Tracking Crime Hotspots

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ABSTRACT

Crime mapping and prediction are important for police resource relocation, informing the public, evaluation of crime reduction initiative programs, and as evidence in criminal proceedings. We propose methods to map, track, and predict movement of crime hotspots. The mapping uses kernel density estimation methods to approximate and graph the crime data. We assess the effectiveness of video tracking techniques such as optical flow and particle filters for tracking crime patterns. To evaluate our methods, we extrapolate future locations of the hotspot and compare them to actual data. Our results indicate that these algorithms can track crime hotspots in certain situations according to the type of data.

1. Introduction

Crime mapping involves the collection and analysis of data pertaining to criminal incidents and offenders. One of the main purposes of crime mapping is to generate information needed to assist in decisions regarding police deployment of resources. Also it can be used to evaluate the effectiveness of programs such as community policing and crime prevention initiatives [5 8 9]. The main goal of our research is to analyze the effectiveness of video tracking techniques in predicting crime hotspots. The analysis of temporal patterns is the traditional approach for crime prediction [10] but in our research we consider spatial patterns. We use kernel smoothing for mapping the crime data because this method makes it easier to interpret spatial patterns. [13] Moreover, we created videos of the kernel maps so we could apply video tracking algorithms. There are many video tracking methods, including optical flow and particle filters. Optical flow attempts to find the velocity field governing the motion in a series of images; on the other hand, particle filters follow the trajectory of the centroid of an object through time [14].

2. Kernel Density Estimation

Kernel density estimation (KDE) is a type of non-parametric density estimator, meaning it uses all the data points to create an estimate [7 15]. KDE is a good method for visualizing crime data because it estimates how the density of events varies over the study area; it produces a smooth map in which the density at every location reflects the number of points in the surrounding area [8 11 12]. Using the data from the Long Beach Police Department from 2000-2005, we create a kernel density map. In kernel estimation we start out by laying a fine grid over the area of study. A circular window of constant bandwidth width is placed on a grid in the study area. The density is calculated within the window. Points closer to the center of the window are given more weight than points further away [8]. We use kernel estimation because the method produces an aesthetically pleasing image from which users can identify hotspots based on contours of density (see figure 2). Because hotspots are not static and densities do not remain the same over time, kernel estimation is able to efficiently analyze this change. In creating our kernel density map, it is important to choose a suitable bandwidth because the bandwidth corresponds to the amount of smoothing that takes place. If the bandwidth used is too big, it will lead to over smoothing and low-density values producing a map that is generalized in appearance. In contrast a small bandwidth will result in less smoothing (see figure 1).

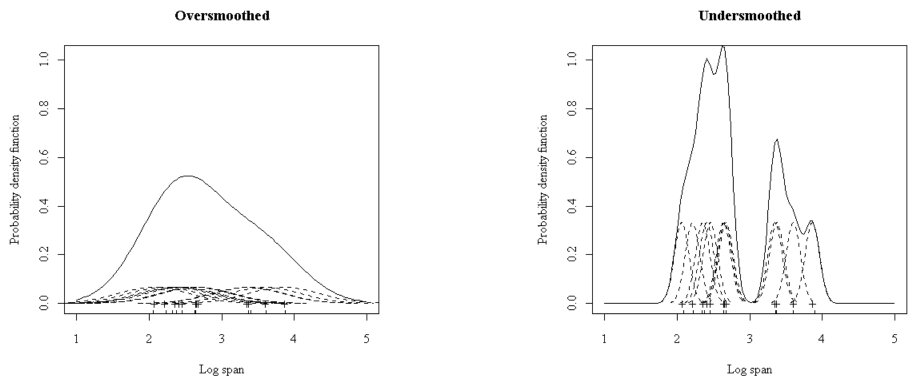

Figure 1: Kernel maps with different bandwidths

After testing out different bandwidths, we determine that a bandwidth of 0.054 is optimal. In the kernel estimation function below we use the Gaussian kernel function.

$$\lambda(s) = \sum_{d_i < \tau} 1/t^2 \, k(d_i/\tau)$$

In the above function, d_i is the distance from point i to grid point s, t is bandwidth and $\lambda(s)$ is the density of crime events at grid point s.

