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SMART CITY DIGITAL TWINS FOR PUBLIC SAFETY: A DEEP LEARNING AND SIMULATION BASED METHOD FOR DYNAMIC SENSING AND DECISION-MAKING

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ABSTRACT

Technological innovations are expanding rapidly in the public safety sector providing opportunities for more targeted and comprehensive urban crime deterrence and detection. Yet, the spatial dispersion of crimes may vary over time. Therefore, it is unclear whether and how sensors can optimally impact crime rates. We developed a Smart City Digital Twin-based method to dynamically place license plate reader (LPR) sensors and improve their detection and deterrence performance. Utilizing continuously updated crime records, the convolutional long short-term memory algorithm predicted areas crimes were most likely to occur. Then, a Monte Carlo traffic simulation simulated suspect vehicle movements to determine the most likely routes to flee crime scenes. Dynamic LPR placement predictions were made weekly, capturing the spatiotemporal variation in crimes and enhancing LPR performance relative to static placement. We tested the proposed method in Warner Robins, GA, and results support the method's promise in detecting and deterring crime.

1 INTRODUCTION

In recent decades, with the rapid expansion of technological capabilities, public safety and law enforcement organizations (e.g., police departments) are striving to improve performance by adopting new technological innovations (Willis et al. 2018). Data-driven law enforcement is enabled by the availability of sensor technology and active or passive sensing and detection of crime patterns. Camden, New Jersey was touted as a large-scale test case of many crime sensing products including gunshot detection, body cameras, license plate detection, community alert systems, and other new tools (Frisby et al. 2019). One of the latest technologies gaining widespread adoption is license plate reader (LPR) technology. The LPR is a scanning and information technology to read vehicle license plates in real-time, check them instantaneously against databases, and give automatic alerts when the license plate number is linked to vehicles and persons of interest (e.g., stolen vehicles and vehicles linked to wanted persons) (Koper, and Lum 2019; Lum et al. 2011). In the U.S., the use of LPRs began in 2002 and spread rapidly over the past two decades. By 2016, about two-thirds of major police agencies with more than 100 officers had adopted this technology (Koper, and Lum 2019). Considering the U.S. is the largest passenger vehicle market in the world, with 1.88 vehicles per household, and the percentage of households without a car or light truck is only around nine percent (U.S. Department of Transportation 2017), a criminal case likely involves the presence of vehicles, and LPRs have the potential to help detect stolen vehicles or assist with specific investigations of crimes.

However, research in this area lacks conclusive or uncontroversial evidence to support the effectiveness of LPRs. Although the effectiveness of LPRs is enabled, in part, by police officers (Lum et al. 2019), it is not clear whether, where, and how LPRs can optimally impact crime detection, deterrence, and prevention. In particular, whether a fixed, a mobile, or a combined deployment of LPRs is the most effective approach to crime sensing. Willis et al. (2018) described that LPRs potentially could be used in versatile ways when mounted on cars and used for additional investigative purposes. Wheeler and Phillips (2018) performed an experiment and compared the number of crimes before and after LPR deployment in Buffalo, NY, and found a 20% reduction in traffic accidents. Koper, and Lum (2019) conducted an experiment in the City of Charlotte and conservatively support the effectiveness of LPR with large-scale deployment and better placement in raising auto theft case clearances and suggest that further assessment is needed. With a place-based block randomized experiment, Lum et al. (2011) concluded that the LPRs did not generate either a general or offense-specific crime deterrent effect. The authors of these studies suggest that a larger scale of LPR deployment and better methods of LPR placement are needed in response to the theoretical dilemma and its unclear implications for practices (Koper et al. 2019; Koper, and Lum 2019; Lum et al. 2011, 2019; Wheeler, and Phillips 2018). Given that 90% of all agencies with LPRs own less than 15 (Lum et al. 2019) while spatiotemporal patterns of crime are dynamic and dispersed, a more strategic placement of LPRs is critical to maximizing their detection and deterrence impact, more accurately evaluating the effectiveness of LPRs in crime reduction and control, and promoting the technological innovation adoption in public safety. In order to improve the impact of LPR deployments on crime rates, it is necessary to proactively sense and predict dynamic patterns of crime in space and over time. Dynamic modeling and prediction of crime patterns can enable prediction of next best placement location for crime sensors (e.g., LPRs), and allow for a dynamic loop of “data - modeling - prediction - action – updating.” This can maximize the performance of LPRs, as the spatiotemporal distribution of crimes is dynamic and uncertain over relatively short time frames (e.g., days and weeks) and requires continuous tracking and decision-making updates.

