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Developing a Spatial-Temporal Method for the Geographic Investigation of Shoeprint Evidence

ABSTRACT: This article examines the potential of a spatial-temporal method for analysis of forensic shoeprint data. The large volume of shoeprint evidence recovered at crime scenes results in varied success in matching a print to a known shoe type and subsequently linking sets of matched prints to suspected offenders. Unlike DNA and fingerprint data, a major challenge is to reduce the uncertainty in linking sets of matched shoeprints to a suspected serial offender. Shoeprint data for 2004 were imported from the Greater London Metropolitan Area Bigfoot database into a geographic information system, and a spatial-temporal algorithm developed for this project. The results show that by using distance and time constraints interactively, the number of candidate shoeprints that can implicate one or few suspects can be substantially reduced. It concludes that the use of space-time and other ancillary information within a geographic information system can be quite helpful for forensic investigation.

KEYWORDS: forensic science, shoeprints, matching, geographic information systems, space-time algorithm, burglary, serial crime, forensic database

The use of geographic information systems (GIS) in the criminal justice field has its roots in an earlier generation of police crime mapping (1,2). Functions such as hot spot analysis, time-series mapping, and pattern detection have become an integral part of crime pattern analysis (3–5). Integration of such spatial analysis tools within GIS have resulted in new opportunities for analysis of forensic evidence. While there is a clear advantage to using GIS for crime mapping, GIS applications for forensic and crime scene investigation have rarely been explored. Although fingerprints are the most prevalent impression evidence, shoeprints, tool marks, and tire tracks are routinely collected at crime scenes. While fingerprint evidence provides a greater than 95% probability of linking a suspect to a crime scene, shoeprints and other impressions have a much lower probability of positive association between evidence and offender. Improved information can enhance the level of confidence and lead to either a positive identification or an exoneration of a suspect (6). In this article, we demonstrate how GIS analysis can enhance the matching of shoeprint evidence.

Shoeprint evidence is sometimes overlooked, even though criminals presumably leave impressions routinely when entering and exiting crime scenes. A lack of focus on the search for, collection, and preservation of shoeprint evidence lowers the recovery rates of shoeprint evidence relative to fingerprints. According to a 2004 London Metropolitan Police report, the evidence recovery rate for shoeprints was 12.4% as opposed to 19% for fingerprints. The report stated that, with greater attention, the recovery rate of shoeprints can be raised to 30% for burglaries (7). In contrast to fingerprints, shoeprints are much less likely to be considered unique. Consequently, even though criminals make little attempt to mask their footwear, investigators may overlook shoeprint evidence at crime scenes (8). The previous lack of attention to shoeprints in criminal investigations presents an opportunity to enhance the value of shoeprint evidence and its use in the apprehension of criminals (9).

Identical or similar shoeprints are frequent and without sifting out unrelated shoeprints it is difficult to establish connections between a shoeprint and a suspect. Forensic principles often look for a match between evidence and suspect beyond a reasonable doubt and most shoeprint evidence does not meet such a high standard. For example, if two matched size 10 Nike prints are found at two different crime scenes, it may be inferred that the two were linked, but it cannot be certain that the crimes were committed by the same suspect. Crime mapping, which draws spatial statistical inference from spatial patterns, can provide some clues for investigating forensic evidence patterns. For example, most crimes are associated with a criminal's activity space—the area he or she is most familiar with (10). If a neighborhood appears as a crime hot spot on a map, it may be inferred that repeat offenders may live or work in close proximity to that location. Local residents can use their mental maps and this hot spot information to avoid certain areas, while police can identify hot spots with GIS and allocate more resources to crime hot spots (3,11). Forensic investigators are also likely to benefit from crime mapping because inferential information, such as the distance and time of crimes for sets of matched shoeprints, can be readily displayed and related to others.

