Agility Maneuvers to Mitigate Inference Attacks on Sensed Location Data

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***Abstract*—Sensed location data is subject to inference attacks by cybercriminals that aim to obtain the exact position of sensitive locations, such as the victim's home and work locations, to launch a variety of different attacks. Various Location-Privacy Preserving Mechanisms (LPPMs) exist to reduce the probability of success of inference attacks on location data. However, such mechanisms have been shown to be less effective when the adversary is informed of the protection mechanism adopted, also known as *white-box* attacks. We propose a novel approach that makes use of targeted agility maneuvers as a more robust defense against *white-box* attacks. Agility maneuvers are systematically activated in response to specific system events to rapidly and continuously control the rate of change in system configurations and increase diversity in the space of readings, which would decrease the probability of success of inference attacks by an adversary. Experimental results, performed on a real data set, show that the adoption of agility maneuvers reduces the probability of success of *white-box* attacks to 2.68% on average, compared to 56.92% when using state-of-the-art LPPMs.**

I. Introduction

Researchers have long discussed privacy concerns rising from inference attacks on location data [6], [7], [8]. An *inference attack* is a data mining technique performed by analyzing data to illegitimately gain knowledge about a subject. For instance, an adversary can infer sensitive locations (i.e., victim's work or home) by monitoring the data points produced, within a time period, by the victim's mobile platform through GPS or Wi-Fi signals [2], [3]. An example is presented in Figure 1 where sensitive locations are marked by a dashed perimeter, whereas location data points available to the adversary are presented as gray circles. Upon obtaining the victim's home and work locations, an adversary could physically harm the victim or violate the victim's privacy in several ways.

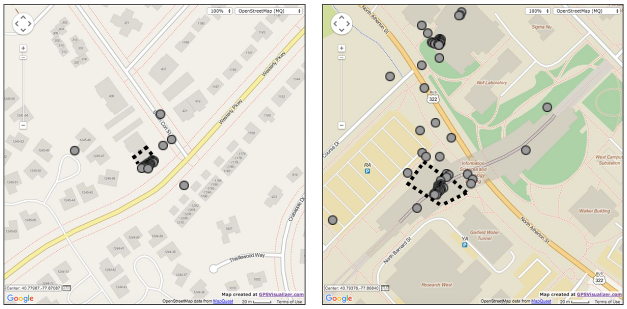

Fig. 1: Location data points around Home (left) and Work (right) with unmodified location data points.

Researchers have proposed various *Location-Privacy Preserving Mechanisms* (LPPMs) such as *Spatial Cloaking* [2], which removes data points that are inside a circular region around a point marked as sensitive by the mobile platform owner. Furthermore, noise, such as *Gaussian* [2] or *Laplacian*, can be added to generate noisy data points. *Distortion* can be used to add random noise to location data and avoid releasing actual locations. *Reduced Sampling* can reduce the sampling interval to decrease the amount of collected location data. Lastly, *Rounding* [2] can be used to round data point values and reduce accuracy. An example of the effects of applying such protection mechanisms to location data is reported in Figure 2. To an extent, these techniques have been shown to be able to reduce the probability of success in identifying sensitive locations when the adversary does not know about the protection mechanisms adopted [2], [3], also known as *black-box* attacks. However, such mechanisms might be less effective when the adversary is informed of the adopted mechanisms to protect sensitive locations, also known as *white-box* attacks.

In this paper, we first analyze how well existing LPPMs can protect sensitive locations against *white-box* attacks. We then propose and evaluate the effectiveness of three new protection mechanisms based on the use of agility maneuvers (e.g., alteration of the environment in response to adversarial action and perceived threat [1]) to better address *white-box* attacks.

II. Adversary Model

In this section, we specify the information available to the adversary while performing inference attacks on location data. In both *black-box* and *white-box* attacks, the adversary has access to location data points (time-stamped latitude and longitude coordinates) produced by GPS and Wi-Fi receivers on the victim's mobile platform (e.g., smartphone). In addition, in *white-box* attacks we assume a powerful adversary who knows not only the mechanism used to protect location data, but also the configuration of the protection mechanism (e.g., parameters used as input to the protection mechanism). For example, if spatial cloaking has been used, the adversary would know the radius used to define the circular region around locations marked as sensitive (a complete list is provided in Table I). Furthermore, we assume the adversary can adopt four heuristics, also used in related work [2], to perform