In this paper, we propose a Smart City Digital Twin (SCDT)-based method for dynamic placement of crime sensors (e.g., LPRs) to enhance crime detection and deterrence. SCDTs are data-informed digital representations of urban dynamics that are continuously enriched by spatiotemporal data stemming from human and infrastructure systems interactions (Mohammadi, and Taylor 2017). They are built for capturing the urban dynamics from multiple timescales from slow incremental changes to fast fluctuations and enabling proactive and dynamic decision-making for cities (Mohammadi, and Taylor 2021). SCDTs can enable crime prediction and what-if scenario analysis for dynamic decision-making and proactive crime control in cities. The crime data is collected continuously for training a deep learning-based crime prediction model. The model is used for predicting the locations of crimes in the next time frame. To determine the specific locations and directions of sensors (e.g., LPRs), a traffic simulation model is built to simulate the movements of suspect vehicles in the city. The proposed method is tested in the City of Warner Robins, GA. To the best of our knowledge, this study is the first attempt to integrate crime prediction and dynamic crime sensor placement. Our study is expected to enhance the detection and deterrence ability of crime sensors (i.e., LPRs in this study), by maximizing the likelihood of crime sensors being placed where there is a higher probability for crime to occur.

2 LITERATURE REVIEW

2.1 The Role of Crime Prediction and Dynamic Sensing in Crime Prevention

Many of the most effective crime prevention strategies involve ‘primary prevention’ (Waller 2019a), meaning that crime can be reduced by impacting communities before a crime occurs. However, many of the primary prevention strategies are not effective in short periods nor can they be enacted by police or 911 services. Other strategies involve ways to improve policing, such as situational crime prevention or diversion. Situational crime prevention involves “designing ways to make crime harder, riskier, or less attractive” and diversion involves “diverting people of elevated risk to treatment for mental health issues, to schools for life-training, and more, as in a hub" (Waller 2019b). To this end, Afzal, and Panagiotopoulos (2020) described in broad terms four main areas, which include crime construction, allocating police resources based on data-informed models of crime location; crime sensing, gathering information on ongoing criminal activity from the community remotely; automated surveillance, using installed sensors to identify crime in specific locations or online networks; and tension modeling, identifying the location of an escalating altercation.

License Plate Readers are widely used in crime sensing. LPRs could potentially be used in various ways when mounted on cars, set beside roads, moved regularly over hotspots, or used for investigative purposes. A mobile and obvious LPR implementation may fill a need in data-driven law enforcement that will allow for improved detection of crime through mobility and improved deterrence through the perceived presence of a guardian. Compared to other data-driven law enforcement approaches, crime prediction is an emerging technology and rapidly evolving. Its purpose is to anticipate when and where crimes will occur and to deploy police resources in advance. Due to its predictive capability, the technology can be used to dynamically place crime sensors in advance at crime locations.

2.2 Deep Learning based Crime Prediction

Instead of crime rate forecasting without spatial features or crime mapping without temporal features, in this study, crime prediction refers to the spatiotemporal prediction, which aims to forecast the specific locations or areas of crimes in specific time points or time windows. Many quantitative analysis approaches have been investigated in this direction, including autoregression (Yadav, and Kumari Sheoran 2018), support vector machine (Shamsuddin et al. 2017), deep learning, and others. Among these methods, deep learning has shown excellent predictive power and has received growing attention.

In studies of deep learning based crime prediction, many features have been explored, including holiday, weather, crime type, point of interest, housing price, street images, etc. (Huang et al. 2018; Kang, and Kang 2017; Wang et al. 2019). The location and time of historical crime records are the most frequently used features. Researchers have used different geographical and temporal intervals to group the crime records before using them as training data. For example, Zhuang et al. (2017) used a 138*164 grid to group the crime points in Portland, OR by every two weeks. Duan et al. (2017) discretized New York City using a 120*100 grid and grouped the crime records in the city by cells and days, and further added the spatial neighborhood of each cell as a feature. The resampled data is used for the deep learning model training and testing. Most of the studies are based on the Recurrent Neural Network (RNN), the Long-Short Term Memory (LSTM) model, or improved models built on these two (Esquivel et al. 2020; Hu et al. 2021; Wang et al. 2019; Wang, and Yuan 2019; Zhuang et al. 2017), as RNN or LSTM are the most fundamental time-series prediction models with a strong ability in modeling temporal patterns. For instance, Esquivel et al. (2020) used LSTM to predict if there will be robbery or larceny in an 8*8 grid representing Baltimore. To enhance the ability of the model in modeling the spatial patterns of crimes, they added a convolutional layer to the LSTM and form a Convolutional LSTM (ConvLSTM) model. Hu et al. (2021) proposed a new architecture for crime prediction, called DuroNet, to reduce the effect of data noise in prediction, and the spatial-temporal convolution network is built on the combination of the convolutional layer and LSTM. Dependent on the differences in resampling, model structure, and evaluation metrics, prior deep learning crime predictions have accuracies between around 50% and 90%, which provides a satisfying foundation for applying the crime prediction to crime sensor placement. Generally speaking, prior research on deep learning based crime prediction, especially the LSTM-based models, has provided a good foundation for us to integrate crime prediction with LPR placement.

