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# SPATIOTEMPORAL ANALYSIS OF FORENSIC CASE DATA: A VISUALISATION APPROACH

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**Abstract**
Whether for investigative or intelligence aims, crime analysts often face up the necessity to analyse the spatiotemporal distribution of crimes or traces left by suspects. This article presents a visualisation methodology supporting recurrent practical analytical tasks such as the detection of crime series or the analysis of traces left by digital devices like mobile phone or GPS devices. The proposed approach has led to the development of a dedicated tool that has proven its effectiveness in real inquiries and intelligence practices. It supports a more fluent visual analysis of the collected data and may provide critical clues to support police operations as exemplified by the presented case studies.

**Keywords**
crime analysis, forensic intelligence, spatiotemporal visualisation, visual data analysis.

***Résumé***
*Que cela soit à des fins d'enquête ou de renseignement, les analystes criminels sont souvent confrontés à la nécessité d'analyser la répartition spatio-temporelle des crimes ou des traces laissées par des suspects. Cet article présente une méthode de visualisation soutenant des analyses récurrentes telles que la détection de séries ou l'analyse des traces laissées par des appareils numériques tels que des téléphones mobiles ou des GPS. L'approche proposée a conduit à l'élaboration d'un outil dédié qui a prouvé son efficacité dans de véritables enquêtes et à des fins de renseignement. Il permet une analyse visuelle et dynamique des données recueillies, facilitant ainsi la production de renseignements utiles à la définition d'opérations de police, comme le montrent les études de cas présentées.*

***Mots-clés:***
*analyse criminelle, renseignement forensique, visualisation spatiotemporelle, analyse visuelle de données*

## 1. INTRODUCTION

Visualisation is a pillar of crime intelligence. Link diagrams between relevant entities (persons, objects), maps, quantitative representations (e.g. histograms) or timelines are always more frequently used in this context, and chosen depending on the problem to be analysed. Combined visualisations of those perspectives are challenging, and very few methodological support and computerised tools are available for this purpose.

The importance to develop frameworks and tools is particularly evident, when realising that spatiotemporal information are at the core of the study of crime: criminal behaviour, more often than not, follows patterns, that crime analysis tries to discern from collected data. Crime mapping techniques are now well established for representing the distribution of crimes, detecting crime concentrations or simply displaying set of events to be interpreted. Chronologies of events are represented generally on separate visualisations such as event charts or flow diagrams. When considering that crime occurs within highly specific situations, at a certain time, when the immediate social and physical environment offers opportunities, it clearly appears that space and time dimensions are closely related. Thus, visual possibilities of combining both perspectives in representing information are critical.

Examples where the spatiotemporal dynamic underlying specific problems must be analysed are manifold. For instance, hypothesis developed in the course of an investigation are frequently tested through the study of victim's and suspect's journey. This involves always more routinely the analysis of digital traces such as GSM or GPS records, supported by spatiotemporal visualisations. Such data also frequently help to link a suspect activity with known offenses (Birrer and Terrettaz-Zufferey, 2008) or to locate him.

Other frequent analytical tasks concern the detection and understanding of crime repetitions. They support the development of investigative hypotheses (e.g. geographical profiling) and, occasionally, the development of the series can be predicted through the pattern detected, allowing most relevant measures, preventive and repressive, to be taken. The study of when certain types of premises located at certain places are repeatedly victimised also form the basis for strategic intelligence products.

Spatiotemporal visualisation techniques are available for dealing with such a variety of complex situations. However, a lot of difficulties have to be faced, already when time and space dimensions are represented separately: how to represent time imprecision and uncertainties (when did the crime occur?), how to deal with the overlapping of symbols representing different events, how to avoid overwhelming the reader with quantities of symbols, how to choose appropriate visual forms and levels of aggregations in order to avoid biasing the judgement of the reader? Combining spatiotemporal perspectives amplify those difficulties and make the representation sometimes intractable for its user.

The first part of the paper summarizes general concepts about multidimensional visualisation, and adapted to crime analysis. Within this framework, several elements from previous researches have been selected, focusing on static two-dimensional representations that manage spatial overlapping. On this basis, a dedicated methodology and tool will be presented. They combine spatiotemporal representation of set of relevant traces coming from series of events. The solution traditionally used to deal with this problem suggests superimposing a temporal dimension onto the spatial representation (i.e. a map). An effective alternative consists of proceeding the other way round, by dividing the temporal views with an appropriate use of colours corresponding to defined geographical areas shown on a map. On this basis a computerised prototype has been developed. It has demonstrated to be an effective tool for analysing crime data. It was used in a variety of situations for analysing actual crimes series, as well as for displaying several types of numerical traces resulting from the use of electronic devices (GPS, GSM) by offenders during their journeys. We illustrate the approach with two recurrent crime analysis tasks: mobile phone records analysis and crime series analysis.