Crime mapping and spatial inference can contribute to forensic shoeprint matching in four ways. First, clusters exist at the street, neighborhood, and city scales and the relative importance of factors that influence hot spots at the street scale differ from those that influence hot spots at the neighborhood or city scale (11,12). The bloody shoeprints found at the scene of the double murder of Nicole Brown Simpson and Ronald Goldman, for example, were deemed to be from a relatively rare Bruno Magli "Lorenzo" model size 12 boot (13). Even in a city the size of Los Angeles it is likely that few individuals would wear the same model and size of Bruno Magli shoes, but if we enlarge the area to nationwide, we may find

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that scores of individuals owned a pair. In fact it was determined that only 29 pairs of black, size 12, Lorenzo Bruno Magli shoes had been sold in the U.S. (13). Secondly, crimes occur in different time frames and one can exclude some evidence on the grounds of time constraints. If two crime scenes are 10 miles apart it would be impossible for the same person to be involved if they were known to be committed only 5 min apart. Thirdly, crimes can be grouped by frequency on the basis of location or certain types of individuals (11). Because many crimes are committed by a repeat offender who commits at least three offenses, geographically connected and matched evidence can be useful for identifying related crime scenes. Finally, shoeprint retrievals at crime scenes are often enhanced and stored as images in a database that also includes information on type of crime, mode of entry, date and time of suspected crime occurrence, geographic coordinates of a crime scene, etc. (14,15). This ancillary information can enhance the value of the forensic evidence. Alexandre (7) lists three common uses for a shoeprint database: (i) determine the brand and type of shoe that left the impression at the crime scene; (ii) compare identified impressions with suspects' shoes; and (iii) demonstrate that a particular impounded shoe left the shoeprint at the scene. In this article, we provide an additional way of utilizing shoeprints by using a GIS for spatial inference of shoeprint clustering.

Data and Geospatial Issues for Shoeprint Investigation

A forensic shoeprint dataset was extracted from the Bigfoot database maintained by the Forensic Analysis Unit of the Metropolitan Police Service in London, England (16). The Bigfoot database contains *c.* 10% of all crime sites in the Metropolitan district and since 1997, more than 10,000 shoeprints have been recorded per year. When forensic evidence is collected it is usually photographed, or gelled and then entered into an image database along with the geographic coordinates of the site. Criteria for matching shoeprints are based on the same guidelines as fingerprints. In other words, a pair of matched shoeprints should have identical brand name, model, size, and degree of wear. If two shoeprints have an identical name-model-size combination, but different wear, they are coded as being similar to each other, but not identical. If a serial offender wore two types of shoes, and both types are matched multiple times, the two types of shoeprints are treated as worn by two "separate offenders."

This study is based on data recorded for *c.* 100,000 burglaries in 2004. A total of 10,096 shoeprints were recovered for the year 2004. Of those, 9210 were assigned shoeprint codes, and 886 were coded "unknown," which were excluded from the analysis. For those with a known name and brand, the real shoeprint label was changed to protect the confidentiality of the data. Figure 1 provides a sample of 201 "MARK175" shoeprints in the database from 33 London boroughs and it is inconceivable that all of them were left by a single suspect. The challenge is how to group them so that one suspect is likely to be associated with each group of shoeprints that has an identical brand, model, size, and wear.

To perform spatial analysis on the massive shoeprint database, we need to assess several geospatial issues for shoeprint data. The first issue is that an area with a high concentration of crime does not necessarily have a concomitantly high concentration of forensic evidence. The amount of forensic evidence depends on how much evidence remains at the crime scene and how much effort is made to recover that evidence. Before analyzing a particular set of evidence geographically, one should establish quality measures, such as certain ground conditions that may be more likely to imprint shoe marks than others. Shoeprint data quality may be assessed by the number recovered, coded by brand names and model number. This leads to the "recognizable impression rate," the ratio of clearly coded shoeprints to the total number of shoeprints in a geographic area. A high recognizable impression rate is associated with high quality shoeprint evidence, which is related to shoeprint wear, ground conditions, evidence preservation methods, and shoeprint impression generating processes. A second measure is the "recovery rate," the ratio of the total number of shoeprint evidence records and the total number of crimes in a geographic unit. If recovery rates across boroughs are fairly evenly distributed, it