2.3 Dynamic Sensing and Placement of Crime Sensors

The number of crime sensor placement studies (i.e., LPR camera systems in this study) is limited to addressing the set covering problem in the literature. Most of the relevant studies attempt to enhance the coverage of multiple cameras in a small area (e.g., parks, intersections, communities), considering camera specifications, such as visual distance, visual angle, and resolution (Conci, and Lizzi 2009; Jun et al. 2017; Kim et al. 2008). Yabuta, and Kitazawa (2008) modeled the visible area of public video surveillance cameras and maximized the coverage of multiple cameras in a 20m*15m area. Different from the typical set covering problem studies, Kweon, and Lee (2016) integrated the space syntax method to assign weights to the road network nodes that should be covered by the cameras, and implemented the proposed method in an area of several blocks beside an elementary school. Very few studies are about city-wide dynamic placement of camera sensors. Koper et al. (2019) mounted LPR camera systems on police patrol cars and compared two strategies for moving the sensors: the first strategy emphasized longer periods of surveillance at a small number of high-risk road segments, and the second strategy is based on larger hot spot areas and more frequent movement among the high-risk road segments. Lewenhagen et al. (2021) developed a web-based prototype and visualized the points of crimes by type in Malmö, Sweden, and suggest that future studies could integrate machine learning algorithms to help determine the placements of surveillance cameras.

The shortcoming of prior studies is that they ignore that urban crime is constantly changing spatiotemporally, especially over a short time frame (e.g., weeks), and do not make full use of the flexibility of crime sensors placement and crime prediction to capture this dynamic change, in order to enhance the performance of crime prevention and detection. If the spatiotemporal distribution of crimes can be “traced” in advance, crime sensors (i.e., the LPR in this study) placement would have greater potential to further enhance crime prevention and detection. Although, crime prediction research has a certain degree of practical, theoretical, and technical foundation, dynamic placement of crime sensors is a more complex task, which requires the capacity for dynamic-decision making and what-if scenario testing, currently missing in data-driven law enforcement research.

3 METHOD

In response to the gap in prior research, we established a system framework for the dynamic placement of crime sensors (e.g., LPRs). The system requires historical crime data in the city, which is used to train a deep learning model for crime prediction. The model predicts the locations of crime incidents in the next time frame (e.g., a week). A traffic flow model is built subsequently, assuming that the suspect will drive away, following a random route, from the locations where the predicted crime incidents occur. By using the Monte Carlo method, the probability of detecting a crime vehicle can be obtained for a single LPR placement (i.e., location and direction of the LPR). The placement of multiple LPRs can be derived based on the ranking of the probabilities. The crime records are updated continuously every time before predicting the crimes in the next time frame, to track the changes in crime patterns. The proposed framework is continuously enriched by the spatiotemporal data stemming from the interactions between human and road network, which constitutes a smart city digital twin for crime prediction and dynamic crime control decision-making in cities. Figure 1 shows the workflow of the proposed system.

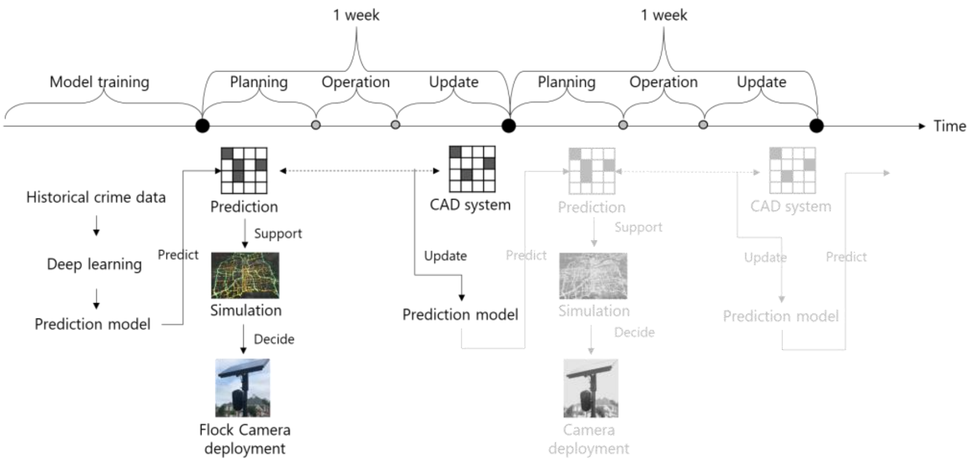


Figure 1: Workflow SCDT for dynamic sensing and placement of crime sensors.

