A new approach for pedestrian density estimation using moving sensors and computer vision

Sensing the city

ERIC K. TOKUDA*, University of São Paulo, Brazil
YITZCHAK LOCKERMAN*, New York University, USA
GABRIEL B. A. FERREIRA, University of São Paulo, Brazil
ETHAN SORRELGREEN, Carmera, USA
DAVID BOYLE, Carmera, USA
ROBERTO M. CESAR-JR., University of São Paulo, Brazil
CLAUDIO T. SILVA, New York University, USA

An understanding of pedestrians dynamics is indispensable for numerous urban applications including the design of transportation networks and planning for business development. Pedestrian counting often requires utilizing manual or technical means to count individual pedestrians in each location of interest. However, such methods do not scale to the size of a city and a new approach to fill this gap is here proposed. In this project, we used a large dense dataset of images of New York City along with deep learning and computer vision techniques to construct a spatio-temporal map of relative pedestrian density. Due to the limitations of state of the art computer vision methods, such automatic detection of pedestrians is inherently subject to errors. We model these errors as a probabilistic process, for which we provide theoretical analysis and through numerical simulations. We demonstrate that, within our assumptions, our methodology can supply a reasonable estimate of pedestrian densities and provide theoretical bounds for the resulting error.

Additional Key Words and Phrases: Computer vision, Objects detection, Urban Computing, Simulation, Agent-based modelling

1 INTRODUCTION

Pedestrians are an integral and pervasive aspect of the urban environment. Real estate, consumer patterns, public safety, and other aspects of city life are deeply intertwined with the variations of pedestrian densities across a city. However, current methods for estimating the distribution of people within a city tend to be expensive and mostly produce a sparse sampling of a few locations.

In this paper, we examine a new method to obtain a dense estimate of pedestrian density. We utilize recent advances in computer vision to find people within a previously intractable large collections of images to compile a relative density map.

In order to take into account the errors inherent to visual objects detection, we model it as a probabilistic detection. Using our model, we provide a closed form and bounds for the asymptotic error of the sampling process. We compare these formulas to numerical simulations of the sensing process. Our results suggests that computer vision produces usable data, despite the inherent noise.

To test our method, we utilized over 40 million street-level images provided by Carmera. The images provided by Carmera were a portion of the images obtained via their partnerships with high coverage fleets operating daily on city
Fig. 1. Examples of the images utilized for pedestrian detection. Each of these pictures were automatically captured by vehicles. More then 10 million such images were used for pedestrian detection in Manhattan. Faces and other details have been concealed to protect privacy.

streets that traveled through the region of Manhattan Island in New York City over the course of a year. A sample of this data was used to benchmark several state-of-the-art computer vision algorithm. We then utilized the top performing algorithm in a case study to map pedestrian densities in Manhattan.

The contributions of this paper can be summarized as

1. A new method for the analysis of the spatial variation of urban pedestrians densities utilising state of the art, but imperfect, computer vision algorithms.
2. A closed form function and bounds for the asymptotic error of the resulting pedestrian densities.
3. The results of simulations validating the sampling process and the derived asymptotic error.
4. A benchmark of several of detection algorithms, along with the variation in their parameters, for the purpose of pedestrian detection.
5. A case study demonstrating the resulting densities for a collection of images from the City of New York.

2 RELATED WORK

There are many ongoing efforts on the use of urban data to achieve citizen-centered improvements [68]. Governments and organizations in urban environments collect a vast amount of data daily [61] encompassing a large assortment of information including mobility, crime and pollution. The collection and use of this information has been attracting attention from the academics, governments and corporations [62]. The work [3] explores the correlation of visual appearance of pictures and the attributes of the region it pertains. They collected images from [16] and also indicators from multiple regions and trained a model [6] to predict the indicator based on images. The city attributes include violent crime rates, theft rates, housing prices, population density and trees presence. Results show that the visual
A new approach for pedestrian density estimation using moving sensors and computer vision

Data can be efficiently used to predict the region attributes. Additionally, the regressor trained in one region showed reasonable results when tested in a different city.

A pedestrians map of the city has numerous applications for urban planners including the design of public transport network and of public spaces [66]. One approach to obtain a citywide count of pedestrians is to have people scattered around the city manually counting the pedestrians nearby. This approach though is laborious because it requires dedicated people to perform the measures. Another possibility explored in [50] is to use cellphone use data to perform the pedestrian count. One clear limitation of this approach is that these data are not public and their coverage are restricted to the places where the carrier signal is present. Additionally, it is hard to know wether the cell signal is from a pedestrian or from someone in a building or from someone in a car.

Alternatively, we can consider the visual task of finding the pedestrians in city images. A remarkable work in this task consists in using the histogram of oriented gradients as the features vector and a support vector machines for the classification task [11]. In the context of deep neural networks [30, 55], the work of [51] introduced an approach that tries to solve this task by using a unified network that performs region proposal and classification. In this way, the method accepts annotations of multiple sized objects during the training step and during the testing stage, it performs classification of those objects in images of arbitrary sizes. In [10] the authors follow the two-stage region proposal and classification framework of [51] and proposes the Region-based Fully Convolutional Networks (R-FCN) which incorporate the idea of position-sensitive score maps to reduce the computational burden by sharing the per-RoI computation. Such speed alterations allow the incorporation of classification backbones such as [19].

There are several city images repositories that contemplate pedestrians, some of them obtained using static cameras [44, 59, 63] and others obtained using dynamic ones [9, 15, 39]. Such configuration of sensors arrangement have long been studied in the sensor network field [1, 2, 46] and an important aspect of these networks is whether the sensors are static or mobile. In [65] the authors explore the setting of a network composed of both static sensors and of mobile sensors. The holes in the coverage of the static sensors network are identified and the mobile sensors are used to cover the holes. A common problem in sensor networks is the k-coverage problem defined in [22], that aims to find the optimal setting of sensors such that any region is covered at least by k sensors. In [67] the authors perform the task of counting people based on images obtained through a wireless network of static sensors.