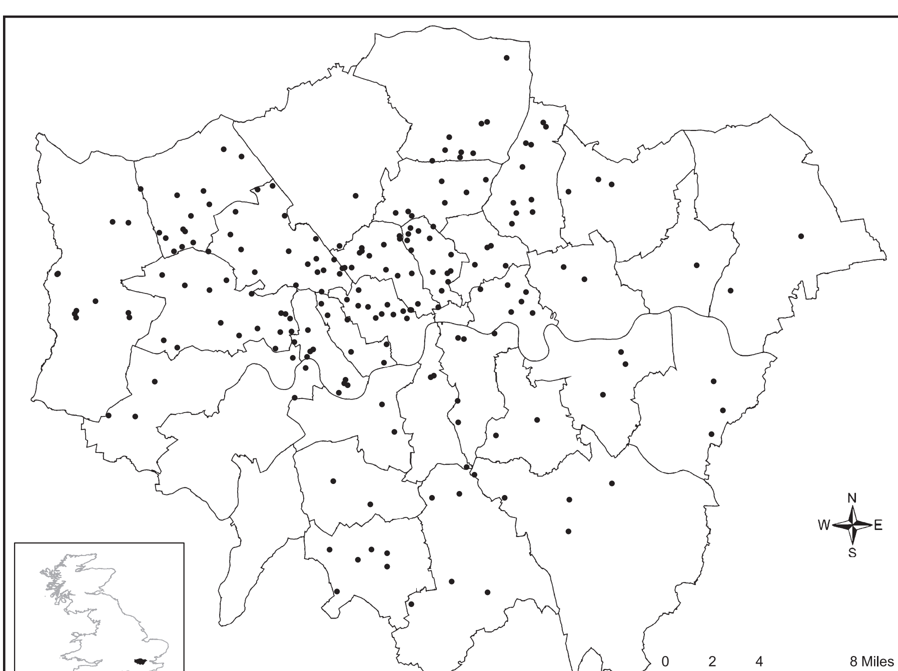

FIG. 1—*MARK175 shoeprints distribution in London metropolitan area.*

implies that the collection was without operational and environmental constraints. The spatial distribution of prints can be considered unbiased. In the preliminary assessment of data quality, we disaggregated the 10,096 shoeprints to the 33 metro-London boroughs and divided them by burglary incidences from March 2004 to February 2005 for each borough. We found a recovery rate of about 10% for each borough, and there is no spatial clustering of recovery rates or bias toward a few boroughs.

The second issue is that shoeprint evidence can be classified according to rarity. Many shoeprints with the same size and similar patterns of wear will be found for a common brand and model. For a forensic investigator, the problem is not about matching shoeprints for a rare brand and model, because they face much less resistance to be admitted as evidence. When a large number of matched shoeprints are presented, their admissibility as evidence could be problematic. Hence, it becomes a challenge for a forensic investigator to connect the matched prints for a common brand and model from a relatively large number of crime scenes. Traditionally, shoeprints were connected through a descriptive report, mostly for rare brands, leaving a large number of matched shoeprints underutilized (7,8). When these more common shoeprints are in a GIS database, several methods can be used to enhance their usability. For instance, the probability of similar impressions being from the exact same shoes decreases with distance. Based on the concept of journey-to-crime, a space-time constraint can be set out to restrict the scope of matched evidence. If two matched shoeprints are too far apart for a given distance-time constraint among 201 matched shoeprints in Fig. 1, then the two shoeprints should not point to the same suspect, or one print should be excluded from a focused analysis.