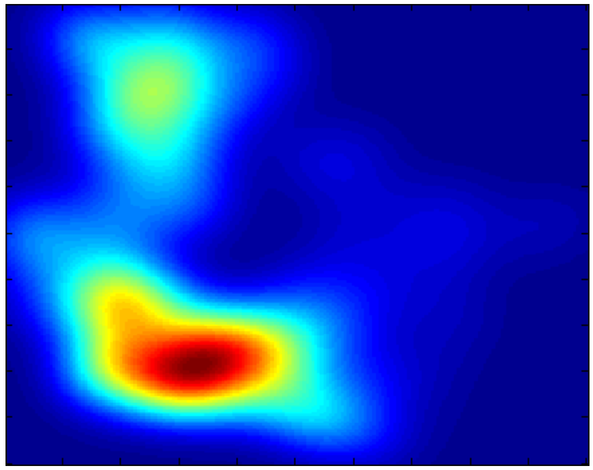

Figure 2. Kernel density map with red regions showing areas of highest crime

In the figure above the hotspot areas appear as the red regions with the blue region indicating no crime. After creating the kernel map, we make a movie with each frame representing one-month period. We create the video so that we can use video tracking algorithms to track crime and try to predict where it will be in the future.

3. Video Tracking Methods

Optical flow attempts to find the velocity field governing the motion in a series of images. Several methods have been proposed to address this problem. They can be divided into the following types: differential methods, phase-based, region-based, and energy-based methods. Differential methods can be further divided into global and local methods. While global methods produce dense fields and are sensitive to noise, local methods are robust under noise and do not produce very dense fields [3].

In this project, we focus on differential methods, which are based on the assumption that the intensity value of a pixel remains constant as it moves. Using Taylor expansion, a constant equation can be derived. Because there are more unknowns than equations, the aperture problem arises. The goal of different differential methods is to create another constraint so the velocity field can be found.

One of the classical methods for determining optical flow is a global differential method from Horn and Schunck [2,14]. The additional constraint proposed by Horn and Schunck is called the smoothness constraint. The way of expressing the smoothness constraint used in [14] is to minimize the square of the magnitude of the gradient of the optical flow velocity.

Another famous method for optical flow is the Lucas and Kanade local differential method. It employs the assumption that an optic flow vector is unchanged in a region and minimizes the function

$$K_\rho * (f_x u + f_y v + f_t)^2$$

where K_p is the standard deviation of the Gaussian, f is the image intensity, and u and v are the velocities in the x and y directions respectively. A system of linear equations is obtained because the partial derivatives of the function above must be zero at a minimum. The advantage of this method is that it is easy, fast, and accurate; however, it gives errors at boundaries [6].

In our research we evaluate the Horn and Schunck method as well as Lucas and Kanade method against ground truth data. There are two interpretations as to what the ground truth data actually is; the first is to compare with the ground truth optical flow field and the second is to compare with the ground truth motion field. The optical flow field is the direction field which morphs one image into the next; it is important to note that the optical flow field is not uniquely defined as pixels can map to more than one location and multiple pixels can map to the same location. The ground truth motion field is the literal projection of the motion of objects within the image onto the image plane. Comparison with the optical flow field is appropriate for applications such as video compression while comparison with the motion field is appropriate for tracking applications [17]. Thus, we compare our results with ground truth motion fields that we create for some synthetic image sequences. One of the sequences is a square moving in a sine wave and the other sequence is a translating "blob" made using our kernel density function. To compare we use two metrics: an angular velocity error as described in [2] and the standard L2 norm. We use Horn and Schunck because it generally performs better on the synthetic data (see table 1) and it yields dense flow fields which we need for the image reconstruction we apply later on. Although it is sensitive to noise, this is not a problem for our data because the kernel smoothing introduces little to no noise in our images.

Translating Blob 12.8 (2.2) pixels per frame

	Angular Error	**Standard Dev**	**L2 Norm**	**Standard Dev**
Horn and Schunck	4.4431 (1.6122)	16.4734 (6.337)	0.77112 (.07896)	2.1331 (.27632)
Lucas and Kanade	6.3194 (2.0896)	22.41 (9.7919)	1.591 (.086348)	3.6869 (.36117)

Sine Wave Square 8.1 (1.4) pixels per frame

	Angular Error	**Standard Dev**	**L2 Norm**	**Standard Dev**
Horn and Schunck	6.6791 (2.51)	22.7291 (10.8105)	2.3078 (.075608)	17.9903 (.32852)
Lucas and Kanade	3.7941 (2.7931)	17.1307 (12.4529)	0.30059 (.15687)	1.8585 (1.0332)

Table 1: Evaluation results for optical flow techniques on synthetic data.

When applying the Horn and Schunck optical flow method to our data we employ a threshold to increase the reliability and fill in the fields to increase the density of our flows. Figure 3 shows the flow calculated between two frames in our kernel movie.