Apart from controllable mobile sensors network, many works explore data collected from collaborative uncontrolled sensors [4] such as from vehicles GPS [25, 53], mobile phones sensors [31, 49, 52] and even from on-body sensors [8].

The work of [36] considers the problem of using GPS data from a network of uncontrolled sensors to reconstruct the traffic in a city. They do that in two steps: initial traffic reconstruction and dynamic data completion. Such approach allowed the authors to get a complete traffic map and a 2D visualization of the traffic.

There are many ways to model the movement of mobile nodes in a sensor network, the so-called mobility models [7]. A simple one is the random walk mobility model [12] where at each instant in time each particles gets a direction and a speed to move. In the random waypoint mobility model [24], in turn, particles are given destinies and speeds. They travel toward their goal and once they get the destination a new goal and speed are given. The Gauss-Markov mobility model [37] attempts to eliminate abrupt stops and sharp turns present in the random waypoint mobility model. It is done by computing the current position based on the previous position, speed and direction.

Simulation of wireless sensor networks has long been studied [34, 42, 64] because it allows a complete analysis of system architectures by providing a controlled environment for the system [38]. The real-life systems non-determinism is simulated by the use of pseudo random number generators [28]. Among the large number of pseudo random number generators [47], a popular algorithm is the Mersenne Twister [40] due to its efficiency and robustness.
Fig. 2. An hypothetical illustration of the type of detection errors considered in this paper. The person on the left was not identified by the detector and is a false-negative. The rightmost detection is a false-positive. The two correct detections in the center are true-positives. Notably missing are true-negatives which are not a useful concept in this situation due to the overwhelming number. Faces and other details have been blurred to protect privacy.

3 PEDESTRIANS AND SENSORS FLOW MODEL

As current pedestrian detection algorithms are far from perfect, it is natural to wonder about the accuracy of any pedestrian count resulting from their use. In this section we provide a theoretical analysis of the effect of algorithmic errors on the final count.

In our model, we assume that the world is modeled by a number of small regions, or buckets, each of which we intend to measure a density. Sensors and people move around a world in some random fashion. At regular intervals, each sensor takes an independent measurement of the nearby pedestrian count and updates the recorded density at its current location, $x$. More formally, each time a sensor takes a sample, it obtains a measurement represented by the random variable $N(x)$. While we don’t specify the distribution of $N(x)$, we assume that the expected value follows the formula

$$E[N_i(x)] = p n_i(x) + \lambda$$  \hspace{1cm} (1)

Here $n_i(x)$ is the actual number of people in the location and time being sensed, $p$ is a number giving the success rate of the vision algorithm and $\lambda$ indicating its false positive rate.

The result of this process is the density of people at each location, $\psi(x)$,

$$\psi(x) = \frac{1}{k} \sum_{i} N_i(x)$$  \hspace{1cm} (2)

For comparison, the ground truth density $\phi(x)$, defined respectively by (where $k$ is the number of steps and samples),

$$\phi(x) = \frac{1}{k} \sum_{i} n_i(x)$$  \hspace{1cm} (3)

We show in Appendix B, Equation 16 that the expected value of $\psi(x)$ is
In other words, $\psi(x)$ is a biased estimator of $\phi(x)$. Unless the our sensing algorithm precisely follows Equation 4, we are unable to transform this biased estimator into an unbiased one. Furthermore, even in the ideal case, $p$ and $\lambda$ may not be known. Instead, we directly utilize $\psi(x)$ and attempt to find a relative histogram. That is, we expect to get a number proportional to the density of the number of people at a location and not the actual density. As such, for any constant $a$, our density is equivalent to one scaled to $\psi' = a\psi$. Treating the distribution as a vector, we measure the direction but not the magnitude. In the terminology of group theory, our measurement suggests a density within the equivalent class:

$$\psi = \{ a \in \mathbb{R}_+ \mid a\psi \}$$

To validate our measurement we need a metric that indicates how well the equivalent class compares to the ground truth distribution $\phi(x)$. To do that, we compare the ground truth to the unique closest element within the equivalent class. As a vector projection, this minimum element is (see Appendix A for a proof):

$$\psi' = \begin{cases} \frac{\psi < \psi, \phi >}{|\psi|^2} |\psi| \neq 0 \\ 0 \quad |\psi| = 0 \end{cases}$$

which we can then compare using the usual euclidean metric $|\psi' - \phi|$. However, this metric depends on the number of locations in the map, as well as the number of people. As such, we normalize the metric to between 0 and 1, to obtain a final metric:

$$\frac{|\psi' - \phi|}{|\psi'| + |\phi|}$$

In Appendix B we show that we expect that over long periods of time we expect the asymptotic error to approach Equation 24:

$$\lim_{k \to \infty} \frac{|\psi' - \phi|}{|\psi'| + |\phi|} = \frac{\lambda}{h} \sqrt{\frac{c^2}{2} \left( p + \frac{1}{h} \right) + \left( pc^2 + \frac{1}{h} \right)^2 - 2 \left( p + \frac{1}{h} \right) \left( pc^2 + \frac{1}{h} \right) \left( pc^2 + \frac{1}{h} \right)}$$