## II. MULTIDIMENSIONAL ANALYSIS AND VISUALISATION

Spatiotemporal analysis covers several recurrent crime analysis tasks, such as understanding past series of events, and predicting future occurrences, by clustering and pattern discovery (Boba, 2009; Helms, 2009; Laxman and Sastry, 2006). If the detection of temporal and geographic patterns of crime occurrences is important for intelligence purpose, more specific questions arise when specific crime activity or a set of traces are analysed for investigative purposes (for example left by an electronic device like a GSM or a GPS). Such recurrent questions are: where was a particular person on a defined time frame? Can we infer the home location of an offender from related crime events? Can we link GPS or GSM data collected from a suspect to known crime events? Moreover, many questions may also involve other information than time and space for both intelligence and investigative purposes: what are the relationships between crimes forming a particular repetition? What are the phone numbers in contact with a particular offender? How many crimes have been perpetrated by a specific group of offenders?

Approaching such a variety of questions, and imagining how to visualise a situation, requires an adequate methodology. It can be based on the grouping of typical situations in four dimensions: temporal, spatial, quantitative and relational. This multiple dimension approach follows a similar paradigm of the multidimensional data cube used in data warehouses and OLAP systems (Kimball and Ross, 2002). The classification of a specific problem by identifying its main dimensions, al-

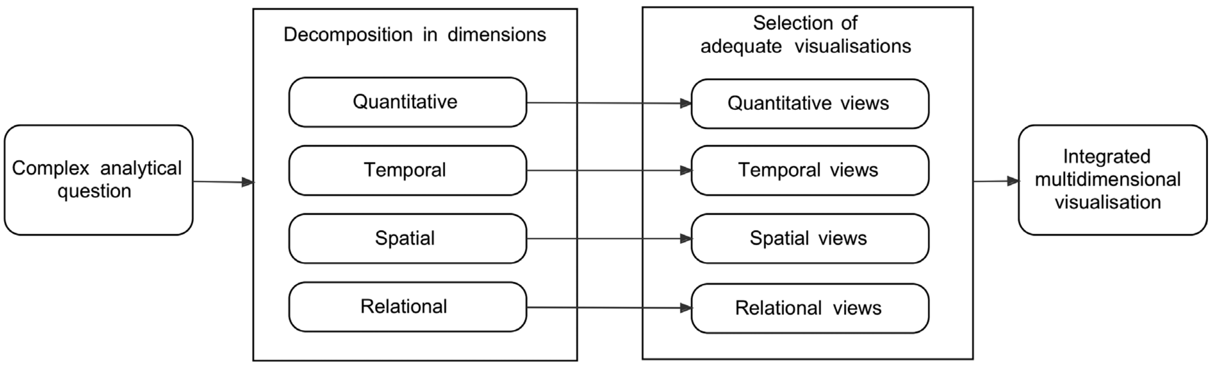


**Figure 1.** Visualisation selection process based on a multidimensional decomposition of crime analysis questions

lows a most appropriate and effective visual form to be chosen. Indeed for each of this dimensions, a variety of visualisations are now routinely used, but fundamental difficulties remains and will be explained.

*The temporal dimension* covers questions where time is the main component: when? On what period of time? How often? Is there a temporal pattern? A sequence? Unlike other quantitative variable, the temporal dimension has a complex semantic structure. Indeed, time has a hierarchical structure and many possible aggregation levels with varying divisions: sixty minutes, twenty-four hours, seven days of the week, twelve months of the year, etc. Furthermore time is analysed linearly and by cycles that may be regular (e.g. day of weeks) or irregular like holydays (Aigner et al., 2007). This intrinsic complexity requires the usage of multiple and dedicated visual forms in order to detect temporal patterns. They consist mainly of timelines and cyclic views.

Moreover, analysing the temporal distribution of crime events requires dealing with uncertainties. Indeed, many crime data are stamped by a time period, which is often not directly related to the duration of the event. It rather results from a lack of knowledge about when it precisely occurred. For instance, the temporal imprecision of burglaries is generally defined by when the victims left their premises. The timeframe is bounded by the period of absence at the location: during the night for shops and industries or daytime for apartments for instance. Several approaches are used to handle this imprecision that may affect distribution analysis (e.g. when a set of crimes tend to occur) or defining queries when searching a database. The simplest way to deal with such time intervals is to arbitrary chose the starting date/time or ending date/time or to use more elaborated approaches like mean calculation or an approach called *aoristic* (for details about this method see (Ratcliffe, 2000)). Temporal uncertainties have also to be handled in visualisations. Similarly, one immediate solution, consist of displaying an event on a timeline at an arbitrary defined date/time (e.g. starting, ending or mean date and time). A second approach is to use a box to represent the period, like with popular Gantt charts. In temporal distributions views, the aoristic approach can be used.

Temporal overlapping is another difficulty. Due to temporal imprecision or to the amount of data, time intervals associated to events can overlap. Specific strategies are used to avoid or manage this problem. As the time dimension is often depicted with the horizontal axis of the plan, the vertical axis is commonly used to distinguish overlapping events. For example, if two datasets of telephone calls have to be compared, they can be plotted in parallels, one on top of the other (e.g. in parallel plots or stacked views, see figure 3 for an example). When the vertical axis cannot be used, a dedicated visual property like the colour or transparency of the symbols can be used (e.g. lines charts sharing the same vertical scale).