The third issue is how to communicate the results of spatial analysis of forensic evidence. A hot spot of multiple crime incidents may be attributed to one or many suspects, but forensically and geographically matched shoeprints may reasonably be linked to one suspect. For a spatial analyst, it is a trivial matter to highlight a unique shoeprint, even though each unique shoeprint may point to a single suspect; neither is it a challenge to identify two matched shoeprints. Spatial hot spot analysis becomes important when the goal is to implicate one suspect's involvement in several crime sites on the basis of a number of matched shoeprints. The frequency distribution of the number of matched shoeprints found in the Greater London area is shown in Fig. 2. Note that the unique shoeprint category had more than 900 observations, so the value 1 was omitted from the *x*-axis. One hundred and fifty-eight unique shoeprint codes had two matched shoeprints. Likewise, 91 unique shoeprint codes had just three matched shoeprints. At the other extreme, eight shoeprint codes having at least 200 "identical" shoeprints were found in the Greater London area. These high frequencies suggest that a large number of matched shoeprints point with a low degree of certainty to one or few suspects, and thus may not yield any useful information.

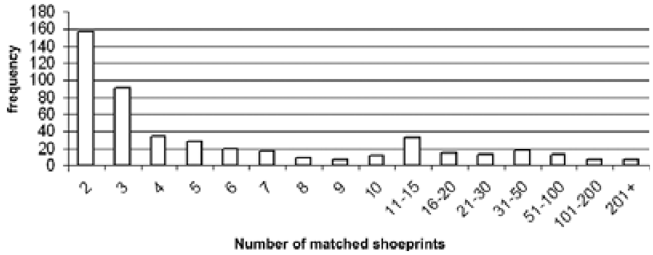

FIG. 2—*The distribution of the number of matched shoeprints in London: 2004.*

Unlike a crime hot spot, which does not distinguish suspects, a hot spot for shoeprints should point to a single suspect or few suspects. For this reason, the emphasis of forensic evidence examination is not to draw statistical inference for a crime hot spot, but to reduce information from a large number of matched shoeprints to a relatively manageable set. Based on the somewhat limited human capacity for processing information simultaneously (17), it would be hard to infer from a set of matched shoeprints corresponding to more than seven (plus or minus two) crime incidents. Our interviews with forensic investigators suggest that a set of matched shoeprints with 10 or fewer occurrences may allow an investigator to explore the options, but more than 10 presents too many alternatives. Reducing the number of possible alternatives can be achieved through further analysis. For example, shoeprints coded MARK21 have a total of eight observations. Even though eight of 10,096 observations suggest that the probability of the print being made by the same offender is high, we can further examine them geographically (Fig. 3). There are four marks within 2 miles of central London, and the likelihood of these marks being left by the same offender was quite high, because the evidence was recovered from crime scenes within 12 days of each other and the type of offense in each case was residential burglary. Furthermore, information about the mode of operation (MO) is also useful. In this case, the description of the crime is similar, e.g., "suspects kicked in front door of flat and entered premises and searched through occupier's property." This example suggests that by analyzing the spatial pattern and using ancillary information, it is possible to reduce the number of matched shoeprints for further investigation to 10 or fewer.

To summarize, the evaluation of geographic aspects of shoeprint evidence involves assessing the quality of the spatial sample, reducing the sample size from a large set to smaller and manageable sets, and finally the investigation of subsets linking several crimes to a suspect. From the perspective of this paper, the second issue is most critical: reducing the number of matched shoeprints from a large set. In the following section, we present a method of reducing a large set of matched shoeprints to smaller sets.

Space-Time Algorithm for Shoeprint Subsetting

The journey-to-crime literature suggests that criminals tend to commit crime in geographic locales that are familiar to them (12). Leitner et al. (18) profiled burglars' journey-to-crime based on London data and found that the distance from the safe haven ranged from <1 mile to >2 miles. Two likely crime site locales are neighborhoods near the offender's residential and employment locations. For instance, we might assume that a burglar might only burglarize a house within one mile of his residential location. However, if he burglarized twice, one toward the east, and one toward the west of his residential location, we would need a threshold distance of two miles to cover the two matched shoe marker incidents. In spatial journey-to-crime profiling, suspect location is a reference point to a crime location in radius; in spatial forensic profiling, an evidence location acts as a reference point to another evidence location.

