Spatio-temporal Probabilistic Modeling Based on Gaussian Mixture Models and Neural Gas Theory for Prediction of Criminal Activity

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Abstract

Criminal risk models are used to assist security forces both in the identification of zones with high of criminal activity for better resource allocation and prediction of future criminal events for the prevention of new crimes. In this sense, spatio-temporal models are widely employed by their capacity of characterizing the criminal risk inside of a zone of interest and updating the model to new crime data. This paper improves an existing method based on spatio-temporal probabilistic risk functions. The spatial probabilistic characterization uses geo-referenced information of criminal incidents related to public services to approximate a risk function based on a Gaussian Mixture Model (GMM). The temporal characterization is supported by Importance Sampling methods and Neural Gas Theory to incorporate the information from new measurements, in a recursive manner, updating the spatial probabilistic risk function. Finally, we propose a prediction scheme for criminal activity that also uses Neural Gas Theory, in conjunction with hypothetical future criminal events sampled from a GMM that characterizes the spatial distribution associated with recent criminal activity. The time index related to each hypothetical future crime event is probabilistically characterized using an exponential distribution. Results using real data and the defined performance indexes show an improvement both in the temporal updating as well as the proposed prediction approach.

1. Introduction

Day by day security forces monitor criminal incidents both to protect the victims and understand the offending behaviour. Thanks to location technologies, it is possible to include geo-referenced and temporal information, which can be used by analysts to find spatio-temporal patterns of reported incidents, with the aim of predicting new criminal events. In this way, many approaches have been developed to address this prediction problem. One of these is the Hot-Spots Theory (Eck, Chainey, Cameron, & Wilson, 2005), in which criminal incidents are located on a plane, forming clusters that are assumed to be invariant for any prediction horizon. Unfortunately, this technique fails to reflect changes in crime patterns as the environment changes. To overcome this drawback, more sophisticated statistical models have been developed. For instance, in Xue and Brown (2006) and Smith and Brown (2007) work with models based on spatial decisions, where criminals are assumed to choose places that can be modeled in terms of profit maximization, which depends simultaneously on the gain in committing the crime and the likelihood of being arrested. The disadvantage of such models is that they do not directly incorporate the temporal component, and when it is modeled using time series (for example), space-time interactions are not considered (Ivaha, Al-Madfai, Higgs, & Ware, 2007). Furthermore, Caplan and Kennedy (2011) develop a method that uses geographic information system techniques to explore the relationship between crime and the spatial features that influence it (i.e., bars, houses, parks, public transport hubs). Finally in Wang and Brown (2012), generalized additive models (GAM) are studied to combine spatial and temporal data, as well as diverse characteristics for prediction.

In a previous work (Flores et al., 2015), the authors proposed a methodology to model and predict future criminal activity based on spatial probabilistic risk functions and a characterization of their temporal evolution as new data becomes available. To accomplish this, Hot-Spots and Gaussian Mixture Models (GMMs) were used to characterize the spatial component of the criminal activity. And, for the temporal component, Importance Sampling and Bayesian Inference were used. The methodology can be summarized in three main points. The first, the method uses geo-referenced information of public services (e.g., bars, banks, parks, shopping centers) and criminal incidents to approximate an spatial risk function (called "prior") using GMMs. The second, the methodology includes a characterization of the temporal evolution of crime activity using Sequential Monte Carlo Methods and Importance Sampling. This part incorporates information from new measurements, in a recursive manner, to approximate an updated spatial probabilistic risk function (called "posterior") associated to the position of the particles on the map. The third method includes a prediction scheme for criminal activity that uses Gaussian fields centered on hypothetical future criminal events, which are sampled from a GMM that characterizes the spatial distribution associated with recent crime activity. The time step related to each hypothetical future crime event is probabilistically characterized using an exponential distribution fitted from the temporal information of the registered criminal events. The results of the spatio-temporal model showed a high performance in the prediction of criminal activity (using real data, the majority of future events occur within risk modeled zones). Despite this interesting result, some elements in the methodology need further revision to reach a better performance. One of them is the calculation of the "posterior" risk function, which uses a "tuning parameter" that may be difficult to tune and can significantly affect in the criminal activity prediction performance.

To improve the results of the calculation of both the posterior and prediction spatial risk functions, this paper proposes a new approach based on Neural Gas Theory for defining the "movement" of the particles in the map according available measurements.