*The spatial dimension* covers questions where space is the main component of the question: Where did the crime occur? In what area? Which path was followed? The interest in dealing with the spatial dimension of crime resides in the not-random nature of crime occurrence, even if no consensus is reached on how to explain it (Canter, 2000). The first maps of crimes are attributed to the works of both André-Michel Guerry (1833) and Adolphe Quetelet (1842) (Friendly, 2008). The creation of these maps is connected to police reforms made at the time, when more structured processes for criminal data gathering and recording were developed. Since that time and with the development of computerisation, maps of crime have been progressively more systematically and widely used to detect and follow crime activities in an intelligence-led perspective (Anselin et al., 2000; Boba, 2009; Chainey and Ratcliffe, 2005).

Spatial data also suffer from uncertainty. Often, the exact location of the event is known (for example, in GPS data analysis or for crime events analysis from which the location is generally known), but some datasets may contain inaccurate or imprecise spatial information. For instance, the location of a particular mobile phone connected to a cell is often defined by the area the cell covers. This area can be small (micro-antenna in buildings) or wide (rural antenna). This impreciseness cause many visualisation problems. In particular, it may result in spatial overlapping. When events overlap in space, they cannot be visually distinguished (i.e. variations of symbols or colours are inefficient). One solution is to use spatial aggregates (one symbol sized by the number of occurrences) or small multiples (see below).

Other visualisation problems arise when location is encoded at various level of accuracy. For example, it is not possible to produce a density estimation map (i.e. a *hotspot* map) with a dataset that is geocoded at varying levels of accuracy such as an address, a street, an area or a city. The same problem occurs with mobile phone data since the accuracy of the location is variable in regards of the type of the cell. If a choropleth map can by used to standardize levels of accuracy they may lead to the well known ecological fallacy. Graduated symbols map is than the only remaining visual forms that can be used.

The *quantitative dimension* deals with recurring questions in crime analysis containing *how many of…*. Obviously, crime analysis benefits from visual forms that have been designed in history to cover quantitative analysis. William Playfair (1759-1823) is considered as the inventor of many of them e.g. line and cyclic graphs, histograms, etc. (Friendly, 2008; Playfair et al., 2005). Quantitative visualisation techniques have been widely study as evidenced by the encyclopaedic list described in Harris (2000). However, the seminal work of Edward Tufte (Tufte, 2001) and the fundamentals provided by Jacques Bertin (Bertin, 2005, first edition in 1967) have significantly contributed to theorise and structure their modern use. Stephen Few add some useful distinctions by defining quantitative analysis as the study of relationships between values. Consequently, dedicated visualisations can be classified in regards of them: part-to-whole and rankings, deviations, distributions, correlations and multi-valuated patterns (Few, 2009).

Finally, *the relational dimension* deals with the most elementary analytical task: identifying relevant entities (e.g. events, persons, objects, traces) and their relationships. Specific visualisation methods are used, such as graphs, trees, diagrams or flow charts. These graph-like techniques are particularly useful for representing criminal networks, smuggling of goods, links between events, as well as telephone records and financial data. In this context, visualisations are used along many objectives, such as analysing traces and information gathered, evaluating a cold-case, helping along the categorization of a particular offense, facilitating the transmission and receipt of a case or supporting an argument at trial (Rossy and Ribaux, 2012). The visualisation of the relational dimension faces also many fundamental difficulties, but we will mostly remain focus here on spatiotemporal and quantitative dimensions.

A variety of problems faced in crime analysis can be handled along one of the four dimensions. However, this is a very strong limitation, as the study of real cases often necessitates the combined analysis of several dimensions. This is particularly true for spatiotemporal analysis. Using separate visualisation can thus necessitate jumping from a static map to a temporal view or vice-versa. This inevitably causes damageable ruptures in the reasoning process. Thus, supporting the interpretation of spatiotemporal information by displaying both variables on single charts, or by providing links between perspectives when a computerised system is available, are crucial for crime intelligence and the analysis of forensic case data in particular.

## III. COMBINED SPATIOTEMPORAL VISUALISATION APPROACHES

The challenge of spatiotemporal visualisation is to produce representations of data that allow the exploration, analysis and communication of information in both dimensions at a glance. Several techniques and tools have been developed to support multidimensional visualisation (Andrienko et al., 2003; Brunsdon et al., 2007; Guo et al. 2006; Ratcliffe 2004). However, as Buetow et al. (2003) note there are still few techniques that let examine a single dataset from multiple perspectives. They propose a multiple views tool made of a timeline, a periodic data visualisation and a map (Buetow et al., 2003). Beyond this kind of work, there is still a clear need to search for the most effective way of combining representations in function of the situations to be visualised. Indeed, recent approaches proposed to visualise spatiotemporal datasets are based on 3D visualisations, in particular with space-time cubes (for examples, see: Wolf and Asche, 2009; Nakaya and Yano, 2010). Other studies focus on the display of crime displacements and journey to crime (for a recent discussion upon theses techniques, see: Wheeler, 2013).