Here $h > 0$ is the average density of people and $c \geq 1$ describes the distribution of $\phi$. However, $c$ can best be thought of as parameters that describe the asymptotic error. Both of these parameters depend on the resolution of the heat map in addition to pedestrian distribution. In many cases $c$ can not be determined, as such we can use the inequality in Equation 26 of Appendix B:

$$\lim_{k \to \infty} \frac{|\psi' - \phi|}{|\psi'| + |\phi|} \leq \frac{\sqrt{c^2 - 1} \lambda}{2c^2 h p} \leq \frac{\lambda}{4 h p}$$

It is important to note that $h$ needs to be the ground truth density of people, in the same units of $\phi$. If only the sampled average density, $\hat{h}$, is known, the unbiased estimator of $h$, $\frac{h - \lambda}{p}$, can be used. This leads to the bounds

$$\frac{1}{4 h p} \leq \frac{1}{4 \hat{h} - \lambda}$$
This final formula is only dependent on the false positive rate of the sensing algorithm and the average density of sensed objects measured by process, making it suitable for practical sensing applications. We wish to emphasize that this inequality is true whenever Equation 4 holds regardless of the underlying probability distribution. This function is only useful when $\lambda \leq \bar{h}$. In that domain, it is a monotonically increasing function of $\lambda$. Thus, if $\lambda$ is not precisely known, it is best to err on the side of larger values.

3.1 Simulation

The real-life acquisition process lacks some of the simplifications we used in our model. For example, samples taken in spatial and temporal proximity are correlated. To examine the performance of the sensing systems in the face of these non-ideal circumstances, we created a discrete event simulation \cite{32} to compare sensed distributions to a known ground truth.

As illustrated in Figure 3, we simulated a number of mobile sensors that detect nearby particles. Each sensor has a circular coverage of radius $r$. Collision among particles and sensors are ignored for simplicity. Sensors and particles move with uniform speeds $v_{\text{sensor}}$ and $v_{\text{particle}}$ respectively. The simulation world is mapped as a graph, as in \cite{57}. Each node in the graph is a traversable point by both sensors and particles and edges represent a path between the end nodes.

We assume that, in each time step, sensor has an independent chance, $p$, of detecting each of the $n(x)$ persons within range along with an independent chance per location to obtain a false positive. These assumptions lead to $N(x)$ being sampled from the sum of a binomial distribution with mean $p$ and a Poisson process with a given expected number $\lambda$. A calculation of the expected value indicates that Equation 1 is satisfied and that our theoretical error calculations and bounds should be valid.
A new approach for pedestrian density estimation using moving sensors and computer vision

Algorithm 1: Mobility model of sensors and particles of the simulation.

Initialization(map, currentposition, destination);

while indefinitely do

if destination = ∅ then

    destination ← random(map)
    path ← A*(currentposition, destination, map)

else

    currentposition ← pop(path);

end

end

Table 1. Parameters of the simulation along with the values we used in the experiments.

| Parameter                          | Symbol | Values          |
|------------------------------------|--------|-----------------|
| Number of people                   | N_{people} | 50000          |
| Person speed                       | v_{person} | 1              |
| Sensor speed                       | v_{sensor} | 3              |
| Number of sensors                  | N_{sensors} | 10000         |
| Sensor true positive rate          | p      | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0 |
| Sensor exp. number of false positives | λ     | 0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.1, 1.2 |
| Sensor range                       | r      | 1              |

The system state can be described by various state variables: sensors and particles positions, sensors and particles waypoints, real density of particles and sensed density of particles. Sensors and particles move with a variation of the random waypoint model [24], differing to it by the fact that sensors and particles are not allowed to change speeds; they have fixed speed given by the system parameters $v_{sensor}$ and $v_{particle}$. When a new destination is randomly picked, the trajectory on the map graph is computed using the $A^*$ algorithm [18] and the points of the trajectory are pushed to a heap (please refer to Algorithm 1).

As time progresses we obtain a 2D histogram for the sensed density as well as the ground truth density of particles. We are primarily interested in the difference between them, as given by the metric in Equation 7.

The source code of this implementation is publicly provided.

3.2 Simulation results

We evaluated different true positive rates and expected number of false positives of the sensors, $p$ and $\lambda$ and we used a Mersenne Twister pseudo number generator [40].

The various values for the parameters used in our experiments are listed in Table 1. For the 143 possibilities combination of values, we ran the simulation for 20,000 time steps 20 independent times.

The code is primarily implemented in Python with performance-sensitive sections implemented in Cython [5]. The average time to run a single experiment of this optimized code is of 11,718 seconds. A single processing and single machine processing would take roughly 1 year to run all the experiments but running them in parallel, it took 11 days.

For each experiment we examine the decay of the metric given by Equation 7 as a function of the cumulative number of samples captured by all the sensors. We assume the error continues to decay until it reaches an asymptotic
minimum error within the 20,000 simulation time steps. Afterwords, we take the average decay curve of all 20 runs for each settings configuration and take the average of the last 200 values to find the asymptotic value.

We can visualize the results from the simulations in Figure 4 which shows how the variation of true positive rate and false positive rate affect our histogram error. If we take a horizontal profile of say 0.2 of true positive rate we can see how the errors are greatly affected by the variation of the expected number of false positives, varying from very low to high error values (represented by the variation on the color saturation). We compare these values to our theoretical formulas (see Equation 8), and show they are approximately equal. Finally, We show that they are within the bound given by Equation 9.

4 COMPUTER VISION SENSING

Carmera uses a fleet of camera equipped cars (such as in [33]) traveling through Manhattan to acquire a temporally and spatially dense collection of pictures. The orientation of the cameras varies and the nature of the images are similar to street level collections provided by many mapping services. However, the images are not stitched into a 360 degree panorama. Every image is accompanied by metadata including the acquisition time, location, and camera orientation. The images are captured as the vehicle travels, with no control of the content, the illumination, the weather, the traffic conditions, or vehicular speed. The typical image depicts a urban scenario as a background and the city dynamics including pedestrians, vehicles and bicycles such as in Figure 1. Our dataset differ from several existing publication [9, 15, 39, 44, 59, 63] by providing dense temporal coverage in addition to dense spatial coverage.