The creation of a cluster of matched shoeprints is a function of space and time. If we set 1 mile as the active area of a suspect, and two matched shoeprints within 1 or 2 h, we can reasonably speculate that the two were from the same suspect. As time increases, another suspect with the same shoeprint may come to the scene. For this reason, the same two matched shoeprints a few months apart, may or may not suggest the same suspect. In order

FIG. 3—*Central London MARK21 distribution by time.*

to infer from one shoeprint evidence location to another, we developed a self-exclusion algorithm by using a space buffer and a time buffer to eliminate points.

The algorithm works this way (Fig. 4): (i) both distance and time thresholds are specified. For convenience, let's say we specify distance as 2 miles, and time as 10 days; (ii) a starting point is randomly selected from all the matched shoeprints for a particular shoeprint code. If the selected point is within the specified distance from another shoeprint site, the point is retained; otherwise, it is dropped from consideration; and (iii) the retained point is checked if it is within the specified time duration to the closed point: if yes, then the point is retained, otherwise it is dropped from consideration. This process is repeated for the next closest point and so on until all prints have been exhausted. The algorithm acts to exclude one point at a time; in order for a point to remain in the set, it has to satisfy both the distance and time criteria. In the enlarged map of Fig. 3 for a central London area, we found four matched shoeprints in four sites, all within 2 miles. Three shoeprints were also recovered within 10 days. If we set the time constraint to within 1 week, then the fourth point will not be included in the reduced set, even though all sites meet the distance criterion. The eventual set of points generated by this algorithm differs in approach from the statistical approach of spatial cluster analysis, where a hot spot can be identified by testing a most likely cluster regardless its size, or by testing for a clustered area against spatial randomness.

Based on previous research and our own exploratory data analysis (18,19), distance constraints of 1, 3, and 5 miles, and time constraints of 15, 30, and 45 days were chosen to assess the effectiveness of the algorithm. This process was repeated nine times to yield the results in Table 1. As expected, the greatest reduction resulted from the smallest time-space constraint of 15 days and 1 mile from the original of 9210 to 2003, a 78.3% reduction. At the other extreme, the widest space-time constraint yielded the largest number of observations with only 28.6% sample reduction. Upon further reviewing the results, it was concluded that

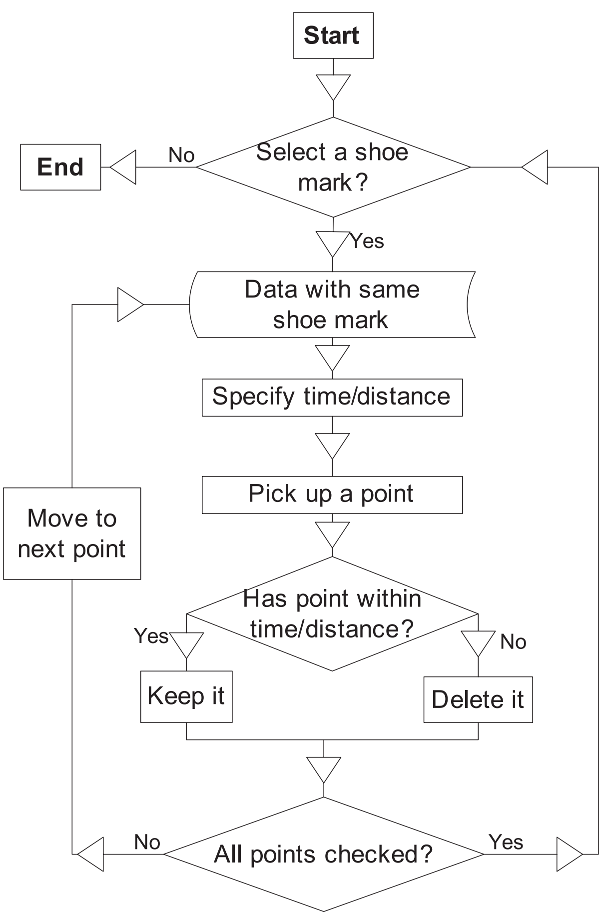

FIG. 4—*Space-time self-exclusion algorithm.*

the 45-day 5-mile time-space constraint was the least useful due to its tendency to produce points that did not generally cluster together. From our calculations of the average nearest distance