The article is structured as follows. Section 2 presents a theoretical background of concepts such as GMMs, Neural Gas (NG), and Evaluation Methods for criminal risk models. Section 3 presents the proposed methodology for the temporal characterization, and prediction of criminal events. Section 4 focuses on the analysis of generated results. Finally, in Section 5 conclusions and future work are presented.

2. THEORETICAL BACKGROUND

The theoretical background presents an overview of the main concepts used in this work. These concepts include GMMs, the NG algorithm, and the performance measures of spatial criminal risk models.

2.1. Gaussian Mixture Models

The GMMs are defined as a weighted sum of single Gaussian distributions as stated in Eq. (1):

$$G(x) = \sum_{i=1}^{M} \alpha_i \cdot f_i(x), \tag{1}$$

where x is a D-dimensional random vector, α_i are the mixture weights satisfying $\sum_{i=1}^{M} \alpha_i = 1$, and $f_i(x)$ are multivariate Gaussian distributions of dimension D, given by:

$$f_i(x) = \frac{1}{(2\pi)^{D/2}|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}\left(x-\mu_i\right)^T \Sigma_i^{-1}\left(x-\mu_i\right)\right) \tag{2}$$

where μ_i and Σ_i are the mean vector and the covariance matrix of the i-th Gaussian of the mixture.

2.2. Neural Gas Algorithm

The Neural Gas algorithm (Martinetz, Berkovich, & Schulten, 1993) is an iterative algorithm to train a network of nodes or prototypes for vector quantization (the process of approximating a large data set of multidimensional data by a reduced number of "prototype" vectors whose probability density closely resembles the probability density function (PDF) of the input data) (Ancona, Rovetta, & Zunino, 1997; De-Alarcon, Pascual-Montano, Gupta, & Carazo, 2002).

The neural gas network is specified by (Orts-Escolano et al., 2015):

- A set P of M prototypes. Each prototype $c \in P$ has a reference vector $w_c \in \mathbb{R}^d$ (position in the input space).
- A set of edges (connections) between pairs of prototypes. Its purpose is to define the topological structure of the network. Each edge has associated an aging scheme used to remove invalid connections due to the motion of the prototypes during the adaptation process.
- The network uses parameters that decay exponentially according to time and the Euclidean distance to the input data.

The sequence followed by neural gas is described in Algorithm (1) (Ancona et al., 1997; Peterson et al., 2009; Orts-Escolano et al., 2015).

2.3. Model evaluation

To evaluate the performance of the proposed risk model, the high-probability areas predicted by the model and the number of crimes that actually occur in those areas must be compared. The characterization of risk model performance at a time t_j is given by the curve that relates the High-Risk Percentage (HRP_θ) vs. True Incident Percentage (TIP_θ) (Wang & Brown, 2012) in which:

$$HRP_\theta = \frac{\left|\left|\left\{a_i|\mathbb{P}(inci_{a_i,t_j}=1)>\theta\right\}\right|\right|}{\left|\left|\left\{a_i\right\}\right|\right|} \tag{3}$$

$$TIP_\theta = \frac{\left|\left|\left\{inci_{a_i,t_j}=1|a_i\subset\left\{a_i|\mathbb{P}(inci_{a_i,t_j}=1)>\theta\right\}\right\}\right|\right|}{\left|\left|\left\{inci_{a_i,t_j}=1\right\}\right|\right|} \tag{4}$$

Algorithm 1: Neural Gas Algorithm

Input: d-dimension input samples x_i $(i = 1, 2, ..., n)$
M prototypes W $\{w_1, w_2, ..., w_M\}$
Output: Organized M-dimensional map

Specify the number of prototypes $P = \{c_1, c_2, ..., c_M\}$ with reference vectors $\{w_1, w_2, ..., w_M\}$ chosen randomly;
Initialize the connection set C, $C \subset P \times P$, to the empty set: $C = \emptyset$;
Initialize the time parameter t, $t = 0$;
Set I a fixed number of iterations;
for k=1:I **do**
    Input a sample vector x;
    Compute de distance $d_k = \|x - w_k\|$ for each prototype w_k;
    Sort the list of prototypes according to d_k;
    Compute the adaptation step Δw_k for each prototype w_k;
    Apply adaptations to each prototype;
end

where $||\cdot||$ is the cardinality of a set, $\theta \in [0, 1]$ is a threshold and $\mathbb{P}(inci_{a_i,t_j} = 1)$ is the probability that criminal incidents occur in an area subdivision a_i and a time window t_j. In this case, HRP represents the percentage of high-risk areas predicted by the model, whereas TIP represents the incidents from a test set that took place within the high-risk areas. Both measures are computed for different θ and plotted against each other obtaining a graphic similar to the receiver operating characteristic (ROC) curve (Fawcett, 2006). If many crime incidents take place in high-risk areas, a curve closer to the upper left corner is expected. In the opposite case, a curve similar to a linear relationship is expected.