3.1 Data Preprocessing and Convolutional LSTM-based Crime Prediction

The raw, anonymized, data of crime records (provided by the City of Warner Robins, GA Police Department), includes 22,436 Group-A crime (Bureau of Justice Statistics, n.d.) records from Jan. 1, 2019 to Apr. 4, 2022, after excluding records with missing information. Each record includes the geographical coordinates of the crime, the time of occurrence, and the type of the crime. Resampling was conducted to aggregate data spatiotemporally and lower the difficulty of prediction. The City of Warner Robins is then divided into many polygons. The major roads of Warner Robins are identified, according to the width of road segments in Google Map, and broken down into road segments between two intersections. The road segments are shown in Figure 2 as orange lines. We assume that the criminals would leave the scene of the crime on the nearest road segment and drive away. Therefore, the city can be divided into many Thiessen polygons close to each of the road segments (Brassel, and Reif 2010). Each Thiessen polygon contains all of the points whose closest road segment is the one in the center of this polygon. The Thiessen polygons are shown in Figure 2 as black lines. The set of Thiessen polygons is represented by $N = \{n_1, n_2, \dots, NN\}$.

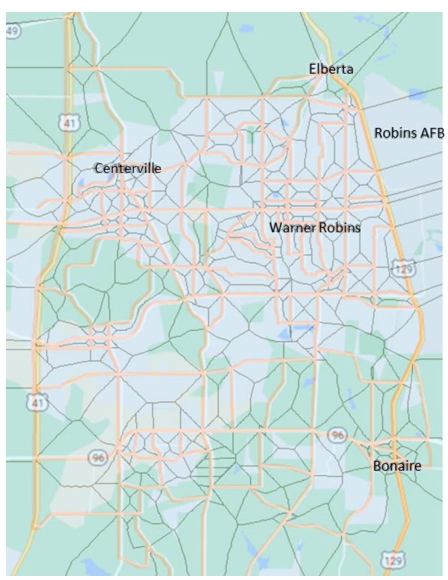


Figure 2: Polygon-based map of the City of Warner Robins (Orange lines: major roads in the city; black lines: borders of Thiessen polygons).

The duration of Q days is regarded as the time interval. The value of Q could be determined as appropriate, according to the frequency of training the model. The crime records are aggregated by N polygons and Q days. The time interval of the dataset and the value of Q will derive a dataset $M = \{m_1, m_2, \dots, NM\}$ in the temporal dimension. Take setting Q as seven as an example, the value of M would be 154 (i.e., 154 weeks). $x^{mn}(m \in M, n \in N)$ is used to represent the number of crimes in Polygon N and Week M. $x^{m}(m \in M)$ indicates the crime map consists of all the polygons in Week M.

The time window is represented by L, which is the number of "Q days" in each observation. In other words, each observation is represented by $X^m = (x^m, x^{m+1}, x^{m+2}, \dots, x^{m+L-1})$. The observations are used to predict the crime in the next Q day. Therefore, the label of the dataset could be represented by $Y^m = x^{m+L}$. The model will be trained using $\{X^m, Y^m\}$. The problem is that given the observation X^m, predict each $x^{(m+1)n}$ in Y^m that is 0 (i.e., no crime) or 1 (i.e., crime).

The preprocessed data is used for training a ConvLSTM model, which sequentially combines a convolutional neural network (CNN) and an LSTM model. CNN is a kind of neural network that uses convolution for matrix multiplication in at least one layer of the model. It is widely used for image recognition tasks and is very strong in modeling spatial patterns in the training data. Filters are applied in searching for local patterns of features. Each filter corresponds to a kernel that is represented by a matrix, which is consistent with the pattern that the filter is trying to detect (Esquivel et al. 2020). The kernels are used for "scanning" the input matrixes and generating convoluted matrixes of the same size. LSTM, which is adapted from RNN, is widely used in time-series prediction and is very strong in modeling temporal patterns of the features. ConvLSTM combines the strengths of CNN and LSTM in spatial and temporal modeling by passing the matrix processed by the CNN layer to the LSTM.