Our proposal starts by limiting the focus on two-dimensional and unanimated representations of data. Indeed, many of intelligence products are delivered through static and two-dimensional supports. Although 3D visualisations offer numerous opportunities to represent multivariate data, they bring additional challenges on their own (Card et al., 1999). For example, the data exploration and analysis made with a three dimensional visualisation needs a dynamic environment (Lodha and Verma, 2000) and information is often hidden by the projection in the planar space (occlusion problem). The overall dataset cannot be seen at once with a 3D visual abstraction (MacEachren, 2004). Modern systems also integrate facilities for animating spatiotemporal visualisations (Brunsdon et al., 2007). Animation is intuitive and can associate a proper time with the data event. But the human ability to remember and process the pertinent aspects in case of long and complex animations is a potential problem. In addition, animation has to be interactively controlled and needs a particular support to be communicated. In crime analysis, most of the products have to be static, mainly because they have to be joined to a written report. This is the main reason why we will not integrate animations at this stage. Even if the proposed visual approach was designed to produce static and two-dimensional supports, the analytical process requires a dynamic environment to go along with reasoning performed by analysts. Thus the developed tool allows the dynamic design of static end products. Having limited the scope to static and 2D spatiotemporal representations, several ideas have been brought together by discussing weaknesses and strengths from the practice of existing approaches.

### A. Two-dimensional and static visualisation of spatiotemporal data

One usual way to visualize spatiotemporal data is to integrate the time dimension in the spatial view. For examples, grey scale encoding of time can be applied for each point in the map or arrows can be used to show movement. The main drawback of these approaches is of course the spatial overlapping of points. In two-di-

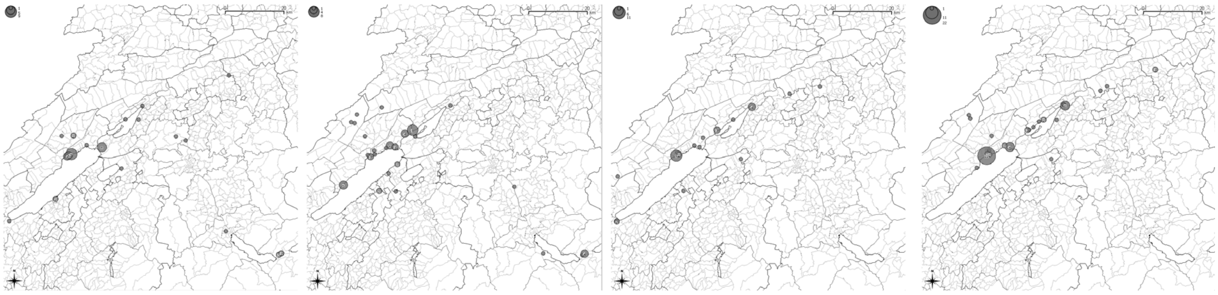

**Figure 2.** Comaps representing the spatial distribution all the communications made with a mobile phone during four consecutive months. All communication made during each month are aggregated on a dedicated map.

mensional static visualisations, two solutions remain to manage the problem of geographical overlapping: map iterations and linked plots (Andrienko et al., 2003). Both approaches have been used in our developments.

### B. The map iteration approach (comap, small multiples)

A *comap* is the juxtaposition of several maps (see figure 2) where each iteration represents a subset of the data, for instance several time frames (Keim et al., 2005). Tufte (2001) defines this concept as *small multiples* of diagrams. He notes that the information slices have to be positioned within the eye-span so that the viewer can make comparison at a glance. According to Tufte comaps are the best representation solution for a wide range of comparison problems. The map iteration approach can allow emphasizing or revealing patterns and multivariate interactions from a period of interest. If the number of iterations increases, the resulting visualisation can be wide. Then, the comparison process can be time consuming and complex. Some scientists of Pennsylvania University reject the use of small multiples to explore problems of multivariate analysis because they judge the comparison too difficult and imprecise (MacEachren, 2004). In our approach comaps are used for the time views (see below), but was not adopted to separate the spatial view, which shows the complete geographic distribution on a single map.

### C. Linked plots - focusing, linking and arranging views

The linked plots approach used multiples views to explore a dataset. To be integrated into a coherent visualisation, all the views have to be linked with each other. Each view depicts one or two-dimensional representation like maps, scatter plots, timelines or cyclic views. The way views are linked depends on whether they are displayed in sequence over time, or simultaneously in parallel (Fredrikson et al., 1999). The main method for linking parallel views is to use same colours in the different representations to encode a particular attribute of the dataset (Chen and Yu, 2000). Linked plots can show patterns from the whole time period and allow a great degree of interaction – for a review of software packages see (Brunsdon et al., 2007). The key idea of linked plots is to create multiples perspectives on data rather than try to find a single optimal view (MacEachren, 2004).