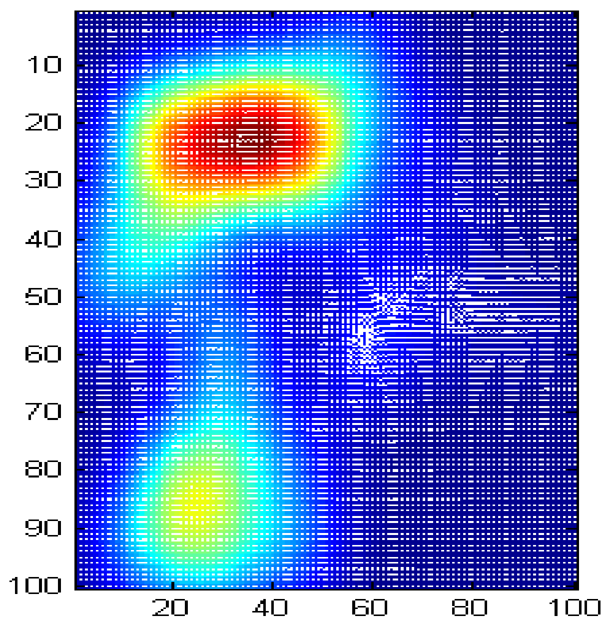

Figure 3: Image of frame one with flow field between frame 1 and frame 2

4. Image Reconstruction

Once we find the flow between two images we proceed to reconstruct the second image. We used a searching algorithm to reconstruct the second image, as described in [1]. Reconstructing the image from known flow fields, we obtain very accurate reconstruction with little error. This indicated that our reconstruction method works with our kind of data, so long as the flow field is accurate. Figure 4 below illustrates this.

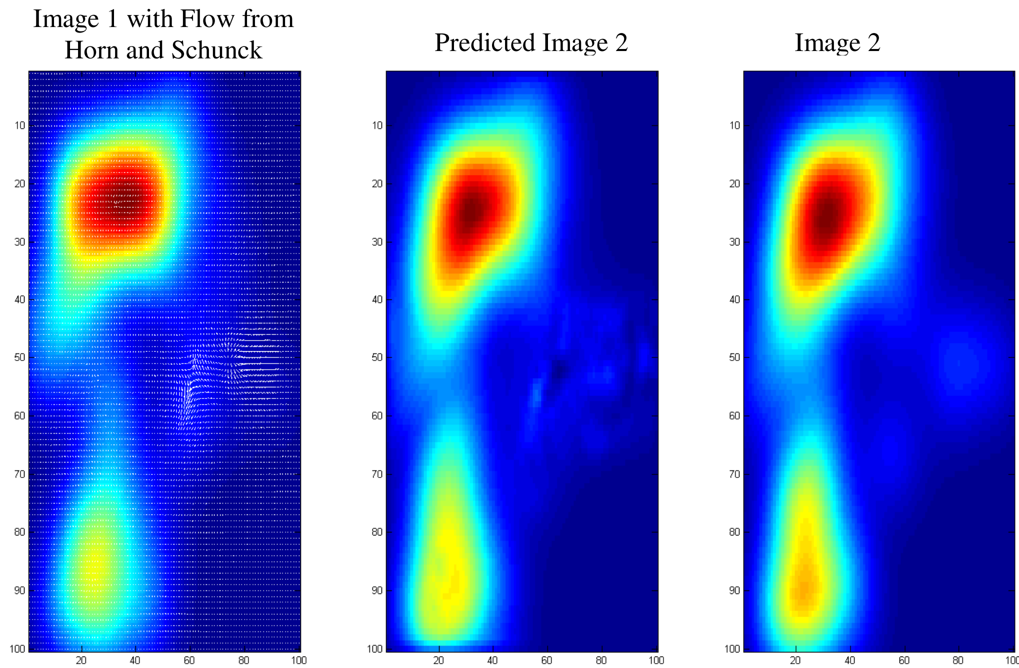

Figure 4: Predicted image using image reconstruction method and field calculated from image 1 to 2

In figure 4 above, we use the root mean square error to evaluate our results and come up with an error of 3.02 pixels. It is an accurate image and the error results from the reconstruction method and the fact that optical flow is not ideal for tracking objects that are changing shape. This, however, may be a deceiving result as we use the second image to get the flow field which creates it. In applications, we will not have the second image, so we will have to make an assumption about the flow fields in order to get some kind of prediction. We try assuming that the flow fields remain relatively constant between the images in the sequence; thus, we substitute the flow field between images 2 and 3 with the flow field between images 1 and 2 when we try to reconstruct image 3. We obtain the results in figure 5 below.