To measure the model quality, we use the concept of Area Under the Curve (AUC). This area takes values between 0.5 and 1, corresponding to the worst and the best possible cases, respectively.

3. METHODOLOGY

In our previous work (Flores et al., 2015), a strategy for spatio-temporal modeling was proposed. This strategy is divided in two stages: Off-line and On-line (Figure 1). The Off-line stage computes an spatial distribution of criminal risk, where geo-referenced crime events are related with information of public services and GMMs are used to generate the spatial distribution. The on-line stage includes: 1) a strategy to model the temporal evolution of the previously computed spatial distribution, where samples are reallocated sequentially as soon as the notification of new criminal incidents are available. 2) A prediction strategy is presented to evaluate the risk level within a specific area and future time period.

The present work is focused only in the On-line stage where the temporal evolution and the prediction module are based on NG and GMMs. As input of the On-line stage, the spatial risk distribution (including Importance Sampling and Resamplig) is computed in the same way as our previous work (Flores et al., 2015).

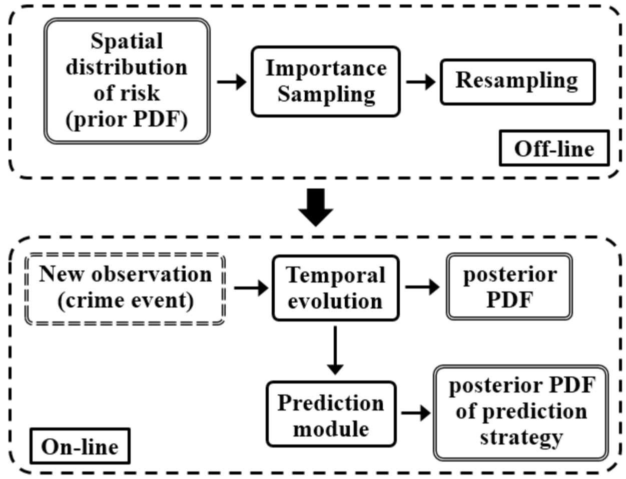

Figure 1. Flowchart of methodology for calculating the posterior PDF and predicted PDF.

3.1. Temporal Evolution (Posterior PDF)

During the On-line stage, a temporary evolution strategy based on NG defines the movement of the particles according to the inclusion of new observations (sequential incorporation of new geo-referenced criminal events). Therefore, every time in which a new criminal notification arrives, some particles will be attracted to the area where the event was reported.

With the purpose to link the resampling step (Off-line stage) with the NG algorithm in the temporal evolution step (On-line stage), the chosen prototypes (number of prototypes and reference vectors) for the initial steps in the NG algorithm (Algorithm (1)) must be the resultant particles of the resampling step. This is observed in Figure 2.A. Then, with the inclusion of new criminal events the position of the particles are updated according to NG algorithm (2.B). Once the temporal evolution is completed, a new GMM can be approximated to obtain a criminal risk spatial distribution. Therefore, each particle becomes to the centroid of a Gaussian bivariate distribution, and the variance corresponds a design parameter (2.C).

3.2. Prediction Module

In absence of new criminal data, our methodology proposes a strategy for prediction, which employs the same methodology based on NG for reallocating particles used in the temporal evolution step.

The prediction strategy assumes that there should not be ma-

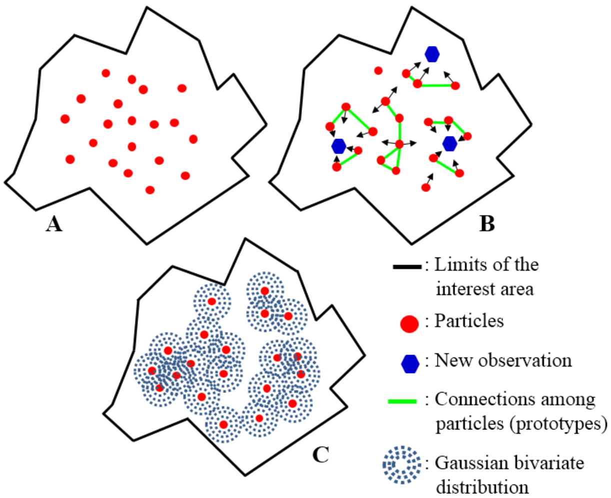

Figure 2. A) Particles after Importance Sampling and Resampling; B) Movement of particles based on NG and new observations; C) Gaussian bivariate distribution centered at each particle.