In this study, a ConvLSTM layer with 20 filters and a 3*3 kernel is built by using the ConvLSTM class in the Keras library (Chollet et al. 2015). The ConvLSTM layer is built on the vanilla LSTM layer. The LSTM layer uses memory cells and gates to control information flow to trap the gradient in the cell and prevents the gradient from vanishing too quickly. However, the LSTM layer unfolds the inputs and hidden states to 1-dimensional vectors and loses the spatial information. Instead, the ConvLSTM determines the future state of a certain cell by the inputs and past states of its local neighbors by using a convolution operator in the state-to-state and input-to-state transitions, which keeps the spatial information to a higher level. The ConvLSTM layer is followed by a batch normalization layer. A convolutional layer with ReLU activation function is attached as the last layer for output. The optimizer used in Adam, and the learning rate was set a 0.001.

3.2 Monte Carlo Simulation based Sensor Placement

Crime prediction can indicate the top locations where crimes are most likely to occur in the next week. Each location is a Thiessen polygon (as shown in Figure 2). LPRs can be placed on the road segments contained in these polygons. However, in many cities, license plates are mounted only on one side of vehicles, the LPRs thus can only capture traffic in one direction. The results in section 3.1 cannot determine which direction is the best to detect suspects' vehicles. In addition, the suspects' vehicles will move within the road network, which may result in some critical road sections or intersections with a higher probability of capturing suspect vehicles but out of the identified polygons in the crime prediction. Therefore, a traffic flow simulation is built to simulate vehicle movement and identify critical road segments.

The simulation is in the framework of Monte Carlo simulation, which executes the simulation a large number of times to obtain stable output metrics. In each run, the criminals are represented by "random walkers", and the random walker in each polygon that is predicted to have crimes will depart from the polygon, chooses a random direction at each intersection, and moves a certain number of steps within the city's road network. The trajectory of these random walkers is recorded, based on which the number of captured random walkers in both directions can be calculated for each road segment. The road segments and directions most likely to capture the suspect vehicles are recorded and the number and probability of capturing the random walker in both directions can be calculated. The road segments and directions most likely to capture the suspect vehicles are chosen for the LPR placement. Once a placement is identified, a new rule is added to each simulation run, that random walkers captured by this placement are removed from the simulation, and only the trajectories of random walkers that are not captured are used to calculate the most critical road segments and directions. As a result, according to the number of LPRs owned by the user, the Monte Carlo simulation can output the required number of road segments and directions that are most likely to detect the suspect vehicles as the LPR placement plan. The pseudo code of the Monte Carlo simulation is shown in the Table 1.

Table 1: Pseudo code of the Monte Carlo simulation.

```
1.  placement → [ ]
2.  for n in [1 to Pre-defined # of sensor]:
3.        for m in the Set of predicted crime locations:
4.              randomWalker_m move randomly in the road network
5.              if placement is not empty and randomWalkerm passes by sensor:
6.                    remove the trajectories of randomWalker_m
7.        record the [location, direction]_n of the alternative sensor placement
          with highest # of randomWalker detection
8.  return placement
```

4 SCDT-BASED CRIME PREDICTION AND DYNAMIC SENSOR PLACEMENT

The method proposed in Section 3 is implemented to determine the locations and directions of the LPRs in the City of Warner Robins, GA. The proposed method has two main parts: crime prediction and Monte Carlo simulation. In the crime prediction part, the ConvLSTM model is trained according to the description in Section 3.1. F1 index, which is the harmonic mean of the precision (i.e., the ratio of true positive results and positive results) and recall (i.e., the ratio of true positive results and all samples that should have been identified as positive), was selected for evaluating the prediction performance of the trained model. Figure 3a demonstrates the F1 score of the prediction over test weeks. The mean value of the F1 score is 0.64.