All images included in the sample have a resolution of 1280 x 960. We used a sample of images captured from March 2016 to February 2017 containing 10,708,953 images. This sample presents a dense spatial sampling of the whole region over a year, but irregular spatio-temporal sampling on a daily basis (see Figure 5). All resulting heatmaps are weighted sampling according to this distribution.

We evaluated how three computer vision algorithms for pedestrian detection perform on our dataset. The first one is based on histogram of oriented gradients features [11]. The second one is based on the extraction of features by
A new approach for pedestrian density estimation using moving sensors and computer vision

Fig. 5. Distribution of pictures by day of the week and by hour of the day. Our resulting pedestrian density is approximately a sum of the time varying densities weighted by this distribution.

Fig. 6. Variation of the ground truth annotations for different minimal person size thresholds. When the threshold is small (left) all people in the images are annotated. As the threshold increases (middle and right) the number of annotated people decreases. Those remaining tend to be closer to the camera. Faces and other details have been blurred to protect privacy.

means of convolutional neural networks [51]. The third utilizes fully convolutional networks for accuracy and speed improvements [10].

We manually tagged 600 images to use as a ground truth. We adopt the same metric as Everingham et al. [13] when comparing the detected objects in an image to the ground-truth. A detected object is considered to correspond to a particular ground truth objects if their is a minimum ratio of 50% between the overlap of the detected bounding boxes $B_{detected}$ ground-truth bounding boxes $B_{truth}$, and the union of the two areas (see Equation 11).

$$\frac{|B_{detected} \cap B_{truth}|}{|B_{detected} \cup B_{truth}|} \geq 0.5$$  (11)

The recognition of distant objects in an image is difficult for humans and is even more difficult for computers. We assume that, on average, the size of a person within an image is an indicator of the distance that person to the sensor and try improve accuracy by considering a minimal size of the people detected. Thus, bounding boxes smaller than a new hyperparameter threshold are ignored, as shown in Figure 6.
As discussed below, we decided to utilize R-FCN, which we ran over our entire data set in parallel and created a database with the number of pedestrians detected in each image. This database is then aggregated in space and time to create a visualization of the pedestrian counts by finding the average number of pedestrians per image in each region.

4.1 Survey of Algorithms

We used a total of 10,708,953 images, covering the region of Manhattan, Monday to Friday from 7am to 6pm. We evaluated three methods for the task of people detection [10, 11, 51] over a sample of our dataset. We used the Matlab [56] implementation of [11], with an 8 × 8 stride of the detection window, 1.05 for the pyramid scaling factor and model trained on the 96 × 48 resolution images from the INRIA pedestrian dataset [11]. The detection thresholds ranged from 0.0 to 0.1, spaced by 0.01. The implementation of [51] is published by the authors and the model we used is a VGG16 network [54] trained with Pascal VOC 2007 dataset [13] with a non-maximum suppression [26] threshold of 0.3. We evaluated the method with scores ranging from 0.0 to 1.0, spaced by 0.1. The R-FCN algorithm [10] was also trained on the Pascal VOC 2007 dataset but with the 101-layers neural network architecture proposed by [19]. Here again, we evaluated the method with detection scores ranging from 0.0 to 1.0, spaced by 0.1.

Figure 7 shows the results of the evaluation of the three methods over a random sample of 600 images of our dataset. The images were manually annotated and precision and recall values were computed. Ground-truth pedestrians in this comparison included tiny pedestrians, which explains such low values for recall. We can see that the overall accuracy of R-FCN was the best in our experiments. The detection times for each image are on average 5.7s for [11], 3.9s for [51] and 4.1s for [10].

None of methods in Figure 7 achieve recalls exceeding 80% and this fact is inherent to the difficulty of object detectors in detecting small objects as discussed in Section 4. To mitigate such issue, the detection model we propose assumes a finite radius of coverage (see Figure 3) and thus, we establish a limit on the size of the objects detected in the image.

Figure 8 shows the results of the adopted detector over our sample as we vary the minimum acceptable height. As we can see, the higher the ground-truth height threshold, the higher the precision and specially the recall of the method.
A new approach for pedestrian density estimation using moving sensors and computer vision

Fig. 8. Evaluation of R-FCN [10] for different ground-truth height thresholds. The utilized model has a Resnet-101 backbone [19] trained on the Pascal VOC 2007 dataset [13].

Fig. 9. A comparison of the ground truth pedestrian count and the measured pedestrian count from the 600 tagged test images. While the actual true positive and false positive counts do not match the expected statistics (left), the total measured pedestrian count can be close to approximated as linear (right). It should be noted that this is only an approximation as, even taking sampling errors into account, the mean measured count do not fit a linear model. Error bars are the 95% confidence interval of the mean, calculated by assuming the sampling process described in Section 3.

4.2 Case Study

Based on the results of Section 4.1 we adopted a R-FCN using a residual network of 101 layers [19] trained on Pascal VOC 2007 [13], as proposed by [10]. The model was trained using a weight decay of 0.0005 and a momentum of 0.9. Assuming a method minimum score of 0.7 and height threshold of 120 pixels, overall 7,474,623 pedestrians were detected.

We compared the number of measured pedestrian count as a function of the average number of ground truth pedestrians in each of the 600 manually labeled images to test the linear assumption used in Equation 4. Error bars for the mean were computed using the 5% to 95% values of the median of the appropriate sample process given in section 3. We measured the true positive rate (p) to be 0.54 and the average number of false positives (λ) to be of 0.117.