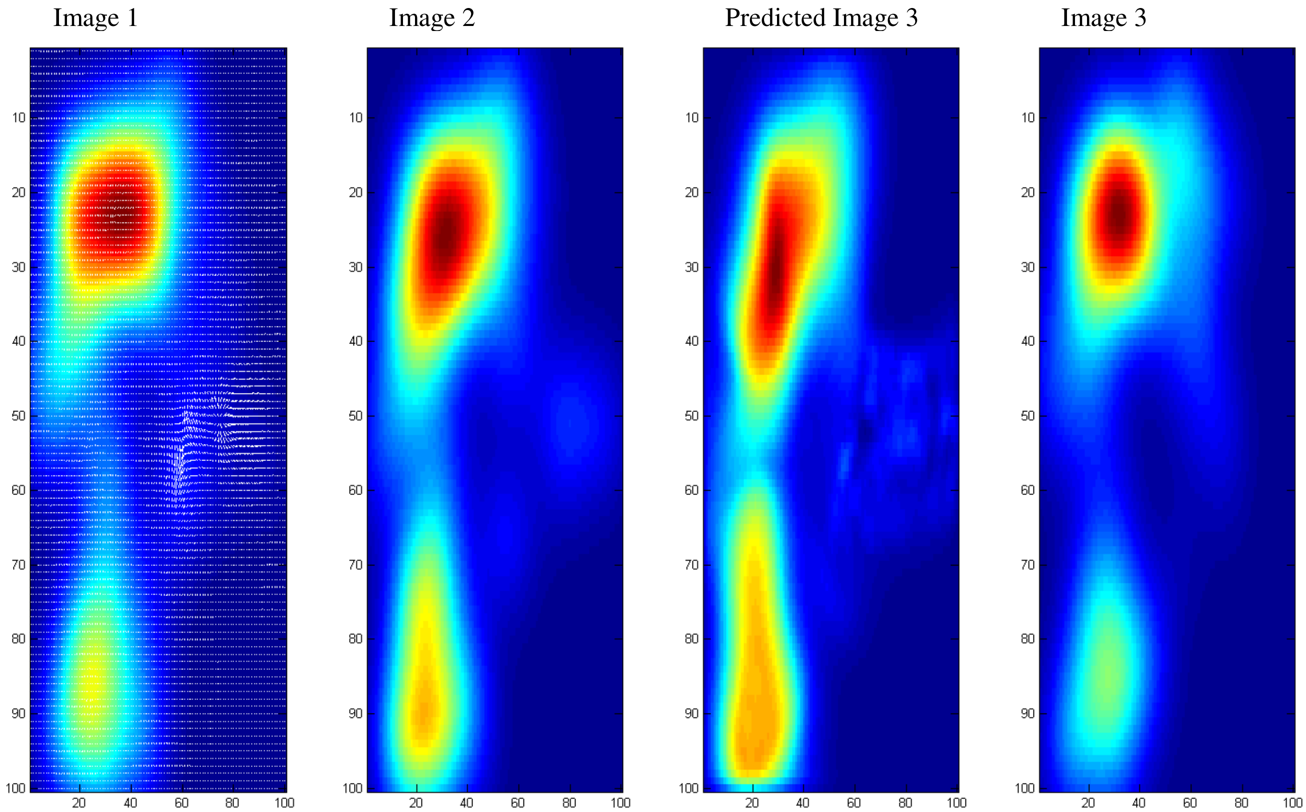

Figure 5: Image reconstruction assuming relatively constant flow fields

Note in Figure 5 that the prediction of image 3 looks more like image 2 than image 3. The RMS error for this image is 29.05. This discrepancy is a result of the fact that the flow between images does not remain relatively constant for our data. We try modifying the flow field in a few different ways, but it does not appear that the flow field is changing in a predictable way.

5. Tracking using Particle Filters

Aside from optical flow, we work with particle tracking techniques to try to predict the locations of hotspots. Particle tracking follows a single point and outputs its trajectory. In our method, we track hotspots by considering them as particles and following their centroids' trajectory through time. We can detect the hotspots that fall in a given range of pixel intensity and area (see Figure 6). Once the hotspots are determined, we track their centroid through each frame. From this tracking, we obtain every hotspot's horizontal and vertical trajectory [4].