jor changes on the spatial position of the criminal activity in the short term (the crimes are distributed according to a stationary PDF). Hence, the historical data of recent criminal events is used to update the posterior risk PDF, as shown in Figure 3.A in color blue. The procedure then uses these events to generate a GMM representing the risk PDF associated with recent criminal activity, denoted by GMM_{pred}, as shown in Figure 3.B. Then, to propagate uncertainty throughout time, future crime events are simulated by sequentially drawing samples from
GMM_{pred} (coloured in black in Figure 3.C). Future temporal evolution is characterized by the movement of particles which are driven by these simulated events. This evolution is also based on NG, where the "initial state" of the prototypes network (number of prototypes, reference vectors, and connections among prototypes) is equal to the "final state" of the prototypes network of the temporal evolution of the posterior PDF. Once the prediction stage is finished, a Gaussian kernel is centered at each particle, in the same manner as when characterizing the posterior risk PDF, and a GMM is approximated to obtain a criminal risk spatial distribution (3.D).

4. RESULTS

The same database of our previous work (Flores et al., 2015) was used to test the proposed methodology (185 criminal events are used to test the updating stage, and 185 are used to validate the proposed risk prediction approach). In the same way, the results of the Off-line stage in (Flores et al., 2015) are used as an input to the On-line stage in the present work.

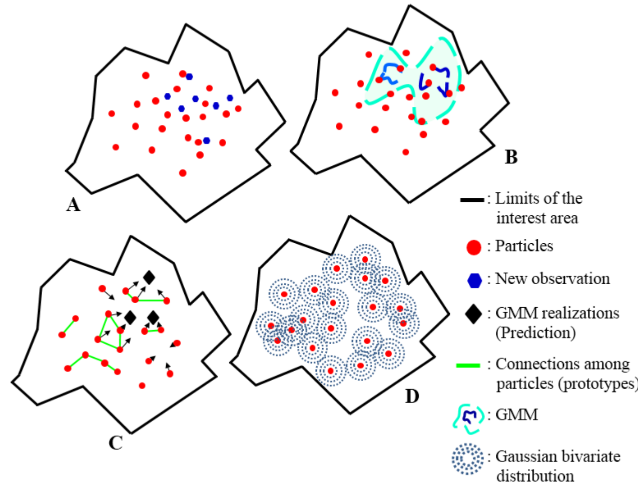

Figure 3. A) Recent criminal activity (used to compute the posterior; B) GMM using recent criminal activity; C) Movement of particles based on NG and simulated criminal events; D) Gaussian kernel centered at each particle.

4.1. Posterior Spatial Risk Probability Function

For the prior spatial risk distribution obtained in (Flores et al., 2015) (after importance sampling and resampling), 185 crime events are sequentially used to compute the posterior spatial risk probabilistic function (Figure 4).

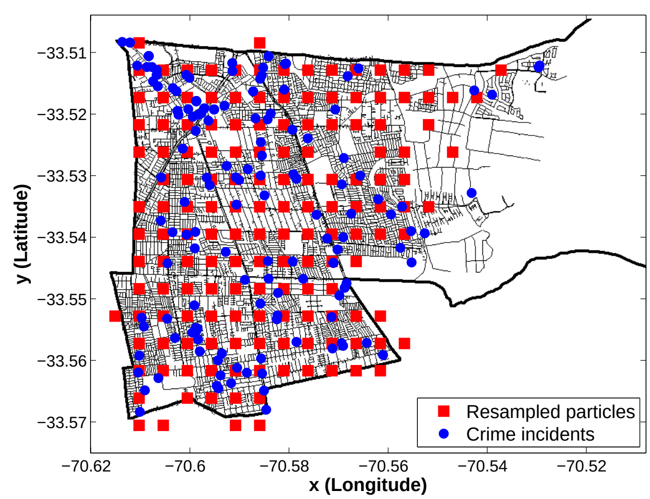

Figure 4. Grid and location of 368 particles associated with the prior spatial risk function. Blue dots indicate the location of 185 criminal events that are used to compute the posterior risk function.

