Spatiotemporal Characteristics of 9-1-1 Emergency Call Hotspots

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Abstract

We are interested in the use of pattern-detection and data mining techniques for the automatic detection of medium to large-scale emergency events such as earthquakes or fires based on an analysis of the spatiotemporal characteristics of 9-1-1 call activity. This can be used to inform emergency responders about the presence and extent of such events, helping them take proactive steps in their response efforts, and to inform them during their call-by-call response. For this purpose, our project has collected several years of 9-1-1 call activity and developed algorithms to automatically detect such events. This paper describes an algorithm that detects clusters of abnormally high levels of 9-1-1 calls, and analyzes its performance with respect to major emergency events as reported in the news for San Diego County and the San Francisco Bay Area. We explore the spatiotemporal characteristics of the detected hotspots and describe appropriate parameter settings for the algorithm.

1. Introduction

When a 9-1-1 emergency call is made [1], it gets routed to the nearest available Public Safety Answering Point (PSAP), where a call taker directly assists the call-maker, or redirects the call to an appropriate emergency service provider (e.g. law enforcement, fire response, or emergency medical services). The 9-1-1 emergency call system is designed to efficiently answer and respond to individual emergency calls. However, because the geographical coverage of individual Public Safety Answering Points (PSAPs) is limited, and because the coverage of different PSAPs overlaps, call takers can be unaware of other calls happening around the location of the emergency call maker. Access to the totality of 9-1-1 calls on a larger scale such as a city or county would make it possible for emergency responders not only to be aware of these other calls and inform their individual responses, but also to detect the presence and extent of medium to large-scale events such as earthquakes or fires. Such information would also be valuable for planning a response to the wider-scale event.

For this purpose, we have been assessing the possibility of aggregating 9-1-1 call data information on a wider scale than individual PSAPs [2, 3, 4] and using this information to enhance emergency response efforts. Given the large number of 9-1-1 calls that take place at any given time, especially in metropolitan areas such as San Diego County or the San Francisco Bay Area, we have found it desirable and even necessary to utilize pattern-discovering data mining techniques to automatically analyze this information. For this, we created an algorithm that automatically detects hotspots of emergency calls [3]. Hotspots were defined as instances where a large number of calls (for example, 10 or more) happen within a short distance (for example, 1 kilometer) and a short time (for example, 10 minutes) from each other. The algorithm was applied to the data, and hotspots were detected around medium to large-scale emergency events as reported in the news, such as a fire or a small plane crash over a populated area.

The purpose of this paper is to extend the analysis of this algorithm by characterizing the spatiotemporal clustering of 9-1-1 calls as detected by the algorithm, in order to better understand the parameter space and choose a setting that best distinguishes emergency events from normal operation.

This paper is organized as follows: Section 2 describes the data collected so far. Section 3 describes the hotspot detection algorithm, and shows examples of detected hotspots generated by medium to large-scale emergency events as reported in the news. Section 4 explores the algorithm's parameter space by analyzing the hotspots detected during 6 months in San Diego County using different parameter settings. Section 5 draws conclusions.

2. Collected data

Thirty four months of data has been collected for the San Francisco Bay Area (September 1, 2004 to June 30, 2007), with a total of 5,056,766 calls, corresponding to 69 different PSAPs. For San Diego County, twenty months of data has been collected (November 1, 2005 to June 30, 2007), with a total of 1,300,212 calls, corresponding to 20

PSAPs. Fig. 1 shows the area under analysis for San Diego County with 9-1-1 call activity shown for one day (Feb 26, 2007).

Fig. 1. Spatial extent of collected data for San Diego County. One day of 9-1-1 call activity for February 26, 2007 is shown. Red markers indicate landline calls, yellow markers indicate cellular calls.

Information available for each call includes: timestamp, latitude/longitude (dithered to 300 meters for privacy concerns), identification of PSAP answering the call, time to answer call, call duration, and phone type (e.g. business, residence, wireless, etc).

A spatiotemporal analysis of the data [2] shows a daily "rhythm" in the hourly number of calls (see Fig. 2), with a Normal distribution in the daily number of calls (see Fig. 3). This regularity in the data is a first indicator of its possible use to detect medium to large-scale emergency events.

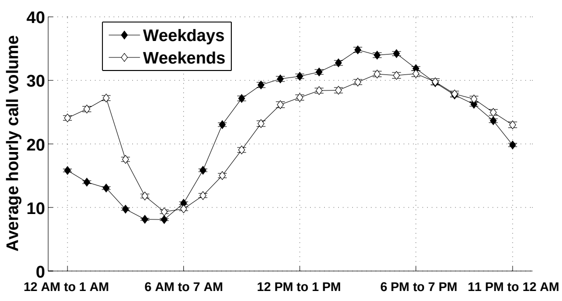

Fig 2. Average hourly call volume (Sep 1, 2004 to Feb 28, 2007) for weekdays vs. weekend days for the San Francisco Combined Emergency Communications Center (CECC) PSAP.