As shown in Figure 8, the actual number of true positive and false positives do not individually fit the linear and content assumptions that we proposed in Section 3. However, the total number of pedestrians detected is closer to being linear, despite statically significant deviations. These stem from the visions algorithm’s better than expected performance for images without any pedestrians and worse than expected performance for images with a single person.
While we do not know how these deviations would effect the error bounds given in Equations 9 and 10, we hypothesize that the two deviations would cancel themselves out and bound may still approximately hold with a slightly larger equivalent $\lambda$.

A visualization of the density of pedestrians in entire Manhattan can be seen in Figure 10. For these maps, we obtained an average pedestrian density ($\hat{h}$) to be 0.587 which, following Equation 9, takes us to an error of 0.062. The actual error may be larger due to the deviations from linearity discussed above.
Pedestrian distributions, like ours, can be useful for city planning, commercial, and other purposes. Depending on the task on hand, a large pedestrian density can be beneficial or detrimental. Taxis seeking riders, food trucks seeking customers, and businesses seeking storefronts all benefit from large crowds. However, traffic and self-driving cars do not. A knowledge of pedestrian densities can allow city planners, civil engineers, and traffic engineers to make better decisions.

Our pedestrian map can also show the effect that features of the city have on its people. As shown in Figure 11, in addition to populated neighborhoods, subway stations, and attractions like the Metropolitan Museum of Art are all associated with a spike in the pedestrian densities. These spikes might be too localized to be detected using traditional methods. Further studies of vision-based pedestrian counts may lead to a better understanding of the interplay between a city's environment and its occupants' walking habits.

5 CONCLUSION

In this project we used a large set of images from a region of Manhattan and automatically detected the number of pedestrians in each image. As a result we obtained a map of pedestrians in the region given by the spatio-temporal sampling. Additionally, we modeled the errors in this process by simulating a sensors network with probabilistic
Eric K. Tokuda, Yitzchak Lockerman, Gabriel B. A. Ferreira, Ethan Sorrelgreen, David Boyle, Roberto M. Cesar-Jr., and Claudio T. Silva
detections. Results give evidence that even considering a faulty detection model, such process can still be used to get a reliable map of pedestrians in the region.

Besides the results presented, there are other potential future avenues of studies as discussed next. First, we should caution that any application of our methodology should perform statistical tests to ensure that their results are statistically significant. While we set bounds on the asymptotic error after the sampling process converges, we have only provided case studies and heuristics for the time to convergence. It would be interesting to find a formal bound on time to convergence as well as provide guidelines for the appropriate statistical tests to validate the data post collection.

Our experiments could be extended to consider alternative mobility models [7], dynamics models including macroscopic ones [20, 21, 23], and more recent detection methods [17, 38] and the combination of them [60]. We can also use data completion algorithms [14, 35, 36] to reconstruct a city-wide pedestrian map.

The pedestrian map generated will then be able to be combined with other urban datasets such from Socrata [43], weather, crime rate, census data, public transportation, bicycles and shadows [41]. We additionally aim to explore apparently disparate datasets such as from wind and from garbage collection.

Another future work is incorporation of advances such as from [48] to visualize our images in the context of the the city and use this visualization to gain additional insights into the other datasets analyzed in Urbane. As a first pass, we are working to render the photographs in the locations they were captured. We hope to use Structure from Motion [29] to improve the accuracy of image location as well as find the orientation that the images were captured.

Additionally, we hope to use 3D popups and/or photo based rendering to fully enhance the images in the three dimensional environments. It is our hope that the context of the images will allow users to better understand the different datasets that analyzed in Urbane.

ACKNOWLEDGEMENTS

We thank Carmera for their collaboration. We also thank Harish Doraiswamy, Fabio Miranda, Alexandru Telea for providing insights, comments, and suggestions that greatly contributed to this work. This work was supported in part by: NSF awards CNS-1229185, CCF-1533564, CNS-1544753, CNS-1730396, CNS-1828576; FAPESP (grants #14/24918-0 and #2015/22308-2); the Moore-Sloan Data Science Environment at NYU, and C2SMART. C. T. Silva is partially supported by the DARPA D3M program. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of DARPA.

REFERENCES

[1] Ian F Akyildiz, Tommaso Melodia, and Kaushik R Chowdhury. 2007. A survey on wireless multimedia sensor networks. Computer networks 51, 4 (2007), 921–960.
[2] Ian F Akyildiz, Weilian Su, Yogesh Sankarasubramaniam, and Erdal Cayirci. 2002. A survey on sensor networks. IEEE Communications magazine 40, 8 (2002), 102–114.
[3] Sean M Arietta, Alexei A Efros, Ravi Ramamoorthi, and Maneesh Agrawala. 2014. City forensics: Using visual elements to predict non-visual city attributes. IEEE transactions on visualization and computer graphics 20, 12 (2014), 2624–2633.
[4] Stefano Basagni, Alessio Carosi, and Chiara Petrioli. 2007. Controlled vs. uncontrolled mobility in wireless sensor networks: Some performance insights. In Vehicular Technology Conference, 2007. VTC-2007 Fall. 2007 IEEE 66th. IEEE, IEEE, Maryland, USA, 269–273.
[5] S. Behnel, R. Bradshaw, C. Citro, L. Dalcin, D.S. Seljebotn, and K. Smith. 2011. Cython: The Best of Both Worlds. Computing in Science Engineering 13, 2 (2011), 31 –39. https://doi.org/10.1109/MCSE.2010.118
[6] Christopher JC Burges. 1998. A tutorial on support vector machines for pattern recognition. Data mining and knowledge discovery 2, 2 (1998), 121–167.
[7] Tracy Camp, Jeff Boleng, and Vanessa Davies. 2002. A survey of mobility models for ad hoc network research. Wireless communications and mobile computing 2, 5 (2002), 483–502.
A new approach for pedestrian density estimation using moving sensors and computer vision

[8] Sunny Consolvo, David W. McDonald, Tammy Tosco, Mike Y Chen, Jon Froehlich, Beverly Harrison, Predrag Klasnjica, Anthony LaMarca, Louis LeGrand, Ryan Libby, et al. 2008. Activity sensing in the wild: a field trial of ubit garden. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, ACM, Florence,Italy, 1797–1806.