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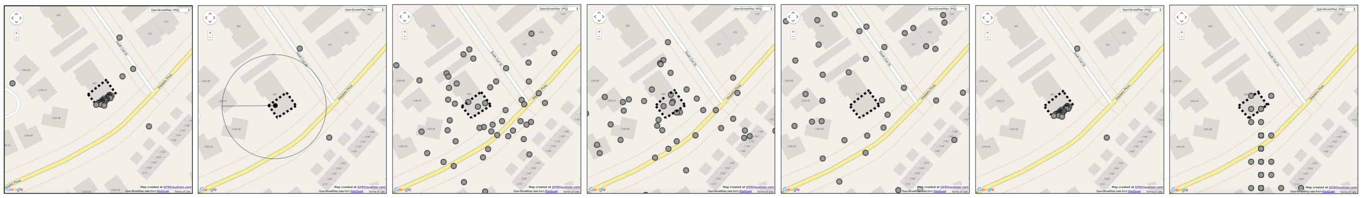

Original Spatial Cloaking Gaussian Noise Laplacian Noise Distortion Reduced Sampling Rounding

Fig. 2: Effect of applying six state-of-the-art LPPMs to the original data points for the victim's home location.

inference attacks. The first heuristic, named *First and Last Destination*, assumes the victim would probably go to work as first destination in the morning and go home as the last destination at night, therefore, the adversary identifies where the victim moves to at the beginning of the day, and where the victim usually terminates the daily journey. The second heuristic, named *Most Stationary Way Points*, assumes the victim spends more time at home and at work than at any other location, therefore, the adversary identifies the most stationary data points by calculating the amount of time spent in a fixed location until the next data point is recorded. The third heuristic, named *Larger Clusters*, assumes that most of the victim's data points will be around home and at work respectively, therefore, the adversary identifies the two clusters with the largest amount of data points. Finally, the fourth heuristic, named *Best Time*, assumes the victim stays at work and sleeps at home during specific time intervals, therefore, the adversary isolates data points during those time intervals.

We assume that anonymization of data is used to protect the identity of the mobile platform owner and exclude simple attacks where the adversary uses web search engines or similar approaches to identify the victim's home or work address.

III. Adoption of Agility Maneuvers

We now introduce the use of agility maneuvers activated upon the occurrence of environmental events to mitigate the probability of success of *black-box* and *white-box* attacks using location data to infer the victim's home and work locations.

A. Agility Maneuvers Activation

In system security, agility maneuvers are systematically activated in response to specific system events (i.e., internal state of sensors) to rapidly and continuously control the rate of change in system configurations and increase diversity in the space of readings, which would decrease the probability of success of inference attacks by an adversary. In our experimental study, we propose and investigate the activation of agility maneuvers when: (1) *the sensed data becomes stationary*, therefore there is no substantial movement; and (2) *no new sensed data points are produced within a short time interval*. We have chosen these events for the activation of agility maneuvers for the following two reasons. First, when the data points become stationary, they start leaking more information regarding places where the victim spends more time, which includes work and home locations. Second, when there is no new sensed data, there is a chance to introduce synthetic[1] data points that potentially would not impact legitimate use of such data but would rather mislead an adversary constantly monitoring the victim's movements. The investigation of the impact on legitimate use and the study on where to place such location security solutions, either at the device or at the edge location server [10], [11], is part of future work.

B. Agility Maneuvers Selection

In this subsection, we present the three agility maneuvers proposed as defenses against *white-box* attacks.

The first maneuver is **Random Obfuscation**, which focuses on the *rate of change* for system configurations. This maneuver *randomly* selects one protection mechanism, from the set of available mechanisms (e.g., spatial cloaking, noise, distortion, rounding and reduced sample rate), every time the sensing data becomes stationary for a prolonged time period. A snippet of the Random Obfuscation Algorithm, with six different protection mechanisms, is reported in Algorithm 1.