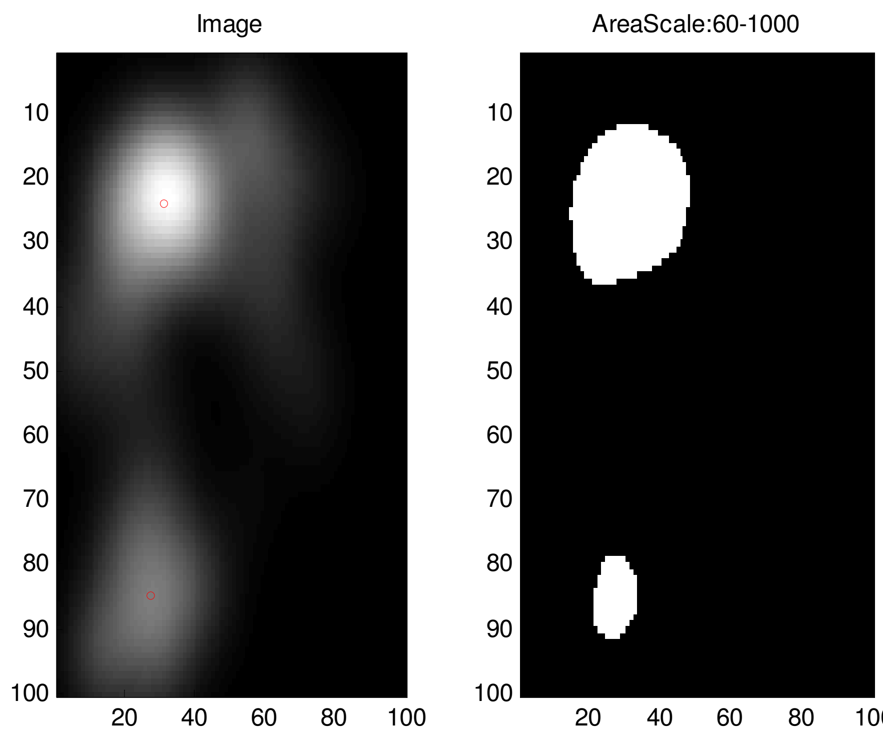

Figure 6: Detecting hotspots on one frame
Left- Grayscale Image with centroids in red.
Right-Binary Image with hotspots in white

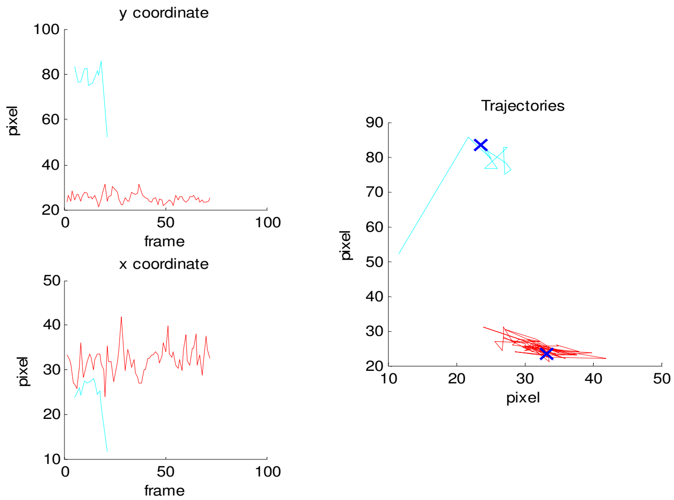

Figure 7: Trajectory of the hotspots
Left-Top - vertical trajectory with respect to frame
Left-Bottom - horizontal trajectory with respect to frame
Right - Trajectories of two hotspots

We can use this trajectory to predict future location of a hotspot. There are two ways for doing this. We can predict the next point in the trajectory, which gives us the coordinates of the centroid, that is, the location of the hotspot. We can also track the distance from several points on the boundary to the centroid in order to predict their distance with respect to the predicted centroid. This approach provides an approximation to the hotspot's future shape, which is more challenging and less accurate. In both cases, we decouple the x and y trajectories in order to obtain the next point, or points, with respect to time.

For evaluating our methods, we look at the shape of the predicted hotspot and the location of its centroid. At most points in time, the prediction of the particle's centroid is relatively close to the real data. We compare original and predicted centroids for every frame by subtracting the x coordinates and the y coordinates. We then obtain the arithmetic mean of all these differences. The predicted coordinates of the centroid gives an average error of 5.0273 pixels for the x coordinate and 3.8892 pixels for the y coordinate.