[9] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. 2016. The cityscapes dataset for semantic urban scene understanding. In Proceedings of the IEEE conference on computer vision and pattern recognition. IEEE, Nevada, USA, 3213–3223.

[10] Jifeng Dai, Yi Li, Kaiming He, and Jian Sun. 2016. R-FCN: Object Detection via Region-based Fully Convolutional Networks. arXiv preprint arXiv:1605.06409 (2016).

[11] Navneet Dalal and Bill Triggs. 2005. Histograms of oriented gradients for human detection. In Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on, Vol. 1. IEEE, IEEE, California, USA, 886–893.

[12] Vanessa Ann Davies et al. 2000. Evaluating mobility models within an ad hoc network. Master’s thesis. Citeseer.

[13] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. 2010. The pascal visual object classes (voc) challenge. International journal of computer vision 88, 2 (2010), 303–338.

[14] Silvia Gandy, Benjamin Recht, and Isao Yamada. 2011. Tensor completion and low-n-rank tensor recovery via convex optimization. Inverse Problems 27, 2 (2011), 025010.

[15] Andreas Geiger, Philip Lenz, Christoph Stiller, and Raquel Urtasun. 2013. Vision meets Robotics: The KITTI Dataset. International Journal of Robotics Research (IJRR) (2013).

[16] Google Inc. Last accessed March 2017. (https://maps.google.com). (Last accessed March 2017).

[17] Jan Hajic jr, Matthias Dorfer, Gerhard Widmer, and Pavel Pecina. 2018. Towards Full-Pipeline Handwritten OMR with Musical Symbol Detection by U-Nets. In Proceedings of the 19th International Society for Music Information Retrieval Conference, Paris, France. 23–27.

[18] Peter E Hart, Nils J Nilsson, and Bertram Raphael. 1968. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics 4, 2 (1968), 100–107.

[19] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep Residual Learning for Image Recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition.

[20] Dirk Helbing. 1998. A fluid dynamic model for the movement of pedestrians. arXiv preprint cond-mat/9805213 (1998).

[21] Dirk Helbing. 2001. Traffic and related self-driven many-particle systems. Reviews of modern physics 73, 4 (2001), 1067.

[22] Chi-Fu Huang and Yu-Chee Tseng. 2005. The coverage problem in a wireless sensor network. Mobile Networks and Applications 10, 4 (2005), 519–528.

[23] Tomoharu Iwata, Hitoshi Shimizu, Futoshi Naya, and Naonori Ueda. 2017. Estimating People Flow from Spatiotemporal Population Data via Collective Graphical Mixture Models. ACM Transactions on Spatial Algorithms and Systems (TSAS) 3, 1 (2017), 2.

[24] David B Johnson and David A Maltz. 1996. Dynamic source routing in ad hoc wireless networks. Mobile computing 353, 1 (1996), 153–181.

[25] Sophia Karagiorgou, Dieter Pfoser, and Dimitrios Skoutas. 2017. A layered approach for more robust generation of road network maps from vehicle tracking data. ACM Transactions on Spatial Algorithms and Systems (TSAS) 3, 1 (2017), 3.

[26] Les Kitchen and Azriel Rosenfeld. 1982. Gray-level corner detection. Pattern recognition letters 1, 2 (1982), 95–102.

[27] Leonard Kleinrock. 1976. Queueing systems, volume 2: Computer applications. Vol. 66. Wiley New York.

[28] Donald Ervin Knuth. 1997. The art of computer programming. Vol. 3. Pearson Education.

[29] Jan J Koenderink and Andrea J Van Doorn. 1991. Affine structure from motion. Inverse Problems 8, 2 (1991), 377–385.

[30] Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. 2012. Imagenet classification with deep convolutional neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition.

[31] Nicholas D Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T Campbell. 2010. A survey of mobile phone sensing. ACM Transactions on Spatial Algorithms and Systems (TSAS) 3, 1 (2017), 3.

[32] Averill M Law, W David Kelton, and W David Kelton. 2007. Simulation modeling and analysis. Nevada, USA, 3213–3223.

[33] Victor Lesser, Charles L Ortiz Jr, and Milind Tambe. 2012. Distributed sensor networks: A multiagent perspective. Vol. 9. Springer Science & Business Media.

[34] Li Li, Yuebao Li, and Zhiheng Li. 2013. Efficient missing data imputing for traffic flow by considering temporal and spatial dependence. Transportation research part C: emerging technologies 34 (2013), 108–120.

[35] Weizi Li, David Wolinski, and Ming C Lin. 2017. City-scale traffic animation using statistical learning and metamodel-based optimization. ACM Transactions on Graphics (TOG) 36, 6 (2017), 200.

[36] Ben Liang and Zygmunt J Haas. 1999. Predictive distance-based mobility management for PCS networks. In INFOCOM’99. Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, Vol. 3. IEEE, IEEE, New York, USA, 1377–1384.

[37] Tsung-Yi Lin, Priyal Goyal, Ross Girshick, Kaiming He, and Pieter Dollár. 2018. Focal loss for dense object detection. IEEE transactions on pattern analysis and machine intelligence (2018).