Algorithm 1 Random Obfuscation

```
Require: $radius$, $granularity$, $mean$, $standard\_deviation$, and $rate$
threshold $\Leftarrow n\ secs$
$method \Leftarrow 1$
while $LocationDataCollectionEnabled$ do
    if $(current\_time - last\_data\_time) \geq threshold$ then
        $method \Leftarrow Math.randint(1, 6)$
    end if
    if $method == 1$ then
        $lat \Leftarrow$ SpatialCloaking($lat$, $radius$)
        $lon \Leftarrow$ SpatialCloaking($lon$, $radius$)
    else if $method == 2$ then
        $lat \Leftarrow$ GaussianNoise($lat$, $mean$, $standard\_deviation$)
        $lon \Leftarrow$ GaussianNoise($lon$, $mean$, $standard\_deviation$)
    else if $method == 3$ then
        $lat \Leftarrow$ LaplacianNoise($lat$, $mean$, $standard\_deviation$)
        $lon \Leftarrow$ LaplacianNoise($lon$, $mean$, $standard\_deviation$)
    else if $method == 4$ then
        $lat \Leftarrow$ Distortion($lat$)
        $lon \Leftarrow$ Distortion($lon$)
    else if $method == 5$ then
        $lat \Leftarrow$ ReducedSampling($lat$, $rate$)
        $lon \Leftarrow$ ReducedSampling($lon$, $rate$)
    else if $method == 6$ then
        $lat \Leftarrow$ Rounding($lat$, $granularity$)
        $lon \Leftarrow$ Rounding($lon$, $granularity$)
    end if
    Output($lat$, $lon$)
end while
```

Randomly changing system configurations by selecting different defense mechanisms would increase the number of required guesses and reduce the probability of success for an adversary. Indeed, even in *white-box* attacks, an adversary would have more difficulty identifying how data has been manipulated and what protection mechanism has been used at a specific time. This should decrease the probability of success of inference attacks because the adversary would know the protection mechanisms adopted but would not be able to predict the rate of change among randomly selected

[1] Fake data points opportunely crafted.

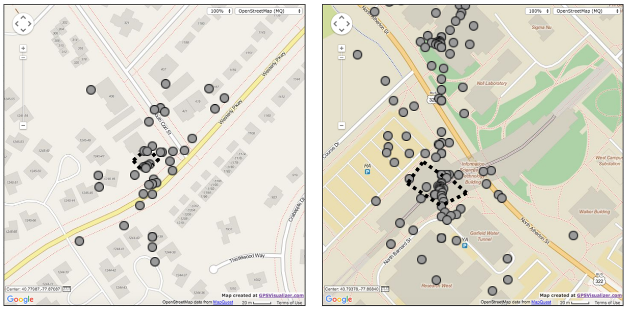


Fig. 3: Location data points around Home (left) and Work (right) with Random Obfuscation.

mechanisms. Figure 3 depicts how the set of data points (gray circles) changes when using this agility maneuver compared with the original set of data points reported in Figure 1.

The second maneuver is **Spatial Distribution**, which focuses on *diversity* in the space of readings. This maneuver aims to uniformly distribute data points in the space of readings by systematically generating synthetic data as new or modified data points[2] *whenever the victim location becomes stationary* for a certain time period. A snippet of the Spatial Distribution Algorithm is reported in Algorithm 2 where the `Distribute` function implements a uniform distribution of data points as explained in Section III-C, and `syn_lon` and `syn_lat` represent the synthetic data generated as new or modified data points provided as output besides real data points.

Algorithm 2 Spatial Distribution

```
Require: $min\_lat$, $max\_lat$, $min\_lon$, $max\_lon$, and $mov\_threshold$
$mov\_threshold \Leftarrow f(feet)$ \\$Small\ Movement$
while $LocationDataCollectionEnabled$ do
    if $(|prev\_lat - lat| \leq mov\_threshold)$ OR
    $(|prev\_lon - lon| \leq mov\_threshold)$ then
        $syn\_lat \Leftarrow$ Distribute($lat$, $min\_lat$, $max\_lat$)
        $syn\_lon \Leftarrow$ Distribute($lon$, $min\_lon$, $max\_lon$)
        Output($syn\_lat$, $syn\_lon$)
        while $NoNewDataPoints$ do
            $syn\_lat \Leftarrow$ Distribute($syn\_lat$, $min\_lat$, $max\_lat$)
            $syn\_lon \Leftarrow$ Distribute($syn\_lon$, $min\_lon$, $max\_lon$)
            Output($syn\_lat$, $syn\_lon$)
        end while
    else
        Output($lat$, $lon$)
    end if
end while
```

Uniformly distributing data points around the space of readings would increase the number of required guesses and reduce the probability of success for an adversary. In fact, it would be difficult to infer sensitive locations among a uniform distribution of data points since, with a uniform distribution, each point would have the same probability to be selected as potential sensitive location (e.g., victim's home or work). Figure 4 depicts how the set of data points (gray circles) changes when using this agility maneuver compared with the original set of data points reported in Figure 1.

