution of α.
- L: The duration of the meeting.

Let the circumflex, or "hat" symbol (^) indicate the equivalent values of the same variables but as applied to the increased probability of attendance case. The above assumptions and notation lead to the system of equations:

$$\begin{cases} P(\text{attend}) + \Delta P = \hat{P}(\text{attend}) \\ \mu_\alpha = \hat{\mu}_\alpha \end{cases} \qquad \text{(Eq. 2)}$$

With this nomenclature, the probability of attendance is $P(\alpha \leq L)$. Then by definition of the cumulative distribution function F,

$$P(\alpha \leq L) = F_\alpha(L) \qquad \text{(Eq. 3)}$$

Let ϕ be the standard normal random variable such that $\mu_\phi = 0$, and $\sigma_\phi = 1$. We have the result (Papoulis, 1991) that $(L - \mu_\alpha)/\sigma_\alpha$ is identically distributed with ϕ, therefore:

$$P(\text{attend}) = F_\phi\left(\frac{L - \mu_\alpha}{\sigma_\alpha}\right) \quad \text{(Eq. 4)}$$

Shah gave a straightforward approximation for the standard normal cumulative distribution function (Shah, 1985) F_ϕ:

$$F_\phi(x) \approx \frac{1}{2} + 0.44x + \frac{x^2}{10} \quad \text{(Eq. 5)}$$

For notational convenience, let λ = *P*(attend) + Δ*P*. Then combining equations 2, 4 and 5 we have:

$$\lambda = \frac{1}{2} + 0.44\left(\frac{L - \mu_\alpha}{\hat{\sigma}_\alpha}\right) + \frac{(L - \mu_\alpha)^2}{10\hat{\sigma}_\alpha^2} \quad \text{(Eq. 6)}$$

Simplifying and rearranging terms gives a quadratic expression in the unknown value $\hat{\sigma}_\alpha$:

$$(5 - 10\lambda)\hat{\sigma}_\alpha^2 + 4.4(L - \mu_\alpha)\hat{\sigma}_\alpha + (L - \mu_\alpha)^2 = 0 \quad \text{(Eq. 7)}$$

Given its canonical form, Equation 7 may be solved readily for the desired variance using the quadratic coefficients formula. Imaginary or negative solutions may be discarded as inapplicable to the physical constraints of Equation 7's context, namely that the standard deviation must be a real number, and it cannot be negative since it is the square root of the variance. This derived variance, along with the original mean, may then be used to generate a new distribution exhibiting the desired characteristics.

To give an example, consider a situation where the following conditions prevail in the ordinary case:

- Meeting length (L, minutes) = 30
- Probability of meeting attendance = 0.68
- Mean arrival time after scheduled start (μ_α, minutes) = 15
- Standard deviation of post-start arrival (σ_α) = 2.25

Now suppose that the increased probability of attendance associated with unusual actions in the community is 0.15. Computing λ = P + ΔP = 0.83 and substituting the given values into Equation 7 gives the quadratic equation $-3.3\hat{\sigma}_\alpha^2 + 66\hat{\sigma}_\alpha + 225 = 0$. Solving this equation in the usual manner yields a pair of solutions; of these, the negative may be discarded as mentioned above, leaving the result $\hat{\sigma}_\alpha \approx 22.97$. Thus the arrival time in the notable, unusual case has normal distribution with mean $\hat{\mu}_\alpha = 15$, and $\hat{\sigma}_\alpha = 22.97$.

The above example is but one instance of a family of situations where an existing parameterization may be used as a springboard to determine the features of a derived approach. This can be useful from the patterns of life point of view because the human condition is ever-evolving, and full data sets from which to determine distribution parameters may not always be available, particularly if the time span between identified need and simulation execution is short.

CONCLUSION

There can be little doubt that the involvement of military forces in areas where substantial concentrations of noncombatants are in close proximity to friendly forces, as well as hostile elements masquerading as noncombatants, will continue for the foreseeable future. This has implications affecting operational planning, as well as the allocation of intelligence resources. Where such operations are to be modeled, the ability to portray the typical and atypical movements of individuals is an essential element of simulations applied to training, analytic, and other use cases.

In this paper we have discussed the importance of human patterns of life in simulations, and a method for describing specifications of information needed to portray such patterns of life using the DDMS format. We describe certain characteristics of that format that have storage and algorithmic performance implications, and two techniques for addressing those issues with respect to the data model, and data encoding efficiency. This work sets the stage for a more in-depth analysis of the attributes needed to encode a description of a population that is usable for the patterns of life use cases mentioned here, and of the technical issues arising from such descriptions.

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