[38] Will Maddern, Geoffrey Pascoe, Chris Linegar, and Paul Newman. 2017. 1 year, 1000 km: The Oxford RobotCar dataset. The International Journal of Robotics Research 36, 1 (2017), 3–15.
Eric K. Tokuda, Yitzchak Lockerman, Gabriel B. A. Ferreira, Ethan Sorrelgreen, David Boyle, Roberto M. Cesar-Jr., and Claudio T. Silva

[40] Makoto Matsumoto and Takuji Nishimura. 1998. Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator. ACM Transactions on Modeling and Computer Simulation (TOMACS) 8, 1 (1998), 3–30.

[41] Fabio Miranda, Harish Doraiswamy, Marcos Lage, Luc Wilson, Mondrian Hsieh, and Claudio T Silva. 2018. Shadow Accrual Maps: Efficient Accumulation of City-Scale Shadows over Time. IEEE Transactions on Visualization and Computer Graphics (2018).

[42] Muaz A Niazi and Amir Hussain. 2011. A novel agent-based simulation framework for sensing in complex adaptive environments. IEEE Sensors Journal 11, 2 (2011), 404–412.

[43] NYC open data. Last accessed March 2017. (https://opendata.cityofnewyork.us/). (Last accessed March 2017).

[44] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster R-CNN: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems. 91–99.

[45] OpenStreetMap. 2017. Planet dump retrieved from https://planet.osm.org. https://www.openstreetmap.org. (2017).

[46] Fabio Miranda, Harish Doraiswamy, Marcos Lage, Luc Wilson, Mondrian Hsieh, and Claudio T Silva. 2018. Shadow Accrual Maps: Efficient Accumulation of City-Scale Shadows over Time. IEEE Transactions on Visualization and Computer Graphics (2018).

[47] Stephen K. Park and Keith W. Miller. 1988. Random number generators: good ones are hard to find. Commun. ACM 31, 10 (1988), 1192–1201.

[48] Photosynth. Last accessed March 2017. (https://blogs.microsoft.com/photosynth/2017/02/06/microsoft-photosynth-has-been-shut-down/). (Last accessed March 2017).

[49] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

[50] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[51] Stephen K. Park and Keith W. Miller. 1988. Random number generators: good ones are hard to find. Commun. ACM 31, 10 (1988), 1192–1201.

[52] Photosynth. Last accessed March 2017. (https://blogs.microsoft.com/photosynth/2017/02/06/microsoft-photosynth-has-been-shut-down/). (Last accessed March 2017).

[53] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[54] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

[55] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[56] The MathWorks, Inc. 2017. Matlab version 2017b. (2017).

[57] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[58] Ben L Titzer, Daniel K Lee, and Jens Palsberg. 2005. Avrora: Scalable sensor network simulation with precise timing. In IPSN 2005. Fourth International Symposium on Information Processing in Sensor Networks. ACM, 105–116.

[59] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[60] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[61] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[62] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.

[63] Jing Tian, Jorg Lahner, Christian Becker, Illya Stepianov, and Kurt Rothermel. 2002. Graph-based mobility model for mobile ad hoc network simulation. In Simulation Symposium. 2002. Proceedings. 35th Annual IEEE, IEEE, California, USA, 337–344.
A new approach for pedestrian density estimation using moving sensors and computer vision

A PROOF OF METRIC FORMULA

Here we derive the formula for the closest point in our class and the ground truth vector. This is equivalent to solving:

$$\min_a |a\psi - \phi|^2$$

(12)

First we expand the distance metric using the euclidean inner-product:

$$|a\psi - \phi|^2 = <a\psi - \phi, a\psi - \phi>$$

(13)

which is minimized by

$$a = \frac{<\psi, \phi>}{|\psi|^2}$$

(14)

when $|\psi|^2 \neq 0$. For $|\psi|^2 = 0$, then $\psi = 0$ and

$$\min_a |a\psi - \phi|^2 = |\phi|^2$$

(15)

regardless the value of $a$.

Substituting this value into $a$, we obtain our equation above:

$$\psi' = \begin{cases} 
\frac{<\psi, \phi>}{|\psi|^2} & |\phi| \neq 0 \\
0 & |\phi| = 0 
\end{cases}$$

When $<\psi, \phi> = 0$ then $\psi' = 0$ and we get the same value. Note that we are assuming that $\phi$ is never zero.

B THEORETICAL ASYMPTOTIC ERROR

In this paper we will derive the equation for sensor error that we give in Equation 8. The error bounds only assume that $E[\psi(x)] = p\phi(x) + \lambda$ for some values of $p$ and $\lambda$. First, we will show that, for the simulation, the values of $p$ and $\lambda$ agree with the parameters of the same name.

As noted in Equation 2, the sampling process for the simulation results in the following sampled values for each location:

$$\psi(x) = \frac{1}{k} \sum (T(n(x)) + F)$$

where $T(n(x))$ is a sampled from a binomial distribution with mean $n(x)$ and $F$ is a Poisson process with a mean of $\lambda$.

At the same time, the ground truth distribution of people at each location is given by Equation 3

$$\phi(x) = \frac{1}{s} \sum n(x)$$

In this appendix we will make the simplifying assumption that $s = k$

The executed value of the sampled can then be found by (noting that the random variables are all independent)
$$E[\psi(x)] = \frac{1}{s} \sum (E[T(n(x))] + E[F])$$

$$= \frac{1}{s} \sum (pn(x) + \lambda)$$

$$= \sum_{x} (pn(x) + \lambda)$$

$$= \sum_{x} (\psi(x) + \lambda)$$

(16)

From this point on, all results will only depend on the equations $E[\psi(x)] = p\psi(x) + \lambda$ and not the underlying sampling process.