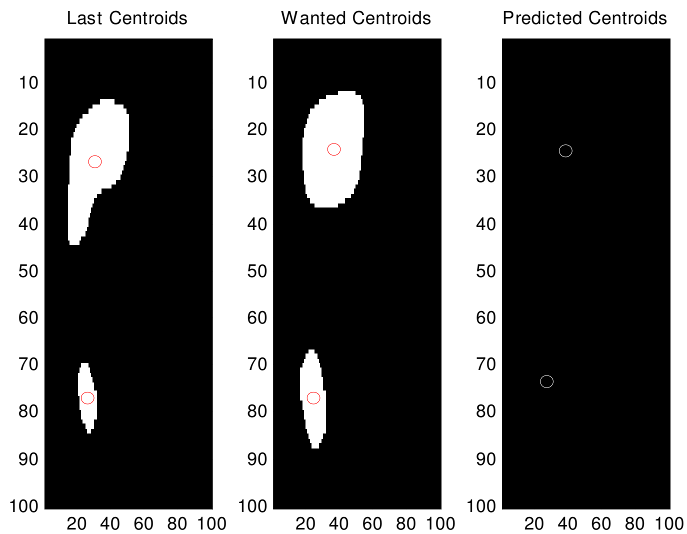

Figure 8: Prediction of centroid
Left– Frame with centroid = (30.7319, 26.6454)
Middle- Next Frame c = (36.1564, 23.9724)
Right- Predicted centroid = (37.9157, 24.2067)
(x-difference, y-difference) = (1.7593, 0.2343)

To measure the accuracy of the shape of the hotspot, we use a qualitative method that involves comparing the expected to the predicted frames (see figure 9). A quantitative method could be developed once the prediction becomes more accurate.

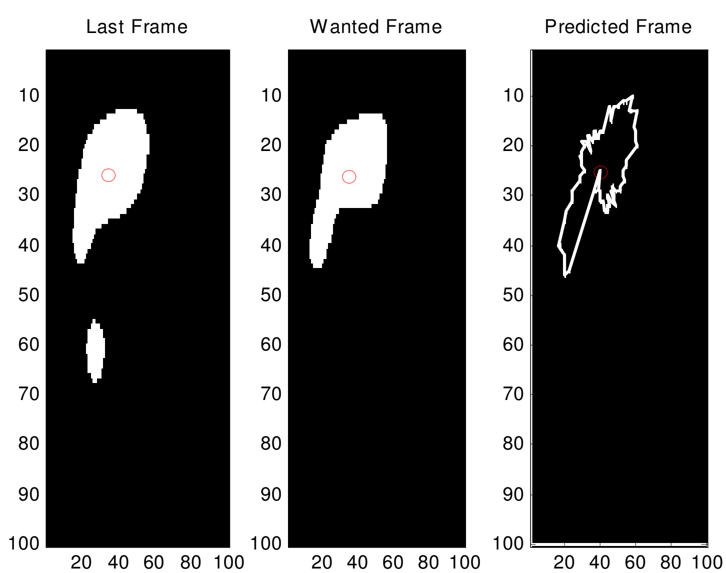

Figure 9: Prediction of the shape

In general, the particle tracking method demonstrates potential to predict hotspots moving through space. Moreover, it shows a different way of approaching the prediction of crime locations by concentrating on the hotspot as a particle rather than the whole crime area.

6. Conclusion

Our results indicate that optical flow techniques, especially Horn and Schunck's, can be used to obtain accurate representations of the flow between two images in a sequence of kernel density maps of crime data. However, when trying to use the optical flow to predict crime density maps in the future, the methods fall short. Because the methods are working on known data, it seems that optical flow techniques can be used to get a visual representation of the way crime has changed spatially in the past. This could be useful for evaluating the effectiveness of crime-reduction efforts such as a neighborhood watch program or increased police activity. In terms of using optical flow techniques for prediction, the type of data it can be applied to will be data that is not changing shape and moves in a relatively constant way.

Furthermore, the results for the particle tracking technique are promising in that they predict the centroids of the hotspots relatively well and with further modification can perform better at predicting the shape of the hotspot. In addition, if the hotspots are not changing shape so rapidly, predicting their shape in the next frame will be an easier task. Therefore, this method is more appropriate for data that has a smooth change in shape between frames. The applications for this prediction can vary. If the objective is to find the location of the hotspot, then predicting the centroid will be the best option. On the other hand, if it is important to look at a neighborhood of criminal activity, then shape is a better piece of information than the centroid.

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