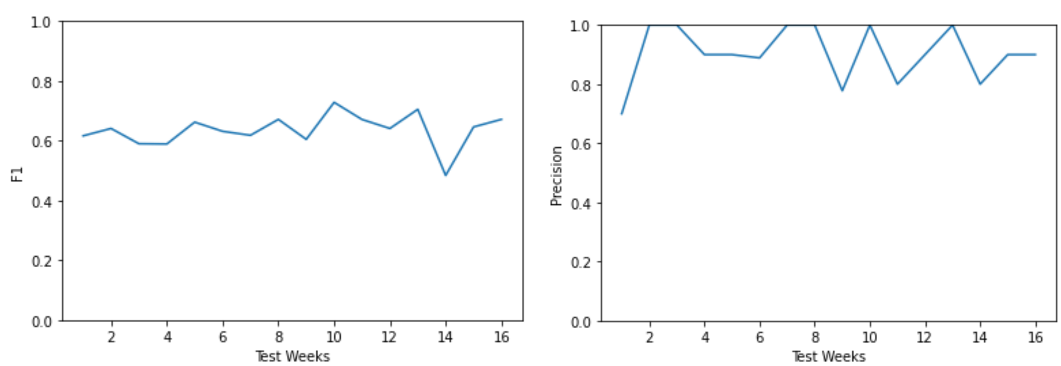
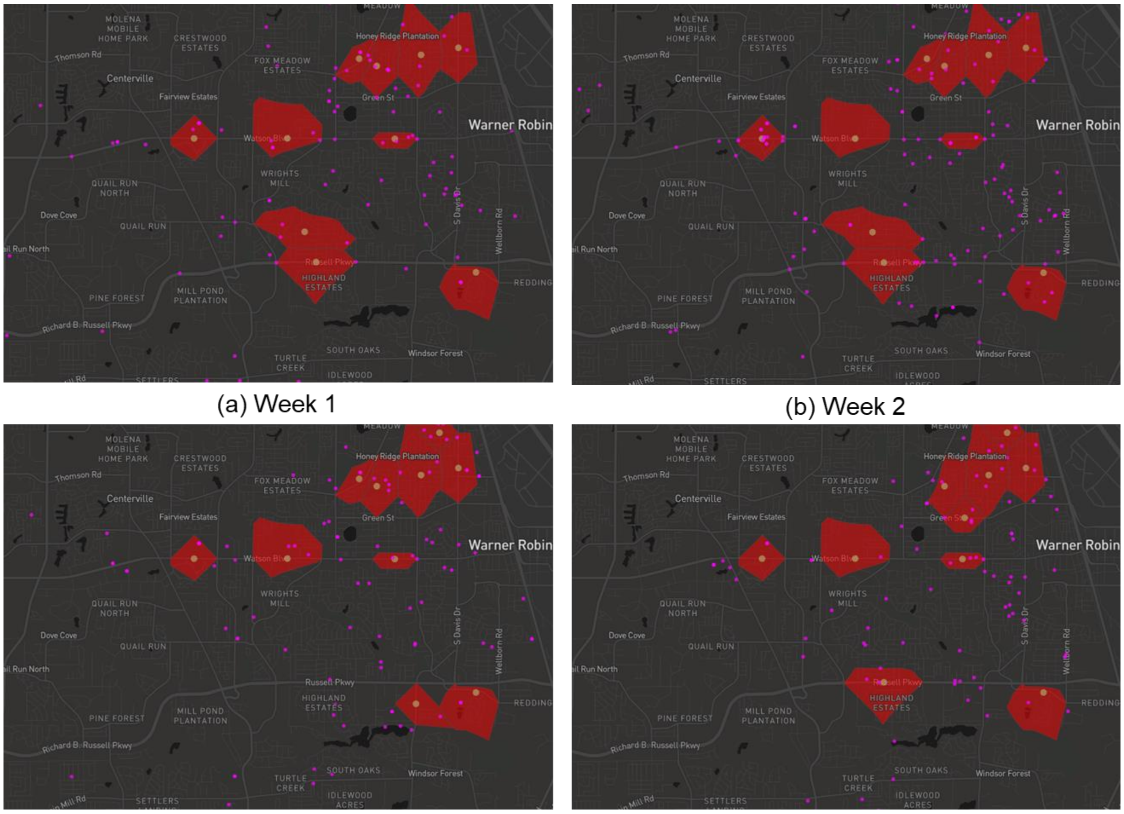


Figure 3: (a) F1 index of the prediction over test weeks and (b) the precision of the prediction over test weeks after decreasing the number of positive polygons.



(a) Week 1 (b) Week 2

(c) Week 3 (d) Week 4

Figure 4: Top 10 polygons that are likely to contain crimes over four randomly chosen weeks.

The number of polygons predicted to be crime-positive is reduced to obtain a certain number of polygons that are most likely to contain crimes. Figure 3b shows the precision (i.e., the ratio of true positive results and positive results) of the prediction over test weeks after decreasing the number of positive polygons. The average of the precision is 0.90. Figure 4 shows the top ten polygons most likely to contain crimes. The purple points are the real crime locations in the dataset. It can be seen from the figure that most of the predicted polygons contain crimes and generally follow the spatial distribution of the crimes. Furthermore, in the four weeks shown in Figure 4a-d, the predicted areas will change with the movement of crime spatial distribution and follow the movement well.