Let $m$ be the total number of people and $r$ be the sampling location. In a real world scenario, $m$ may not be well defined. As such, we will work in terms of $h = \frac{m}{r}$, the density of people.

By the law of large numbers, in the limit of $s \to \infty$, $\psi$ approaches $\psi(x) \to E[\psi(x)] = \phi(x)p + \lambda$.

Using this limit, we can find the asymptotic value of $\psi'$, as defined by Equation 6, can be found:

$$\psi' = \psi <\psi,\phi> / |\psi|^2$$

$$\to (p\phi + \lambda) <p\phi + \lambda,\phi> / |p\phi + \lambda|^2$$

$$= (p\phi + \lambda) p |\phi|^2 + \lambda \langle 1, \phi \rangle / p^2 |\phi|^2 + 2p\lambda \langle 1, \phi \rangle + \lambda^2 \langle 1, 1 \rangle$$

$$= (p\phi + \lambda) p |\phi|^2 + m\lambda / p^2 |\phi|^2 + 2mp\lambda + r\lambda^2$$

$$= \left( \phi + \frac{\lambda}{p} \right) p^2 |\phi|^2 + mp\lambda / p^2 |\phi|^2 + 2mp\lambda + r\lambda^2$$

(17)

Here, $\langle \cdot, \cdot \rangle$ is the Euclidean inner product and $1$ is the vector with all ones. Note that $\langle 1, \phi \rangle = m$ and $\langle 1, 1 \rangle = r$.

The magnitude of $\psi'$ can then be found by

$$|\psi'| = \frac{p^2 |\phi|^2 + mp\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \left( \frac{\lambda}{p}, \frac{1}{p} \right)$$

$$= \frac{p^2 |\phi|^2 + mp\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \left( |\phi|^2 + \frac{r\lambda^2}{p^2} + \frac{m\lambda}{p} \right)$$

$$= \frac{p |\phi|^2 + m\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \left( p^2 |\phi|^2 + r\lambda^2 + 2mp\lambda \right)$$

(18)

Similarly, the difference between $\psi'$ and the ground truth sampling can be found by
into a final form:

\[ \psi' - \phi = \left( \phi + \frac{\lambda}{p} \right) \frac{p^2 |\phi|^2 + mp\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} - \phi \]

\[ = \left( \phi + \frac{\lambda}{p} \right) \frac{p^2 |\phi|^2 + mp\lambda - p^2 |\phi|^2 - 2mp\lambda - r\lambda^2}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} + \frac{\lambda}{p} \frac{p^2 |\phi|^2 + mp\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \]

\[ = \frac{\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \left(-\phi (mp + r\lambda) + p |\phi|^2 + m\lambda \right) \]

The magnitude of which can be found by

\[ |\psi' - \phi| = \frac{\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \sqrt{\left(-\phi (mp + r\lambda) + p |\phi|^2 + m\lambda \right) 1} \]

\[ = \frac{\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \sqrt{|\phi|^2 (mp + r\lambda)^2 + \left(p |\phi|^2 + m\lambda \right)^2 - 2 (mp + r\lambda) \left(p |\phi|^2 + m\lambda \right) m} \]  \hspace{1cm} (20)

Equations 18 and 20 can be used to find our metric as defined by Equation 7

\[ \frac{|\psi' - \phi|}{|\psi'| + |\phi|} = \frac{\lambda}{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2} \sqrt{\left|\phi\right|^2 (mp + r\lambda)^2 + \left(p |\phi|^2 + m\lambda \right)^2 - 2 (mp + r\lambda) \left(p |\phi|^2 + m\lambda \right) m} \]

\[ = \frac{\lambda}{\sqrt{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2}} \sqrt{\left|\phi\right|^2 (mp + r\lambda)^2 + \left(p |\phi|^2 + m\lambda \right)^2 - 2 (mp + r\lambda) \left(p |\phi|^2 + m\lambda \right) m} \]

\[ = \frac{\lambda}{\sqrt{p^2 |\phi|^2 + 2mp\lambda + r\lambda^2}} \sqrt{\left|\phi\right|^2 (mp + r\lambda)^2 + \left(p |\phi|^2 + m\lambda \right)^2 - 2 (mp + r\lambda) \left(p |\phi|^2 + m\lambda \right) m} \]  \hspace{1cm} (21)

However, this equation depends on \(|\phi|\), \(m\), and \(r\) which would not be known for real applications. To account for these variables, we will introduce a new parameter, \(c\):

\[ c = \frac{|\phi|}{m} \]  \hspace{1cm} (22)

While \(c\) may also be unknown, we will be able to take a maximum of the resulting error function to get a bound. Using the bounds of L2-norm in terms of the L1-norm and noting that the L1-norm is equal to \(m\), we obtain the identity

\[ 1 \leq c \leq \sqrt{r} \]  \hspace{1cm} (23)

By substituting, \(|\phi| = c \frac{\sqrt{r}}{m}\) and a bit of algebra, we can transform Equation 21 into a final form:
Note that this formula is a function of $\lambda$. Where the last step comes from the inequality Noting that $\psi|\sqrt{2c}p\lambda| - \lambda$ is always positive and applying Taylor’s theorem, we end up with the inequality

\[
\frac{\psi' - \phi}{|\psi'| + |\phi|} = \frac{\sqrt{c^2 - \frac{1}{4}}}{c^2} \leq \frac{\sqrt{c^2 - \frac{1}{4}}}{2c^2 - \frac{1}{4}} \leq \frac{\lambda}{4\ h}\]

Where the last step comes from the inequality

\[
\frac{\sqrt{c^2 - \frac{1}{4}}}{c^2} \leq \frac{1}{2}
\]