The computation of the posterior risk distribution based on NG algorithm considered $I = 18$ (a 10% of the number of criminal events used to compute the posterior), updating the position of the particles according to the Figure 5. According NG Theory, the algorithm "moves" the network of particles in function of finding a representation of the PDF related to the input data.

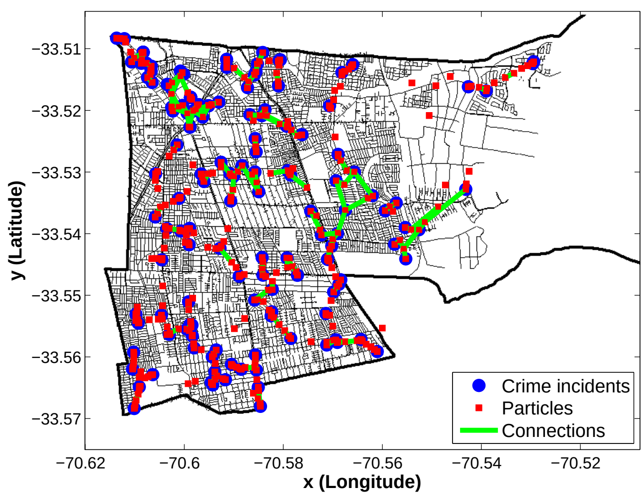

Figure 5. Neural gas network (particles) after sequentially incorporating 185 criminal events, and 18 iterations of the neural gas algorithm. In green is visualized the connections among particles.

After updating the position of the particles, the posterior PDF is built using a GMM, as explained in Section 3.1. Figure 6 shows the posterior spatial risk function built from the 368 particles and Gaussian kernels with a diagonal covariance matrix that characterizes a range of influence of three blocks.

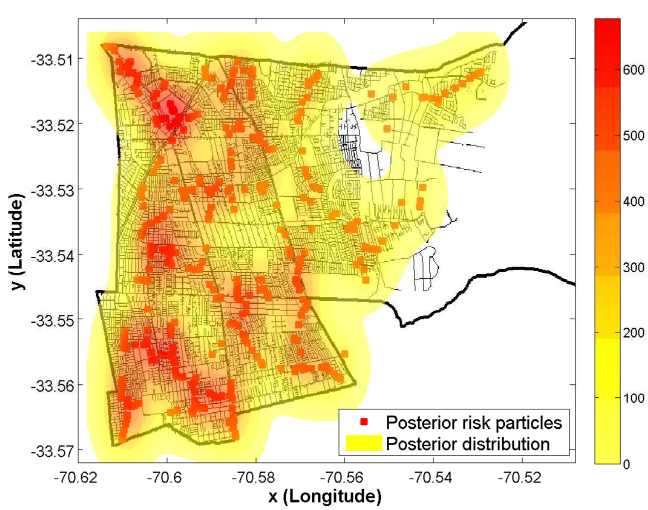

Figure 6. Posterior spatial risk function built from the 368 particles updated through NG algorithm, 185 criminal events, and GMMs.

To evaluate the performance of the posterior spatial risk model, HRP and TIP measures are calculated according to Eq. (3) and (4). In this regard, the AUC is computed assuming different influence ranges for particles (when building the GMM), diagonal covariance matrices, and different grid sizes (measured in blocks); see Table 1. The highest AUC is obtained for a resolution of 1 block, and an influence range of 3 blocks. Figure 7 shows the HRP vs. TIP curve with the best AUC = 0.957.

Table 1. AUC considering [3,7] (rows) for particle influence range and [1,10] (columns) for grid resolution in the posterior spatial risk model (in blocks).