The third maneuver is **Temporal Distribution**, which focuses on *deception* of the adversary constantly reading the victim's location. It consists of uniformly redistributing data points in the space of readings by generating synthetic data points[3] *whenever the location sensors (GPS and Wi-Fi receivers) do not produce new data within a short time interval due to out of reach location or lost signal.* A snippet of the Temporal Distribution Algorithm is reported in Algorithm 3 where the `Distribute` function implements a uniform distribution of data points as explained in Section III-C, and `syn_lon` and `syn_lat` represent the synthetic data points provided as output besides real data points.

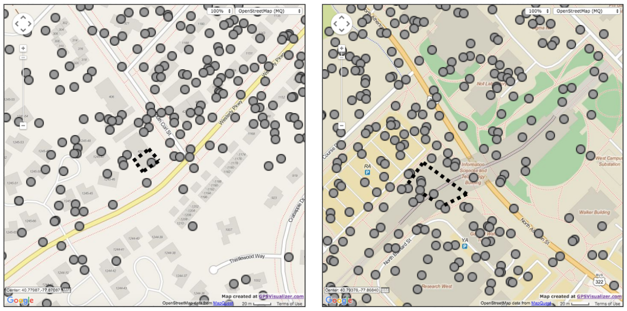


Fig. 4: Location data points around Home (left) and Work (right) with Spatial Distribution.

Algorithm 3 Temporal Distribution

```
Require: $min\_lat$, $max\_lat$, $min\_lon$, $max\_lon$ and $time\_threshold$
$time\_threshold \Leftarrow n\ (seconds)$ \\$Small\ Time\ Interval$
while $LocationDataCollectionEnabled$ do
    if $(current\_time - last\_data\_time) \geq time\_threshold$ then
        $syn\_lat \Leftarrow$ Distribute($lat$, $min\_lat$, $max\_lat$)
        $syn\_lon \Leftarrow$ Distribute($lon$, $min\_lon$, $max\_lon$)
        Output($syn\_lat$, $syn\_lon$)
        while $NoNewDataPoints$ do
            $syn\_lat \Leftarrow$ Distribute($syn\_lat$, $min\_lat$, $max\_lat$)
            $syn\_lon \Leftarrow$ Distribute($syn\_lon$, $min\_lon$, $max\_lon$)
            Output($syn\_lat$, $syn\_lon$)
        end while
    else
        Output($lat$, $lon$)
    end if
end while
```

Generating synthetic data points to uniformly distribute data points around the space of readings, whenever there is no new real data within a short time interval, would avoid time-stamped information from revealing useful information to an adversary. Figure 5 depicts how the set of data points (different shades for different time frames) changes when using the third agility maneuver compared with the original set of data points reported in Figure 1.

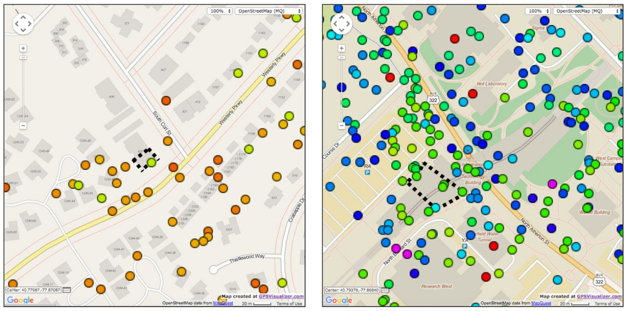


Fig. 5: Location data points around Home (left) and Work (right) with Temporal Distribution. Different shades represent different time periods (one hour granularity).

[2] Provided as output besides real data points to achieve diversity and uniform distribution in the space of readings.

[3] New or modified data points provided as output besides real data to deceive an adversary.

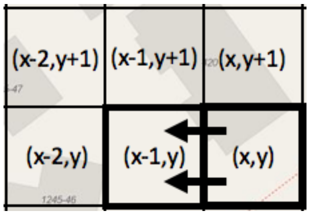
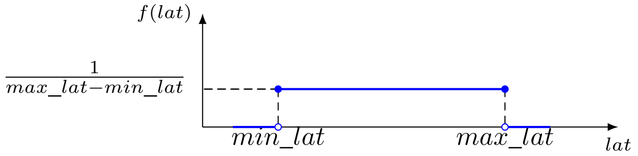


Fig. 6: Incremental Uniform Distribution. Upon a number of data points, equal to a set threshold τ, is reached in zone (x,y) then the current zone is extended by adding an adjacent zone, for instance zone (x-1,y) in the reported example.