One of the main difficulties that occur when trying to link several views to produce a coherent representation of data is the choice of the linking parameter. One common way for linking views is by using a selection process also called *brushing* (Keim et al., 2005). For instance, the user selects a particular time frame within the timeline and the others views are updated and show only the selected items. Similar operations are performed by selecting a particular zone on the spatial views. The main drawback of these approaches is the loss of the overall view. Such global outlook is required to answers questions like *what is the time distribution of the data for each region of interest?* or *what is the spatial distribution for each period?* One solution is to highlight selected items in the other views, which keep the overview of the whole dataset in the view. Another approach is to use colours to represent a specific attribute. The defined colour is then transposed in each view (for an example see (Guo et al., 2006). Linking subviews with colours is generally done on a categorical attribute (like crime types, etc.). Such approach is not efficient for spatiotemporal analysis because of both spatial and temporal overlapping.

## IV. PROPOSED APPROACH: GEOGRAPHICALLY LINKED PLOTS

The proposed visualisation rests on linked-plots, separating temporal views and maps, with colours on temporal views pointing to geographical area. This is a key aspect, as traditionally, time is integrated onto maps in the other way round. The dataset is divided into geographically separated groups that are assigned the dedicated colour used on the temporal views.

The colours (reprint in grayscale) in temporal views

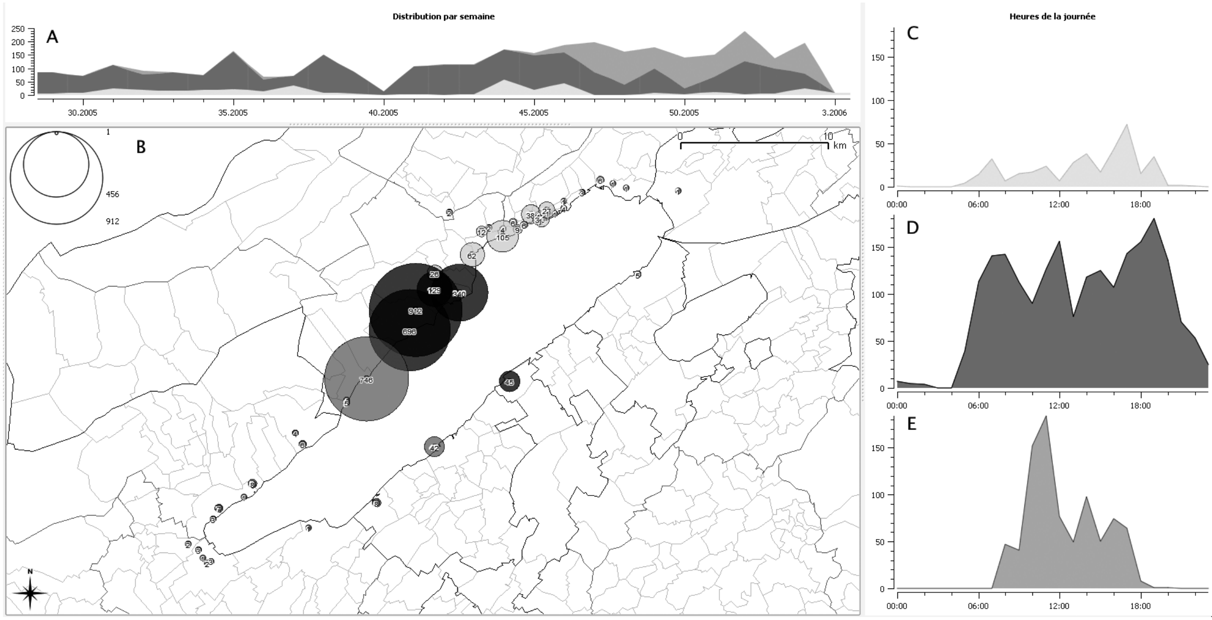


**Figure 3.** Geographically linked plots: a colour/grey level is assigned to spatially defined subsets of the data and applied in the temporal views (timeline on top (A) and hour of the day area charts on the right (C, D, E))

thus depict specific geographic regions. In the method, spatial groups can be either arbitrary defined or by using parametric clustering algorithm (K-mean clustering on both geographic dimensions). Temporal views integrate both linear and cyclic structures at any level of aggregation (e.g. hours of day, days of week, month of year, etc.). Temporal uncertainty is handled by the possibility to choose both start or end date/time or the aoristic calculation that is implemented as suggested by Rattclife (2000). Temporal distributions can be visualised on a single view or on separated small-multiples. Several renders have been integrated such as line graph, histogram or area graph.

Based on these basic principles, a computerised system has been implemented. It is thus hoped to support spatiotemporal inferences with the greatest fluidity. It has been developed as a python plugin of Quantum GIS 1.8 (http://www.qgis.org, last access 05.02.2013) and is available online with installation and usage instructions on http://www.analysecriminelle.org/visualist/ (last access 05.02.2013). It allows dynamic updating of views, at different levels of aggregation, automatic calculations of geographical clusters. Many other facilities have been implemented, but their descriptions fall beyond the scope of this paper. All Figures presented in this article are screenshots of the developed tool.