	1	2	3	4	5	6	7	8	9	10
3	0.957	0.946	0.941	0.933	0.925	0.916	0.919	0.887	0.880	0.882
4	0.950	0.931	0.919	0.919	0.913	0.899	0.906	0.879	0.875	0.866
5	0.942	0.914	0.908	0.897	0.895	0.889	0.887	0.874	0.875	0.865
6	0.936	0.903	0.893	0.888	0.884	0.877	0.871	0.869	0.859	0.862
7	0.933	0.891	0.880	0.872	0.873	0.863	0.861	0.858	0.854	0.853

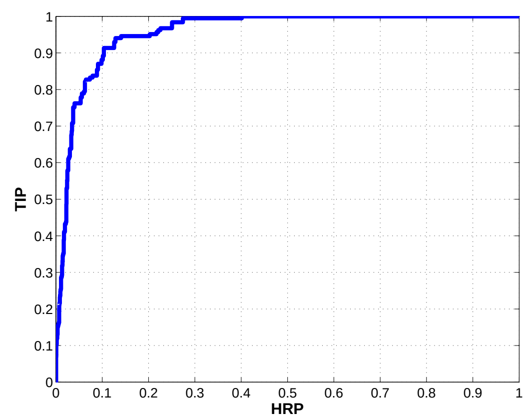

Figure 7. HRP vs. TIP curve, using influence range of 3 blocks and grid resolution = 1 block (AUC=0.957).

4.2. Predicted Spatial Risk Probability Function

Once the posterior spatial risk distribution is obtained, we proceed to generate the GMM Hot-Spot distribution related to recent criminal activity. After applying clustering analysis to recent criminal activity, and testing the number of clusters using the Silhouette algorithm, three clusters are found as the optimal choice for the centroids of the Hot-Spot GMM. From this Hot-Spot GMM, 185 samples are extracted to simulate future criminal activity; see Figure 8.

The inclusion of temporal information related to each simulated crime event is characterized by an exponential distribution with $\beta = 113.09$ [minutes], as it defined in (Flores et al., 2015). In this way, the simulated 185 future crime events define a prediction window of 2 weeks approximately.

The simulated events are used to modify the position of particles, according to NG algorithm as well. In consequence, the predicted spatial risk function is obtained (Figure 9).

The predictive capability of the predicted spatial risk model through the AUC measure, for different values of influence ranges and grid sizes is shown in Table 2. Where the highest

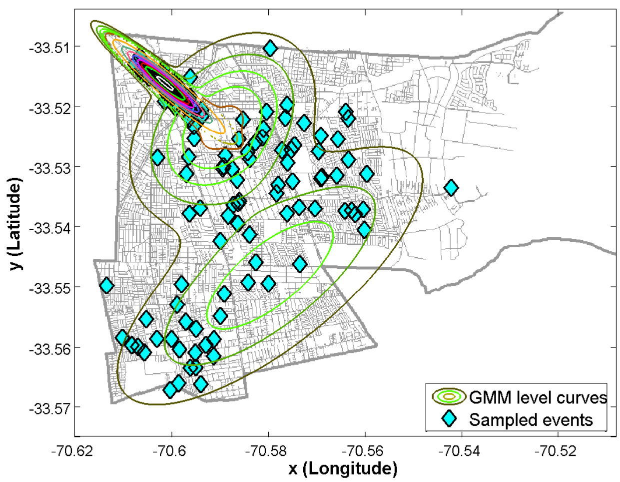

Figure 8. Hot-Spot GMM for recent criminal activity with 3 centroids, and 185 simulated events that are used for prediction purposes.

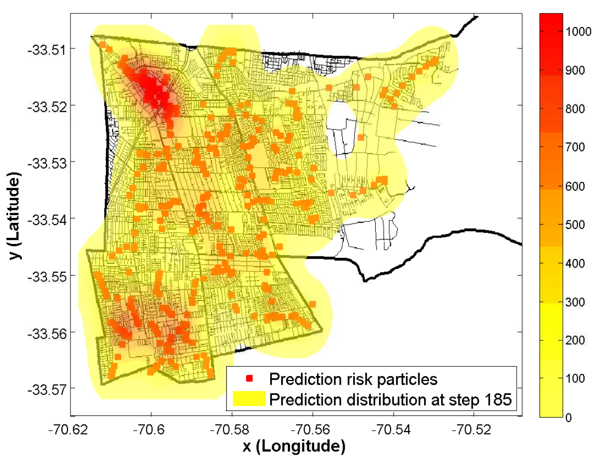

Figure 9. Predicted Spatial Risk Function (GMM after 185 prediction steps).

AUC is obtained for a resolution of 1 block, and an influence range of 3 blocks. Figure 10 shows the HRP vs. TIP curve with the best AUC = 0.946.

Table 2. AUC considering [3,7] for particle influence range and [1,10] for grid resolution in the prediction spatial risk model (in blocks).