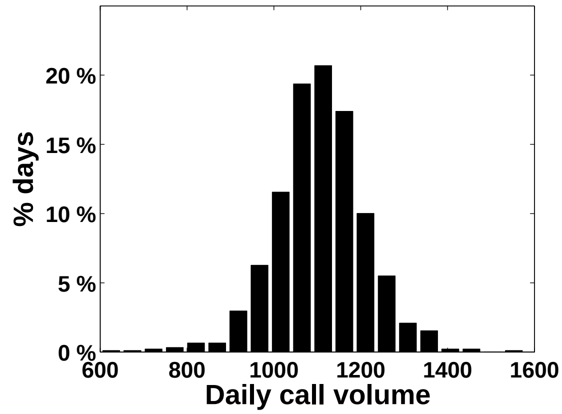

Fig 3. Histogram of daily call volumes for the collected data (Sep 1, 2004 to Feb 28, 2007) for the San Francisco Combined Emergency Communications Center (CECC) PSAP, after removing outliers.

3. Hotspot detection

We define 9-1-1 emergency hotspots with the intention of correlating them with observed medium to large-scale emergency events so that when such emergency events happen, they likely will produce a cluster of calls. We note that only people within visual range of an emergency event tend to call to report it, and they do so immediately in order to expedite the emergency response. Based on this, 9-1-1 emergency hotspots are defined as large numbers of calls that happen within a certain distance, and within a certain time: Any two calls that happen within the minimum distance as well as within the minimum time from each other are clustered together. If any of the two calls also belongs to a cluster, then all calls (i.e. the two calls plus their corresponding clusters) are clustered together. After all clusters are calculated, only those of a certain size are selected as hotspots.

Fig. 4 shows an example of emergency calls and their subsequent clustering (only the spatial characteristics of calls are described; the temporal characteristics used to generate clusters are similar). The calls located on the left of the figure form a cluster since they are close in space (as well as in time). The calls in the middle are close spatially, but their number is not sufficient to be considered a cluster (assuming a minimum of 5 calls for a cluster). The calls on the right form a cluster, even if the one on the bottom is far from the call on the top, because there are intermediate calls connecting them.

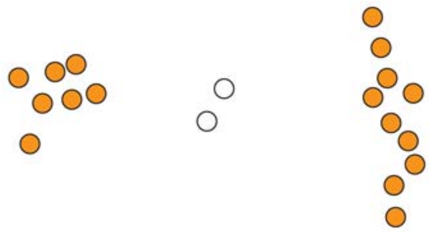

Fig 4. Grouping of calls into clusters. See text for a description of the clustering associated with the calls. Calls marked in orange belong to a cluster, while those marked in white do not.

For the following events, we used a minimum inter-call distance of 1 km, a minimum inter-call time of 10 minutes, and specified that clusters must have at least 10 calls. These were the same parameters as used in [3].

Event 1: Pipeline explosion

On November 9, 2004, 1:30 PM, a gasoline pipeline exploded in Walnut Creek, California, with a loud explosion, smoke, and flames [5]. Fig. 5 shows the location of the explosion, and the clusters of 9-1-1 calls that were generated shortly after the explosion.

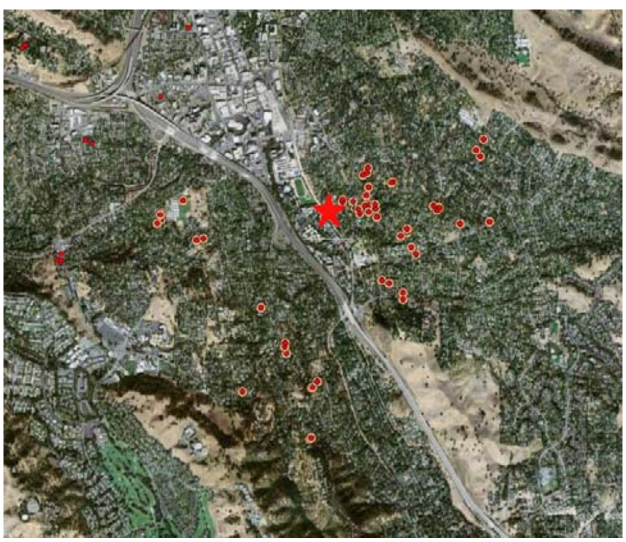

Fig 5. Event1 - Calls generated by a pipeline explosion in Walnut Creek, California. Star indicates the location of the explosion. An orange outer circle indicates that the call is part of a detected cluster.