## V. EFFECTIVENESS OF THE PROPOSED SOLUTION TO REPRESENT RECURRENT SPATIOTEMPORAL ANALYSIS PROBLEMS

It is assumed that the suggested dynamic methodology supports a more fluent visual spatiotemporal exploration of data and supports several forms of reasoning processes during the analysis of traces for both investigative and intelligence purposes. This has still to be demonstrated. In this section, the system is tested on two recurrent forms of spatiotemporal analysis and exemplified by real cases: the analysis of mobile phone billing records and the detection crime series by the combination of traces and spatiotemporal pattern detection.

### A. Mobile phone billing records analysis

One of the most common spatiotemporal dataset in crime investigation (except crime itself) is telephone-billing record. A telephone call is indeed a particularly interesting item to analyse in all dimensions. Each call is composed of a time description (date, time and duration), the spatial position of the cell mast and by definition it describes a particular relationship between two phones. Reasoning with telephone calls data requires the combined use of visual abstractions along all these crime analysis dimensions.

The example presented above (Figure 3) represents all the communications made by a mobile phone during six months. It illustrates the effectiveness of the proposed approach to explore the data by emphasizing interesting patterns useful to support investigation. One recurrent useful inference drawn during an inquiry concerns the location of a suspect. The spatiotemporal analysis of mobile phone data may support this reasoning for instance by selecting calls at specific time periods (e.g. early in the morning) and plotting their spatial positions. Figure 3 shows another approach that consists first of selecting particular spatial areas. The temporal distribution of the black region then reveals a common pattern: more activity early in the morning, at noon and in the evening (see graphic D on figure 3). Moreover, the timeline view reveals that calls are done during the whole period (graphic A). Such pattern allows developing hypothesis about the home location of the suspect.

The multidimensional views may also give other insights. For instance the light grey and grey regions traces daytime activities (graphic C and E) and the timeline (graphic A) reveals several spatiotemporal changes, which indicate ruptures in the use of the cellphone, and, in turn, in the occupational activities of its user. The detection of such patterns through this visualisation process allow analytical hypothesis to be developed. The actual explanation was that the (single) user of the phone was living in the black region and was employed by a society located in the light grey region (which contains the main town of the region). After a period of holydays he was transferred to another branch office (in the grey region). It might be that these patterns would have been detected by other forms of visualisation, data mining technologies or even by sorting a spread-sheet. But the combined spatiotemporal visualisation allows detecting the underlying patterns quickly, dynamically and without complex spatiotemporal modelling knowledge. The method goes fluently along with crime analysis inference structures.

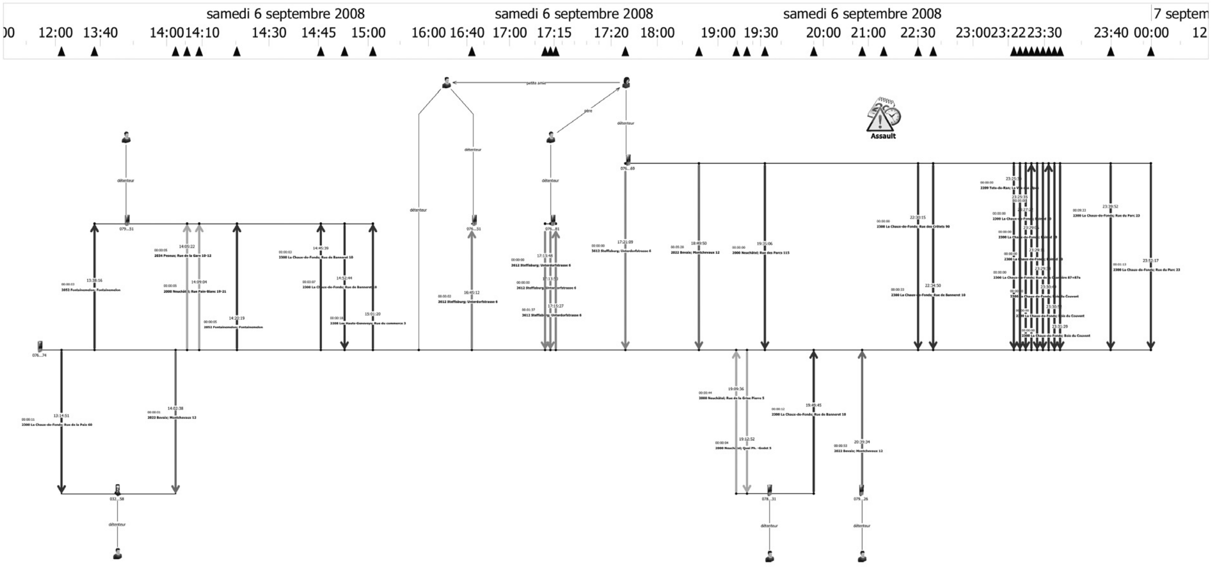


**Figure 4a.** Linked plots with a temporal flow chart created with Analyst's Notebook®. Each coloured arrows represent a communication (outgoing and incoming calls) horizontally fixed along the timeline.