TABLE 1—*Sample reduction from the space-time algorithm.*

Days	1 mile	3 miles	5 miles
45	5427 (41.1)	6214 (32.2)	6578 (28.6)
30	4373 (52.5)	5122 (44.4)	5693 (38.2)
15	2003 (78.3)	2621 (71.5)	3077 (66.6)

% reduction from the original sample of 9210 shoeprints given in parentheses.

among all matched shoeprints, we found that most neighboring shoeprints lie within a mile radius.

To assess how useful the resultant pattern might be, we used the MARK175 print shown in Fig. 1 as an example. The triangles represent the total of 201 matched shoeprints as the background, and the dots represent the remaining 38 shoeprints based on the 1-mile and 15-day criteria (Fig. 5). Cross symbols represent 125 shoeprints based on 3-mile and 15-day criteria. We now turn attention to the 38 shoeprints and their distribution pattern. There are apparently two large clusters and three or four small clusters that can be separately turned over to crime analysts for further investigation. All the clusters have manageable numbers of prints less than seven.

After reviewing the observations, three geographic patterns emerged.

1 *Co-location*—a set of matched shoeprints retrieved from the same crime scene (see the insert). This type of cluster is almost certainly left behind by the same offender.
2 One set of matched shoeprints lies within a borough boundary. The presence of a borough boundary may result in the misinterpretation of possible connection among shoeprints. On the other hand, if the borough represents a coherent socioeconomic entity, we can use it as a reference to link to other demographic, social, and economic information in the database.
3 When a set of matched shoeprints scatters across boroughs without a clear spatial pattern, other ancillary information and statistical tools are needed to group and link it to potential suspects. In the following, we demonstrate how to use the algorithm and ancillary data to enhance information certainty.

E46 marks provide a highly concentrated hot spot within a borough. There were 23 matched shoeprints and four similar to E46 (not shown). Applying the algorithm with a 15-day and 1-mile criteria yielded 13 sites in the London borough of Brent. Using 5 miles and 45 days, five more shoeprints were added. We use the 1-mile constraint because the probability that the marks are left behind by multiple offenders is low and we want to understand the suspect's activity space. We find that the offense pattern is very consistent, 12 of the 13 marks are residential burglaries; nine of the 13 of the crimes were committed in the early or late evening hours. In addition, the MO description of this particular set of matched shoeprints has the term "window" appear in 10 of the 13 and the terms "rear" or "back" in eight of the 13 descriptions, indicating a possible consistent point of entry as a rear or back window. Based on these criteria, it is concluded that the matched E46 shoeprints were probably left by the same offender, and one way to catch him/her is to set surveillance in the area during the early morning and late evening. Alternatively, to prevent him/her from committing further burglaries, the authority should alert residents to have some deterrent device, such as an alarm system for their rear windows.

Borough-specific hot spots can implicate a suspect's living and working activity spaces. For example, the code Rectangle refers to a geometric pattern matched by 34 shoeprints (Fig. 6). While this shoeprint is not matched as a specific type of shoe, it is matched to a specific and generic design of imprint. We ran the algorithm based on 15 days for 1, 3, 5 miles, and yielded 13, 27, and 31 marks, respectively. The resulting markers are concentrated mainly in three boroughs; Haringey, Harrow, and Islington. The 3-mile space constraint was selected for its manageability of clustering potentials within the three boroughs. There are several possible inferences based on the reduced set. One inference is that these shoeprints are from one offender whose home is in one borough and whose work place is in the other. Of the 27 total shoeprints