C. Distribution of Data Points

We now describe the distribution of synthetic data points among the real data points to implement the agility maneuvers presented in the previous section.

Before giving more details about the distribution of data points, we motivate the use of such distribution with the following observation. Inference attacks require high accuracy and continuous reading of data for a prolonged time period in order to allow an adversary to reconstruct sensitive information, so a uniform distribution of data points along the entire space of readings would increase the number of guesses an adversary has to make even for *white-box* attacks. In fact, a uniform distribution of data points in the entire space of readings would hide spatial and temporal patterns otherwise visible to an adversary. By using uniform distribution, all data points within a selected geographical area of interest have the same probability of appearing in the data set available to the adversary, as shown by the equation and plot of the probability distribution function *f(lat)* below:



$$f(lat) = \begin{cases} 1/(max\_lat - min\_lat) & \text{for } min\_lat \leq lat \leq max\_lat \\ 0 & lat < min\_lat \text{ or } lat > max\_lat \end{cases}$$

The two parameters (`min_lat` and `max_lat`) are respectively minimum and maximum latitude (similarly we have `min_lon` and `max_lon` for longitude) selected in order to achieve uniform distribution within a specific geographic area.

Simply applying uniform distribution to data points over the entire space of readings would create unrealistic synthetic data, identifiable by a more advanced adversary. To achieve a realistic distribution of data points we propose an *incremental* uniform distribution that subdivides the entire set of readings into zones. As shown in Figure 6, the entire space of readings (e.g., latitude and longitude on a 2D map) is divided in zones. Starting from the zone containing the current real data (e.g., zone (x,y)), we systematically add synthetic data to achieve uniform distribution within the zone. Once a number of data points, equal to a set threshold τ, is reached within the current zone then an adjacent zone (i.e., zone (x-1, y)) is selected to extend the current zone and increase the area covered by the uniform distribution. This approach gradually achieves an incremental uniform distribution that better simulates real movements while placing synthetic data among real data.

	Protection Mechanism	Information Known by Adversary
LPPMs	Spatial Cloaking	Radius of Circular Region
	Gaussian Noise	Mean Value and Standard Deviation
	Laplacian Noise	Mean Value and Standard Deviation
	Distortion	Exact Digits affected by Distortion
	Reduced Sampling	Sampling Interval (Rate)
	Rounding	Number of Truncated (Less Significant) Digits
Agility Maneuvers	Random Obfuscation	Threshold, LPPMs available and corresponding Parameters
	Spatial Distribution	Zone Size and Threshold, Min/Max Latitude and Longitude
	Temporal Distribution	Zone Size and Threshold, Min/Max Latitude and Longitude

TABLE I: Information available to the adversary in white-box attacks.

IV. Experimental Evaluation

A. Data Set Description

All of the experiments described in this paper were performed using our *CampusLife* data set[4], a collection of over 483,840 time-stamped location data points collected by using GPS and Wi-Fi signals around the Penn State University Campus at University Park, PA. We collected location data by using the GPSLogger app [9] on a Nexus 5X smartphone running Android 6.0.1. The data collection lasted 4 weeks 24 hours/day. The data set reports location data relative to all movements performed by a graduate student working on campus and living off campus, and it is divided in daily reports where each time-stamped data point has the following format:

`<date,time,latitude,longitude,provider>`

The provider field is either *gps* or *network*, based on the signal used (GPS or Wi-Fi) to derive the subject's position.

B. Protection Mechanisms and Adversarial Action Modeling

We implemented six location-privacy preserving mechanisms (described in Section I and Figure 2), by following the description reported in previous related work [2], and three new algorithms for the proposed agility maneuvers (Section III-B). Lastly, we implemented the four heuristics (presented in Section II) to simulate the adversary's action in *black-box* and *white-box* attacks. Additionally, in *white-box* attacks, we used reconstruction functions to simulate the adversary's ability of reconstructing an approximation of the original data points when protection mechanisms are used. For each protection mechanism, we designed a reconstruction function that gets as input the information available to the adversary, for that specific protection mechanism (e.g., radius for Spatial Cloaking or mean and standard deviation for uniform distribution), and returns as output an approximation of the original data points. A summary of the complete information available to the adversary, based on the adopted protection mechanism, is reported in Table I. All algorithms were implemented in `Python` and the source code is made available[5].