Event 2: Two Cessna planes collide in mid-air

On February 8, 2006, 4:42 PM, two Cessna planes collided close to San Diego, California, at an altitude of 2,300 feet [6]. The crash was heard from the ground, and debris from the crash spread over a 1-square-mile area of La Mesa and El Cajon. Fig. 6 shows the location of the fallen debris, and the cluster of 9-1-1 calls that formed shortly after the crash.

As can be seen in the plots, the location of the detected clusters corresponded closely to the location of the emergency event. The detected clusters also happened within minutes of the event (not shown here). Although individual callers might report on their estimate of the extent of the event, these plots give us a clear indication of the areas where the event had an impact on citizens.

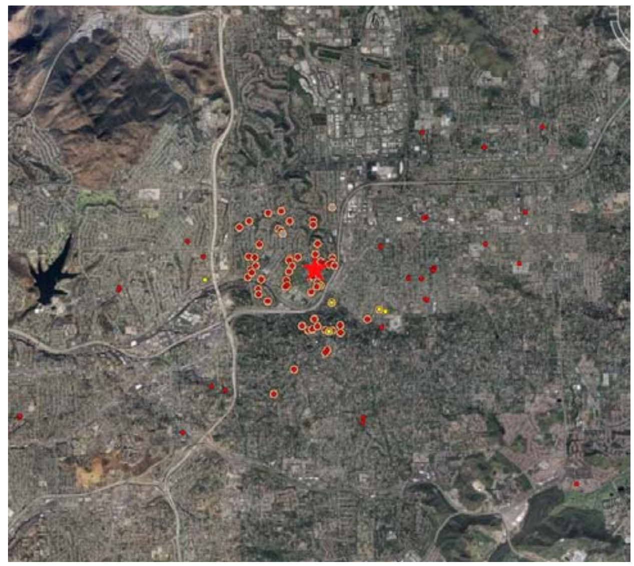

Fig 6. Event 2 - Calls generated by a mid-air Cessna plane crash near San Diego, California. Star indicates the location of the fallen debris. The calls with an orange outer circle indicate that they are part of a detected cluster.

4. Exploring parameter space

This section analyzes the effect of the different values of the algorithm's parameters (minimum inter-call time, minimum inter-call distance, and minimum number of calls per cluster) on the algorithm's cluster detection output. The parameter settings must enable the algorithm to detect the presence of medium to large-scale events such as the ones described in the previous section. There will be instances where the algorithm will detect clusters that are formed by chance alone, that is, where the individual calls are not related to each other but simply happen close together in time and space in large numbers. Ideally, the parameter setting will avoid this as much as possible, while detecting all medium to large-scale events.

As a preliminary step, we look at the inter-call times in San Diego County (see Fig. 1 for spatial coverage). Fig. 7 shows a histogram of the inter-call times. The majority of calls happen within one minute of the previous one. The mean inter-call time rises in the early hours of the morning, as shown in Fig. 8, and is lowest during the evening. At lower spatial resolutions, such as a 1-kilometer radius, the average inter-call time will rise because the total number of calls diminishes. Thus, the parameter setting should be set higher when the inter-call distance threshold is set to a smaller value.

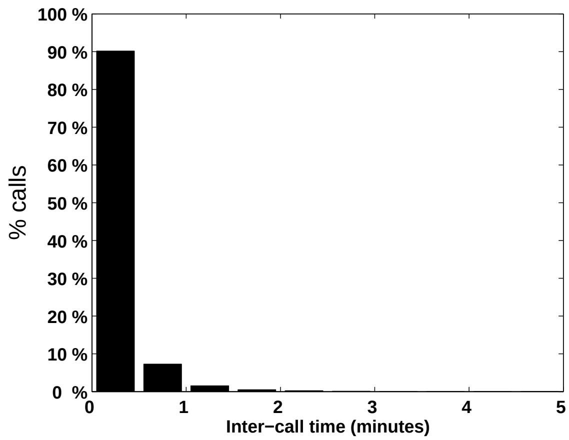

Fig 7. Histogram of inter-call times for San Diego County (see Fig. 1 for spatial coverage), after removing outliers (more than 10 minutes inter-call time).

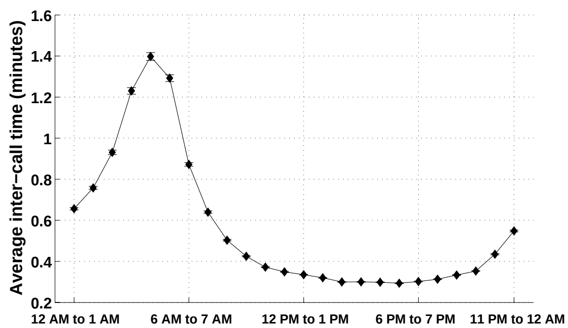

Fig 8. Average inter-call times for different hours of the day, for San Diego County (see Fig. 1 for spatial coverage).