	1	2	3	4	5	6	7	8	9	10
3	0.946	0.933	0.922	0.923	0.914	0.907	0.898	0.898	0.899	0.896
4	0.943	0.926	0.919	0.917	0.909	0.906	0.896	0.888	0.894	0.893
5	0.946	0.920	0.912	0.911	0.903	0.898	0.894	0.885	0.885	0.887
6	0.945	0.918	0.911	0.906	0.900	0.894	0.900	0.882	0.882	0.881
7	0.941	0.912	0.901	0.898	0.890	0.880	0.880	0.874	0.869	0.871

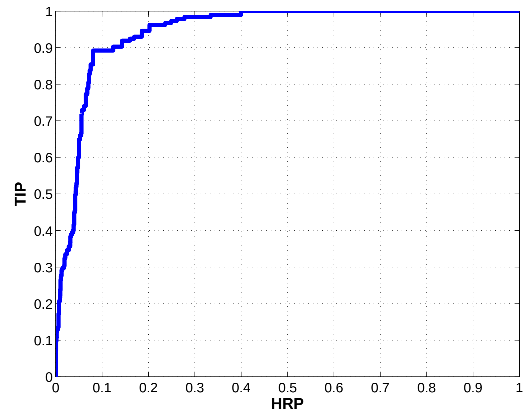

Figure 10. HRP vs. TIP curve, using influence range of 3 blocks and grid resolution = 1 block (AUC=0.946).

5. DISCUSSION

In our previous work (Flores et al., 2015), the best AUC obtained for the posterior spatial risk function was 0.934, and for the prediction spatial risk function was 0.932. For the present work, the calculated AUC were 0.957 and 0.946 respectively. Obtaining in this way, an increase in the AUC metric for both proposed spatial risk models.

The improvement obtained in the AUC metric, may be explained by the capability of the NG algorithm to resemble the probability density function of a determined multidimensional dataset. Hence, the method used to update the particles is different from the one proposed in the previous work. The previous method incorporates a dynamic model for the movement of the particles, which considers the distance among the particles to the new events, and a process noise for uncertainty characterization. This kind of model may have problems with large amount of criminal data events, because the process noise may position the particles outside the interest area. A example of this is shown in Figure 11, where some particles in the posterior spatial risk function calculated in (Flores et al., 2015) are outside of the interest area. On the other hand, Figure 6 shows the posterior spatial risk function calculated in the present work, where all the particles are contained inside the interest area. Both posterior risk functions were calculated using the same amount of particles and criminal events.

The parameters of the NG algorithm used in the present work were set with standard values. Therefore, a tuning of these parameters can be an interesting alternative to explore in a future work to obtain better results.

6. CONCLUSION

This article provides an update of the methodology presented in a previous work intended to characterize the evolution in time of a spatial criminal risk model within a specific area.

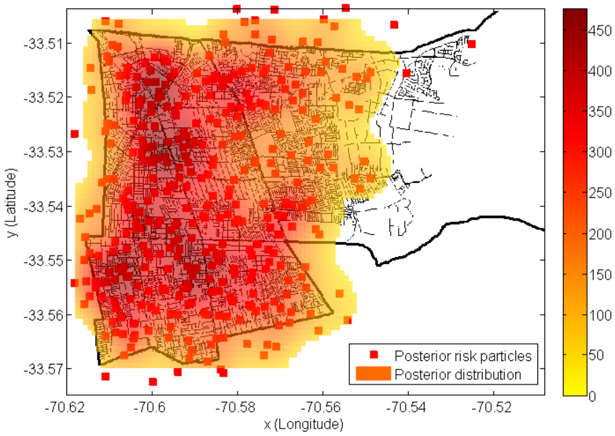

Figure 11. Posterior spatial risk function calculated in (Flores et al., 2015).

The evolution is represented by the movement of particles, which correspond to a discretized version of this criminal risk model. The main contribution of the present work is the characterization of the evolution in time of the spatial criminal risk model through the use of the NG algorithm.

The results of implementing this new strategy show an increase in the AUC from 0.934 (previous work) to 0.957 (current work) in the computation of the posterior spatial risk function. Furthermore, an increase in the AUC from 0.932 (previous work) to 0.946 (current work) in the computation of the predicted spatial risk function is also achieved. Two elements associated to NG implementation might be responsible for this improvement. The first is related to the characteristic of searching a representation for the underlying PDF of the analyzed dataset. The second is associated to the capacity of maintaining the particles inside the interest area after all the new criminal events were processed.

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