C. Experimental Setup

We started our experiments by analyzing the effects of the six location-privacy protection mechanisms (highlighted in

[4] We used our *CampusLife* data set because other publicly available data sets do not report information about subjects' home and work location for anonymization and privacy reasons, however this information represents the ground truth required to validate experimental results. The data set is available for download at $http://sites.psu.edu/petracca/campuslife/$.

[5] $http://sites.psu.edu/petracca/location\_privacy\_code/$

Section I) when applied to the original data points available in our *CampusLife* data set. Each defense mechanism had as input the original data set and produced a modified set of readings to implement the appropriate defense protection mechanism. We tested the four heuristics (discussed in Section II) given each of the modified set of readings to simulate *black-box* attacks. We then reconstructed an approximation of the original data points and tested the same four heuristics given the new data points, to simulate *white-box* attacks. Table I summarizes the information available to the adversary in *white-box* attacks. We finally tested the same four heuristics given the original set of readings from our *CampusLife* data set modified to implement each of the three proposed agility maneuvers (for *black-box* attacks). We then reconstructed an approximation of the original data points and tested the same four heuristics given the new data points (for *white-box* attacks). We measured the percentage of success as the number of times an attacker succeeded in identifying both victim's home and work locations over 28 days (4 weeks) worth of data. The attacker used a daily report of location data to make a single guess (per day) of the victim's home and work locations.

D. Experimental Results for LPPMs

Clearly, the use of LPPMs decreases the number of times the adversary is able to infer the victim's home and work locations by reducing the percentage of success for *black-box* attacks down to 3.57% (best case for Rounding) and on average 39.57% (results are summarized in rows 2-7 in Table II). However, these mechanisms[6] are considerably less effective against *white-box* attacks, with a measured average percentage of attack success up to 56.92%.

In particular, *Spatial Cloaking* performs best against *black-box* attacks that use the Best Time heuristic (3.57%). However, it performs considerably worse against *white-box* attacks (on average 63.39%) because the adversary can identify the area around sensitive location (by means of geometry calculations) by knowing the radius of the hidden area around the sensitive location. *Gaussian Noise* and *Laplacian Noise* perform best against *black-box* attacks using Most Stationary Way Points (on average 55.35% Gaussian and 49.99% Laplacian) or Larger Clusters (on average 53.57% Gaussian and 41.06% Laplacian) heuristics, with *Laplacian Noise* being slightly better (on average -8.95%) because the Laplace distribution has heavier tails than the Gaussian distribution. However, their performance considerably degrades (on average 79.9% Gaussian and 75.89% Laplacian) for *white-box* since an adversary can cancel out the noise applied to the original data points. *Distortion* performs better than Gaussian and Laplacian Noise in both *black-box* (on average 29.02%) and *white-box* (on average 30.35%) attacks. It also performs better (on average -33.04%) than Spatial Cloaking in *white-box* attacks. Furthermore, Distortion is not heavily affected (on average only 1.33% more for *white-box* respect to *black-box* attacks) by the amount of information available to the adversary. This is due to the randomness used to cause distortion of real data points, which is not totally reversible. *Reduced Sampling* is one the least effective mechanisms with an average percentage of success of 82.59% for both *black* and *white-box* attacks. This is because reducing the number of data points available to the adversary is not sufficient to hide specific patterns. Finally, *Rounding* is slightly worse (on average +1.34%) than Spatial Cloaking for *black-box* attacks, but much better (on average -55.8%) than Spatial Cloaking for *white-box* attacks. This is because, the information lost by rounding the data points cannot be reconstructed by the adversary with accuracy.

E. Experimental Results for Agility Maneuvers

Agility maneuvers are less affected by the amount of information available to the adversary. In fact, agility maneuvers are effective in reducing the percentage of success of both *black-box* attacks (overall average[7] 13.13%) and *white-box* attacks (overall average[8] 13.72%) on location data (results are summarized in rows 8-11 in Table II).