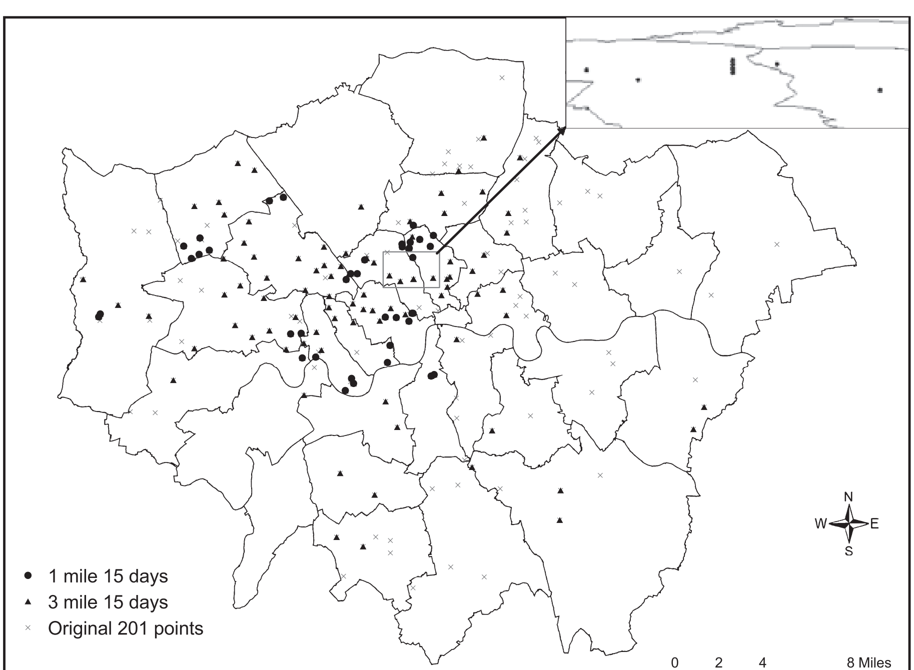

FIG. 5—*Shoeprint set reduction of MARK175: distance = 1 or 3 miles and duration = 15 days.*

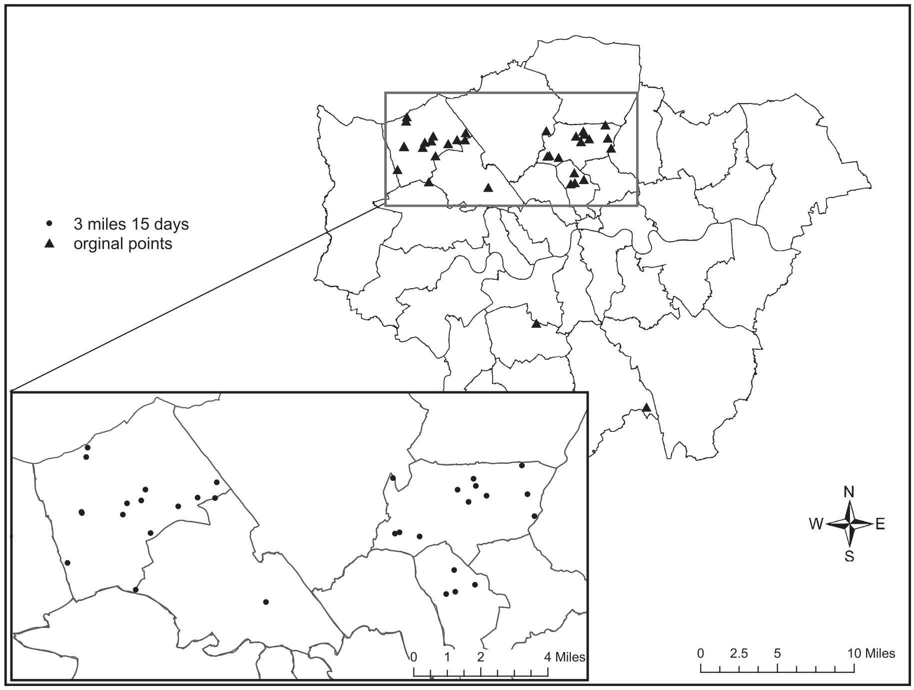

FIG. 6—*Borough-specific pattern Reg: distance = 3 miles and duration = 15 days in box.*