After crime prediction, LPRs can only be placed within the predicted polygons (the golden points in Figure 4), and it is difficult to determine the orientation of the LPRs. Therefore, the Monte Carlo model that was presented in Section 3.2 was implemented. Figure 5 shows the results of the simulation analysis based on the crime prediction in Figure 4d. The locations of most of the LPRs remain unchanged, but one LPR is placed in the upper right corner of the figure, outside of the polygon. The reason for moving the LPR out of polygons is that suspect vehicles departing from the polygons in the upper right corner of the figure have a high probability of converging on the new location, and thus the LPR placed at the new location will have a higher probability of detecting suspect vehicles. The simulation analysis can further help to determine the direction of LPRs. As shown in Figure 5b, each LPR will have a label that shows the direction of that LPR (e.g., east, south, and west). Two LPRs may be placed at the same location. In this case, the label of the LPRs at that location will show two directions (shown Figure 5b).

Figure 5: Top 10 LPR placements that are likely to capture suspect vehicles.

5 CONCLUSIONS

The study provides a novel method to enhance the detection and deterrence performance of crime sensors and takes the dynamic placement of LPRs as an example in this study. Based on the proposed Smart City Digital Twin-based approach, the ConvLSTM model was used to dynamically capture the spatiotemporal distribution of crimes in the city, and the Monte Carlo traffic simulation was used to dynamically find the best location and direction for placing LPRs, based on the results of crime prediction. Although the proposed method is promising in enhancing LPR performance, the study has some limitations.

First, a more systematic and comprehensive validation is needed to further support the validity of the proposed method. Second, generating polygons that discretize the city can further consider the side roads in the city, as vehicles may follow the side roads to more distant major roads rather than the closest major road. Third, traffic flow simulation can consider more specific behaviors of vehicles, such as leaving the city and turning restrictions. As a response, future studies could further map the density of crimes together with the polygons being predicted and check the consistency of both, or use agent-based simulation to test whether the placement from the proposed method could capture more suspect vehicles. Additionally, a more refined GIS analysis could be performed to attach the Thiessen polygons of the side roads to the corresponding main roads. Last but not least, more specific traffic behaviors should be analyzed to improve the fidelity of traffic simulation and the accuracy of LPR placement.

In conclusion, the method proposed in this study demonstrates that the SCDT-based sensor placement approach can capture the dynamic urban spatiotemporal patterns of crime to a higher degree and make sensor placement decisions continuously adapting to such variations. It provides a promising solution not only for LPR, but also for other types of crime sensors that may be deployed to improve the safety and resilience of communities.

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REFERENCES

Afzal, M., and Panagiotopoulos, P. 2020. "Smart policing: A critical review of the literature". In *International Conference on Electronic Government*, August 31th, Cham, 59–70.

Brassel, K. E., and Reif, D. 2010. "A Procedure to Generate Thiessen Polygons". *Geographical Analysis*, *11*(3), 289–303.

Bureau of Justice Statistics. n.d.. *Group "A" Offenses*. https://bjs.ojp.gov/sites/g/files/xyckuh236/files/media/document/offensea_offenseb.pdf .

Chollet, F., and others. 2015. *Keras*. https://keras.io, accessed 8th October 2022.

Conci, N., and Lizzi, L. 2009. "Camera placement using particle swarm optimization in visual surveillance applications". In *Proceedings of the International Conference on Image Processing, ICIP*, November 7th-10th, Cairo, Egypt, 3485–3488.

Duan, L., Hu, T., Cheng, E., Zhu, J., and Gao, C. 2017. "Deep Convolutional Neural Networks for Spatiotemporal Crime Prediction". In *Proceedings of the International Conference on Information and Knowledge Engineering (IKE)*, July 17th-20th, Las Vegas, Nevada, USA, 61–67.

Esquivel, N., Nicolis, O., Peralta, B., and Mateu, J. 2020. "Spatio-Temporal Prediction of Baltimore Crime Events Using CLSTM Neural Networks". *IEEE Access*, *8*, 209101–209112.

Hu, K., Li, L. I. N., Liu, J., and Sun, D. 2021. "DuroNet : A Dual-robust Enhanced Spatial-temporal Learning Network for Urban Crime Prediction". *ACM Trans. Internet Technol.*, *21*(1), 1–24.

Huang, C., Zhang, J., Zheng, Y., and Chawla, N. V. 2018. "DeepCrime: Attentive hierarchical recurrent networks for crime prediction". In *Proceedings of International Conference on Information and Knowledge Management*, October 22th-26th, Turin, Italy, 1423–1432.

Jun, S., Chang, T. W., Jeong, H., and Lee, S. 2017. "Camera Placement in Smart Cities for Maximizing Weighted Coverage with Budget Limit". *IEEE Sensors Journal*, *17*(23), 7694–7703.