In particular, for *white-box* attacks *Random Obfuscation* performs better (-14.04%) than most of the previously analyzed protection mechanisms on average. This is mainly due to the randomness used in selecting the protection mechanisms activated during a specific time frame among those available. However, it is slightly less effective against *white-box* attacks (on average 42.40%) compared to *black-box* attacks (on average 40.05%). Further, it is much less effective than the other two agility maneuvers. On average, the percentage of success of *black-box* attacks increases 35.59% more than Spatial Distribution and 34.37% more than Temporal Distribution. For *white-box* attacks, the percentage of success increases 37.94% more than Spatial Distribution and 37.05% more than Temporal Distributions. *Spatial Distribution*, on average, performs slightly better (-0.98%) than Temporal Distribution, with 4.46% average percentage of success for both *black-box* and *white-box* attacks. Temporal Distribution, however, has an average percentage of success of 5.35% for both *black-box* and *white-box* attacks. In particular, Spatial Distribution performs best (only 3.75%) against Most Stationary and Larger Clusters heuristics. *Temporal Distribution* performs best (only 3.75%) against First/Last Destination and Best Time heuristics. Interestingly, both Spatial and Temporal Distribution remain stable even in *white-box* attacks because a uniform distribution of data points over the set of readings increases the number of possible values an adversary have to chose from.

Our experimental results confirm that Spatial and Temporal Distribution outperform other protection mechanisms. In fact, on average, they perform better (-34.67% for *black-box* and -52.02% for *white-box* attacks) than other location-privacy protection mechanisms, and even better (-1.79% Spatial and -0.9% Temporal Distribution) than Spatial Cloaking[9] for *black-*

[6] With an exception for the Rounding mechanism because information lost by rounding data points cannot be reconstructed by an adversary.

[7] Including data from rows 8-11 columns 1-4.

[8] Including data from rows 8-11 columns 5-8.

[9] Best of all analyzed LPPMs against *black-box* attacks.

lat' and *lon'* are the data points observable by the adversary, whereas *lat* and *lon* are the original data points estimated via reconstruction functions by the adversary.

		Black-Box Attacks				White-Box Attacks					
		First/Last Destination	Most Stationary	Larger Clusters	Best Time	First/Last Destination	Most Stationary	Larger Clusters	Best Time		
Unmodified Data	🏠	**96.43%**	**96.43%**	**96.43%**	**89.26%**	**96.43%**	**96.43%**	**96.43%**	**89.26%**		
	💼	**78.57%**	**71.43%**	**75%**	**71.43%**	**78.57%**	**71.43%**	**75%**	**71.43%**		
State-of-the-Art Location-Privacy Protection Mechanisms										Parameter Values	Reconstruction Functions
Spatial Cloaking	🏠	10.71%	7.14%	7.14%	3.57%	82.14%	78.57%	82.14%	50%	(r) Radius = 2,100 feet	(*lat*,*lon*) = center of the empty circle area with radius *r*
	💼	7.14%	3.57%	7.14%	3.57%	57.14%	50%	60.71%	46.42%		
Gaussian Noise	🏠	64.29%	57.14%	57.14%	71.43%	92.86%	89.26%	89.26%	89.26%	(μ) Mean Value = 0	$lat = lat' - \mu$
	💼	60.71%	53.57%	50%	67.86%	71.43%	67.86%	67.86%	71.43%	(σ) Standard Deviation = 0.15	$lon = lon' - \mu$
Laplatian Noise	🏠	64.29%	53.57%	42.85%	71.43%	92.86%	85.71%	82.14%	89.26%	(μ) Mean Value = 0	$lat = lat' - \mu$
	💼	60.71%	46.42%	39.28%	67.86%	71.43%	60.71%	53.57%	71.43%	(σ) Standard Deviation = 0.15	$lon = lon' - \mu$
Distortion	🏠	50%	28.57%	35.71%	17.86%	53.57%	28.57%	39.28%	17.86%	[d_s-d_e] Distorted Digits = [3-0]	Randomly select *lat*[d_s-d_e]
	💼	42.85%	17.86%	28.57%	10.71%	42.85%	17.86%	32.14%	10.71%		Randomly select *lon*[d_s-d_e]
Reduced Sampling	🏠	92.86%	**96.43%**	**96.43%**	**89.26%**	92.86%	**96.43%**	**96.43%**	**89.26%**	(δ) Sampling Rate = 30 s	$lat = (lat'(t) + lat'(t+\delta))/2$
	💼	71.43%	**71.43%**	71.43%	**71.43%**	71.43%	**71.43%**	71.43%	**71.43%**		$lon = (lon'(t) + lon'(t+\delta))/2$
Rounding	🏠	14.28%	7.14%	10.71%	3.57%	14.28%	7.14%	17.86%	3.57%	(d) Number of truncated less significant digits = 4	*lat* = *lat'*{*d* random digits}
	💼	10.71%	3.57%	7.14%	3.57%	10.71%	3.57%	14.28%	3.57%		*lon* = *lon'*{*d* random digits}
Agility Maneuvers											
Random Obfuscation	🏠	46.42%	42.85%	42.85%	46.42%	53.57%	46.42%	46.42%	50%	(τ_t) Time Threshold = 180 s	Every τ_t seconds change the Reconstruction Function
	💼	39.28%	31.14%	35.71%	35.71%	39.28%	32.14%	35.71%	35.71%		
Spatial Distribution	🏠	7.14%	*3.57%*	*3.57%*	7.14%	7.14%	*3.57%*	*3.57%*	7.14%	(z) Zone Size = 6,000 sq ft	Randomly select a point
	💼	3.57%	*0%*	*3.57%*	7.14%	3.57%	*0%*	*3.57%*	7.14%	(τ) Threshold = 5 data points	in the current covered area
Temporal Distribution	🏠	*3.57%*	10.71%	7.14%	*3.57%*	*3.57%*	10.71%	7.14%	*3.57%*	(z) Zone Size = 6,000 sq ft	Randomly select a point
	💼	*3.57%*	7.14%	7.14%	*0%*	*3.57%*	7.14%	7.14%	*0%*	(τ) Threshold = 5 data points	in the current covered area
Spatial and Temporal Distribution	🏠	*3.57%*	*3.57%*	*3.57%*	*3.57%*	*3.57%*	*3.57%*	*3.57%*	*3.57%*	As for Spatial and Temporal Distribution above	
	💼	*3.57%*	*0%*	*3.57%*	*0%*	*3.57%*	*0%*	*3.57%*	*0%*		