**Figure 4b.** A dedicated colour is assigned to each spatial region and transposed on the flow chart (Figure 4a)

Figure 4 extents the use of geographic transposition of coloured clusters into time views by adding the relational dimension into the workspace of the crime analyst's. The relational timeline view, called temporal flow chart, was created with Analyst's Notebook® software from IBM®. Each theme line (horizontally) represents one involved phone (represented by telephone icons linked to know owners) and all calls are visualized by coloured and arrowed links horizontally aligned horizontally in time. The direction of each arrow depicts the direction of the communication (an outgoing and incoming call). This combination of temporal, spatial and relational dimensions is illustrated by an example of visualisations drawn during an assault's investigation.

The selected dataset includes all the calls made by a suspect the day of the aggression. During the first interview, the suspect denied being involved, and even having visited the red area (i.e. the location of the crime). After he has admitted that he was the only one who used this phone, investigators show him this spatiotemporal representation of his mobile phone activity (Figure 4). Exposed to the traces of his activity, the suspect explains his journey and finally confesses the crime. The detected spatiotemporal pattern brings to light the multiple displacements of the suspect from his home (in the blue area) to the home location of the victim (red area). The suspect even tried to find the victim in the orange location where he gets information the victim might be. He was in fact hunting his victim and the traces were the sign of the premeditation.

Even if the detected pattern is very specific to the case; the overall methodology to perform the spatiotemporal analysis of the traces can be generalised and used for analysing many cases. Moreover, it was illustrative of the need to integrate forensic information, crime analysis methodology and police interviews strategies to solve cases.

## B. Traces and spatiotemporal analysis to detect crime series

The last example concerns the early detection of crime repetitions. This is a very common task in crime analysis. One strategy is to search for concentrations of burglaries where marks or forensic case data with similar characteristics have been collected. This process can be supported through the proposed visual approach.

The detection methodology is explained in previous researches (Ribaux et al., 2003; Ribaux et al., 2006). It is based on the exploitation of shoe-mark's traces collected from crime scenes. A simple classification system of shoe-mark's patterns is used. The analysis consists of producing spatiotemporal views, displaying the occurrence of a selected shoe pattern. If the time structure shows ruptures (temporal hotspot) or the spatial distribution of cases displays a pattern (see 54), this may indicate the activity of a single perpetrator using the same shoes. This hypothesis must be still obviously confirmed by the systematic comparisons of all the information available on each case.

The cumulative curve (on top of Figure 5) shows the occurrences of cases over time. The aim is to reveal particular increases depicting temporal hotspots. The example presented shows a slightly more complex inference structure using this spatiotemporal visualisation. The same shoe-mark's pattern was collected during three short periods spaced each time by almost one

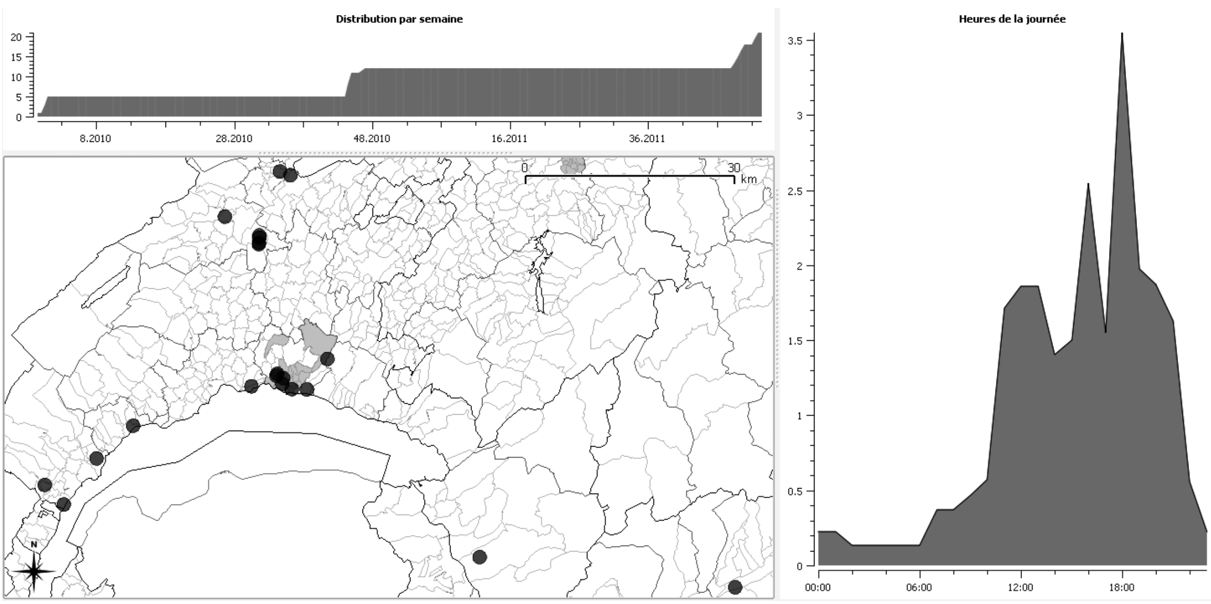


**Figure 5.** Spatiotemporal visualisation of crime events where traces matching a common shoe-mark pattern were collected. The temporal view on the top is a cumulative curve of crime occurrences.