that remain from the 3-mile buffer, 23 are residential burglaries, and 16 indicated forced entries by smashing windows or forcing open windows or doors. In particular, a cluster of residential burglaries exists in the borough of Harrow and seven of the 11 residential burglaries were committed during the workday (7:30 AM–5:00 PM) and are tightly clustered, revealing some consistency within that particular borough. A similar pattern exists for Haringey borough with the smallest space constraint. The smaller distance range suggests nonresidential, because industrial parks are zoned in smaller areas. In fact, four out of the five points were nonresidential burglaries in this borough and all four occurred in the evening or early morning hours, as opposed to usual workday hours. In addition, these four points are not very tightly clustered in time. A lead can be reasonably pursued for one suspect in two locations, one in the suspect's residential location, and the other in the suspect's work location.

Conclusion

The current study explores ways to use a GIS to improve the usefulness of forensic data for crime analysts. As forensic and crime data are often related in a geographic context, we were able to use some existing crime mapping analysis techniques, such as journey to crime, residential and work location inferences, and space-time constraints. Although the quality of forensic data is assessed by a high confidence in matching, not all forensic data achieve the desired quality level. DNA and fingerprint matches often lead to one-to-one linkage of a crime scene to a suspect with 100% certainty, but forensic evidence from industrial products, such as shoe marks and tool marks, can often have multiple matches, and how to reduce a set of evidence with multiple matches poses a challenge for crime analysts. We demonstrate that the use of space-time information within a geographic information system in these situations can be quite helpful.

Shoe impressions from burglaries in the Greater London area were used to demonstrate the space-time algorithm that reduces a relatively large set of matched shoe impressions to manageable subsets based on distance and time constraints. A range of diameters, such as 1, 3, and even 5 miles represented the residential active space for a suspect. Although a habitual burglar can commit a crime anytime during a year, from the point of apprehending the suspect, the most useful information is derived from activities within a short duration, and we found that 15 days in combination with a distance threshold of 1 or 3 miles often yield the most manageable subsets. In general, large numbers of common shoeprints (e.g., more than 200) require a shorter distance to break them to manageable subsets of 7–10 clustered points. For a small set of matched shoeprints (e.g., 50 or fewer), reducing a distance constraint from 3 to 1 mile usually has little effect on the elimination of points from the original set. Although these results are context dependent—Greater London in 2004—they serve as a basis to generate some empirical tables for useful space time constraints. In this way, crime analysts from different places can refer to different space-time criteria for disentangling large geo-spatial forensic evidence databases.

Although it is not an emphasis of the current study, we evaluated the data quality of the shoeprint dataset. In so doing, we needed to distinguish conceptual differences of crime rate from forensic evidence recovery rate in general, and recognizable impression rate from impression evidence in particular. The spatial analysis of the current study is based on the assumption that forensic evidence is evenly recovered over geographic space, and all impression evidence is treated with the same quality standard. Although we do not observe general violations of these assumptions, the results could be biased if evidence from one area is more often recovered than evidence from another area. We also point out conceptual differences of a crime hot spot versus a forensic evidence hot spot in reference to a repeat offender. In addition, ancillary information within an administrative boundary should be used with caution. The results could be interpreted differently if borough boundaries are defined arbitrarily without sociodemographic and zoning implications. Future studies should evaluate how a crime analysis may operate based on different assumptions, such as geographic disparity in evidence recoveries.

Finally, the current study demonstrates only one type of GIS analysis, space-time, for one type of forensic evidence, shoeprints. There are many types of GIS analysis, such as the geographic accuracy of evidence collection, registration, and referencing that can be readily used or integrated with crime scene sketching or computer-aided design (CAD) technologies. This study provides the basis for an analytical approach that can be used for spatial analysis of other forensic evidence.

Acknowledgments

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