TABLE II: Home and work location identification by an adversary. The percentage values correspond to how many times the adversary is able to identify the subject's home location (🏠) and work location (💼) by using daily location data points for a total of twenty-eight days. Best values are reported in *italics* and worst values in **bold**. Last two columns report, respectively, the values of parameters used for the data points transformation and the reconstruction functions used by the adversary in white-box attacks.

box attacks, and better than (-3.13% Spatial and -2,24% Temporal Distribution) Rounding[10] for *white-box* attacks. Finally, combining both Spatial and Temporal Distribution lowers the percentage of success, for both *black-box* and *white-box* attacks, to 2.68% on average, as shown by row 11 in Table II.

Our study is a preliminary evaluation of the efficacy of adopting agility maneuvers (e.g., alterations of the environment in response to adversarial action and perceived threat) as more resistant protection mechanism against an adversary that is aware of the location-privacy mechanism used to protect sensitive locations, also called *white-box* attacks. These preliminary results are promising and we plan to implement a first prototype on a real mobile operating system, to estimate the efficacy and effectiveness of such maneuvers on real system, and their effects on real applications.

V. Related Work

Krumm [2] examined location data gathered from volunteer subjects to quantify how well four heuristics can be used by an adversary to identify the subjects' home locations. We extended Krumm's work by analyzing how well three agility maneuvers work against both *black-box* and *white-box* attacks.

Golle *et al.* [3] showed that obfuscation techniques are less effective if the subject's home and work location are known or deducible from external sources (i.e., online search engine). We extended their work by studying how well six previously known and three new protection mechanisms prevent *black-box* and *white-box* attacks aiming to identify victims' home and work locations from location data.

Andrés *et al.* [4] proposed geo-indistinguishability, a mechanism to add controlled noise to the user's location in order to obtain an approximate version of it to be sent to Location-Based Services. Theodorakopoulos [5], instead, proposed a mechanism based on maximum-entropy as alternative to spatial-cloaking and geo-indistinguishability. We proposed an alternative approach that makes use of agility maneuvers for the manipulation of real location data.

VI. Conclusion

This paper has considered a new science of environment reconfiguration called system agility, by proposing agility maneuvers that have been evaluated against heuristics adoptable by cybercriminals for inference attacks on location data. We found out that agility maneuvers are more robust against *white-box* attacks resulting in a probability of success of only 2.68% on average, compared to an average of 56.92% when using state-of-the-art Location-Privacy Preserving Mechanisms. Future work should investigate the impact of agility maneuvers on legitimate uses of location data, and the users themselves.

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