Kang, H. W., and Kang, H. B. 2017. "Prediction of crime occurrence from multimodal data using deep learning". *PLoS ONE*, *12*(4), 1–19.

Kim, K., Murray, A. T., and Xiao, N. 2008. "A multiobjective evolutionary algorithm for surveillanace sensor placement". *Environment and Planning B: Planning and Design*, *35*(5), 935–948.

Koper, C. S., and Lum, C. 2019. "The Impacts of Large-Scale License Plate Reader Deployment on Criminal Investigations". *Police Quarterly*, *22*(3), 305–329.

Koper, C. S., Taylor, B. G., and Park, S. 2019. "Optimizing the geographic deployment of hot spot patrols with license plate readers". *Journal of Experimental Criminology*, *15*(4), 641–650.

Kweon, J., and Lee, K. H. 2016. "Proposed placement model for public CCTV systems in student safety zones considering surveillance probability on pedestrian streets". *Journal of Asian Architecture and Building Engineering*, *15*(2), 231–238.

Lewenhagen, K., Boldt, M., Borg, A., Gerell, M., and Dahlen, J. 2021. "An Interdisciplinary Web-based Framework for Data-driven Placement Analysis of CCTV Cameras". In *Proceedings of the 2021 Swedish Workshop on Data Science, SweDS 2021*, December 2nd-3rd, Online, 0–5.

Lum, C., Hibdon, J., Cave, B., Koper, C. S., and Merola, L. 2011. "License plate reader (LPR) police patrols in crime hot spots: an experimental evaluation in two adjacent jurisdictions". *Journal of Experimental Criminology*, *7*(4), 321–345.

Lum, C., Koper, C. S., Willis, J., Happeny, S., Vovak, H., and Nichols, J. 2019. "The rapid diffusion of license plate readers in US law enforcement agencies". *Policing*, *42*(3), 376–393.

Mohammadi, N., and Taylor, J. E. 2017. "Smart City Digital Twins". In *2017 IEEE Symposium Series on Computational Intelligence*, November 27th to December 1st, Honolulu, Hawaii, USA, 1-5.

Mohammadi, N., and Taylor, J. E. 2021. "Thinking fast and slow in disaster decision-making with Smart City Digital Twins". *Nature Computational Science*, *1*(12), 771–773.

Shamsuddin, N. H. M., Ali, N. A., and Alwee, R. 2017. "An overview on crime prediction methods". In *2017 6th ICT International Student Project Conference (ICT-ISPC)*, May 23rd-24th, Johor, Malaysia, 1–5.

Waller, I. 2019a. "Introduction". In *The Science and Secrets of Ending Violent Crime*. Rowman, and Littlefield.

Waller, I. 2019b. "Smarter Use of Police and Prisons". In *The Science and Secrets of Ending Violent Crime*. Rowman & Littlefield.

Wang, B., Yin, P., Bertozzi, A. L., Brantingham, P. J., Osher, S. J., and Xin, J. 2019. "Deep Learning for Real-Time Crime Forecasting and Its Ternarization". *Chinese Annals of Mathematics. Series B*, *40*(6), 949–966.

Wang, S., and Yuan, K. 2019. "Spatiotemporal Analysis and Prediction of Crime Events in Atlanta Using Deep Learning". In *2019 IEEE 4th International Conference on Image, Vision and Computing, ICIVC 2019*, July, 5th-7th, Xiamen, China, 346–350.

Wheeler, A. P., and Phillips, S. W. 2018. "A quasi-experimental evaluation using roadblocks and automatic license plate readers to reduce crime in Buffalo, NY". *Security Journal*, *31*(1), 190–207.

Willis, J. J., Koper, C., and Lum, C. 2018. "The Adaptation of License-plate Readers for Investigative Purposes: Police Technology and Innovation Re-invention". *Justice Quarterly*, *35*(4), 614–638.

Yabuta, K., and Kitazawa, H. 2008. "Optimum camera placement considering camera specification for security monitoring". In *Proceedings of IEEE International Symposium on Circuits and Systems*, May 18th-21th, Seattle, WA, USA, 2114–2117.

Yadav, R., and Kumari Sheoran, S. 2018. "Crime Prediction Using Auto Regression Techniques for Time Series Data". In *2018 3rd International Conference and Workshops on Recent Advances and Innovations in Engineering (ICRAIE)*, November 22nd-25th, Jaipur, India, 1–5.

Zhuang, Y., Almeida, M., Morabito, M., and Ding, W. 2017. "Crime Hot Spot Forecasting: A Recurrent Model with Spatial and Temporal Information". In *2017 IEEE International Conference on Big Knowledge (ICBK)*, August 9th-10th, Hefei, Chian, 143–150.

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