Fig. 9 shows the results of applying the algorithm with different parameter settings. Six months of data, corresponding to January 1, 2007 to June 30, 2007, were used. The plot shows how smaller minimum inter-call spatial or temporal separations result in more stringent conditions for cluster detection, reducing the number of detected clusters.

If we expect that medium to large-scale events will generate at least 10 calls, we can see that even the least stringent of the explored parameter settings (minimum inter-call distance of 1 km, minimum inter-call time of 10 minutes) will generate around three such clusters per day (adding the ’10-15’ and ‘> 15’ results in Fig. 9 top). As shown in [2,4], most of the 9-1-1 calls resulting from an event happen in short-lived bursts immediately after the onset of the event, so that the 10 minute minimum inter-call interval is considered reasonable. Thus, we would expect that a parameter setting of 10 calls minimum cluster size, minimum inter-call time of 10 minutes, and minimum inter-call distance of 1 km, as used in [3] as well as in the examples shown in the previous section, would be able to capture most medium to large-scale events. While there could be some false alarms with this setting, we would expect not many more than three on an average day for this geographical area (San Diego County), which would correspond to the worst case of all of them being false alarms. We believe the effort of investigating these clusters would be offset by the benefit of obtaining an early indicator of the presence, location, and spatial extent of the medium to large-scale event, which would enhance the emergency response efforts.

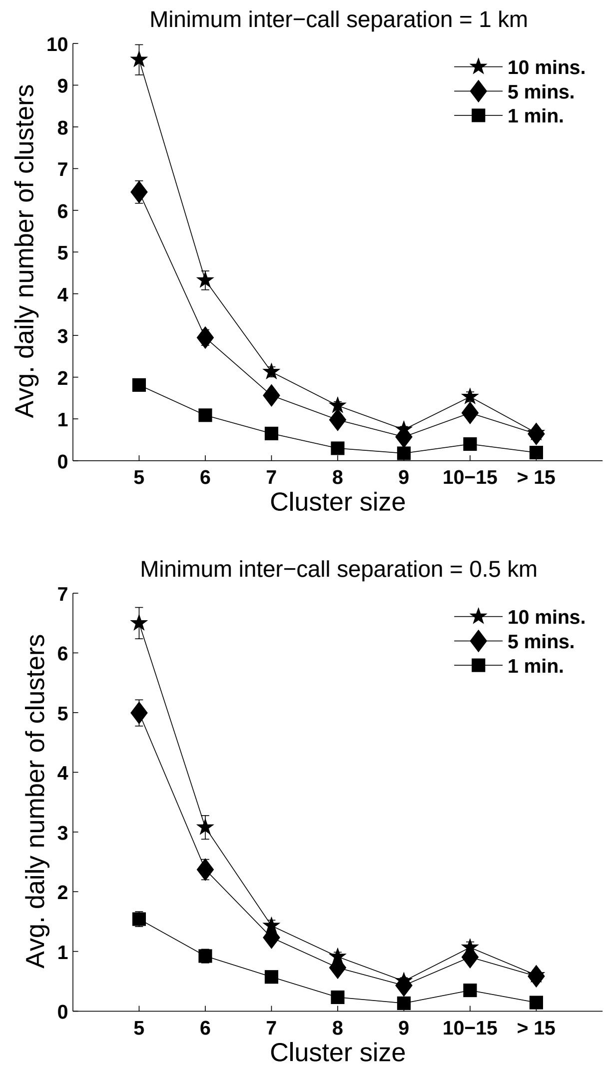

Fig 9. Average daily number of clusters for San Diego County, for different values of minimum cluster size, minimum inter-call spatial separation (top: 1 km; bottom: 0.5 km), and minimum inter-call temporal separation (10, 5, and 1 minutes) of our algorithm. Error bars indicate standard errors.

5. Conclusion

The collection of 9-1-1 call information at a level higher than individual PSAPs has proven to be effective for detecting the location and extent of major emergency events [2, 3, 4]. Given the amount of data generated and the time-critical requirements of emergency responses, we have been using pattern-discovering data mining approaches to automate the process [3, 4]. This paper extended the analysis of the hotspot detection algorithm described in [3] by exploring the effect of different parameter settings, in particular the effect of minimum inter-call temporal and spatial distances on the daily number of daily detected number of clusters. A reasonable set of parameters was suggested suitable for the detection of medium to large-scale events. The effectiveness of these parameters should be further investigated by monitoring reported emergency events.

6. Acknowledgments

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7. References

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