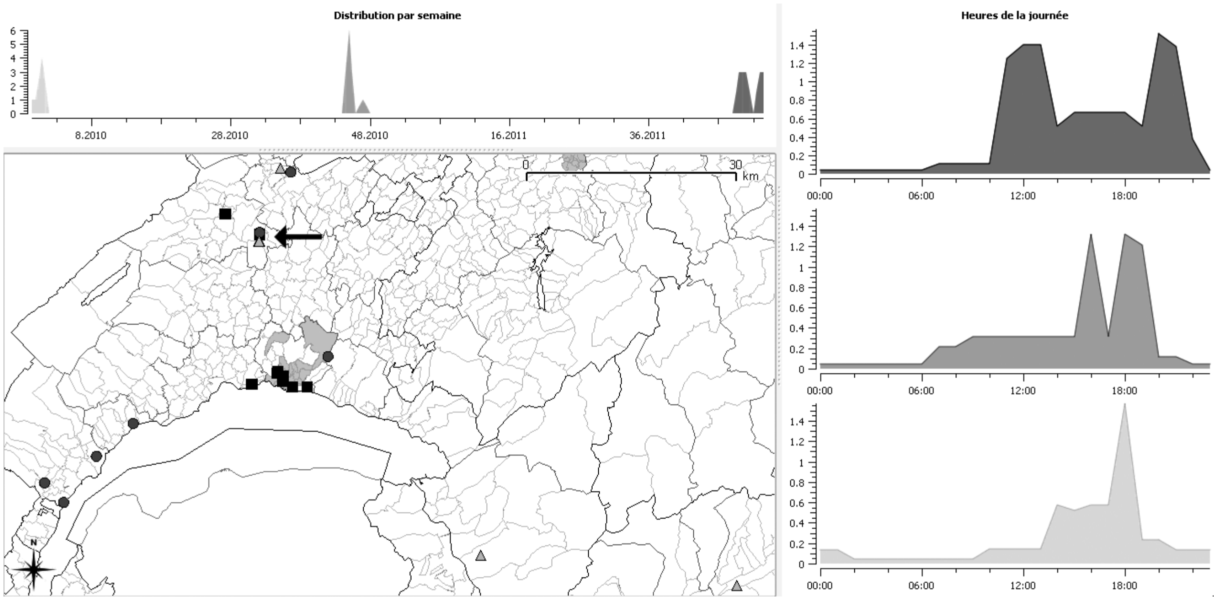


**Figure 6.** Comparison of the spatial distribution of the three temporal hotspots. The time frame is divided in three periods (from light grey to dark grey). The spatial distribution of the crimes for each period is represented on the map with the same colours and dedicated symbol (respectively: triangles, circles and squares).

year. Such a long period may suggest the activities of separate offenders and support the hypotheses of three distinct series. However a deeper look on each temporal hotspot and a cross-comparison of each spatial distribution reveal a new pattern (see Figure 6).

This appears by assigning a dedicated colour (reprint in grayscale) to each temporal hotpot. It reverses the way to link views. Spatial patterns and spatial hotspots are then revealed for each time frame. One unique region where cases are committed during the three periods appears clearly by these operations (pointed-out by the arrow). This region is a small town called C. Interestingly almost every cases were committed during the evening (see temporal views on the right) except three of the four cases occurring at C which occur near midday. The hypotheses that all cases are linked and that one offender may lives or has a particular anchor point near C can then be developed and lead to investigative recommendations. For instance checking police databases for already known offenders living near the detected town might be a relevant suggestion.
This example shows how complex inference structures, alternating detection of patterns and specific operations for testing hypotheses drawn (e.g. targeted comparisons of forensic case data), can be supported with fluidity by the spatiotemporal methodology and its derived tool (Ribaux et al., 2006).

## VI. CONCLUSION

Traditional spatiotemporal visualisation methodologies used superimposition of the temporal dimension onto the spatial representations. An effective alternative consists of proceeding the other way round, by dividing the temporal views with an appropriate use of colours corresponding to defined geographical areas shown on a map. On this basis a computerised prototype has been developed.

The proposed combined spatiotemporal visualisation methodology has shown great potential for the analysis of all sorts of crime data, in particular forensic case data. It allows approaching a broad spectrum of situations through the visualisation and detection of complex spatiotemporal patterns and well support inferences drawing. It has been exemplified with two recurring crime analysis problems: the analysis of mobile phone billing records in crime investigation and the detection of crime series by the combination of traces and spatiotemporal pattern detection.

The case studies presented show how the approach may be used to support reasoning in investigation or more broadly in crime intelligence. In practice, several Swiss police forces currently use the developed tool for the analysis of traces left by digital devices (e.g. GPS or GSM) and for both operational and strategic analysis of crime repetitions. Indeed, the developed methodology also well supports more general analysis of spatiotemporal trends of crime phenomena.

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