Scaling 911 Messaging for Emergency Operation Centers During Large Scale Events

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ABSTRACT

In this paper we imagine that one day soon, mass crisis events will result in thousands of people trying to get emergency help multiple via multiple mediums. Public Access Service Points and 911 Centers will not be able to meet the demand of text-message calls for help during a large scale disaster. While 911 dispatchers will need to respond directly to each individual text message, we present the development and testing of a system that aims to provide this data, in real-time, directly to emergency managers during a large-scale crisis. The system is designed to accept, sort, triage and deliver hundreds of direct text messages from the PSAP and provide them directly to emergency management staff, who can leverage their content. In the hands of the emergency manager, these data can be used to inform resource allocation decisions, enhance their operational situational awareness, and potentially improve the response to the crisis.

Keywords:

911, Crisis, Disaster, Emergency Management, Emergency Operations Center, Public University, Situational Awareness, Text Messaging.

INTRODUCTION

While the U.S. is making strides to include communication other than voice with emergency dispatchers during an emergency, current systems are generally designed to handle routine emergencies. In a mass crisis event, where thousands of individuals may be trying to engage emergency channels via multiple mediums, we believe that 911 centers will not be able to meet the demand. The current, voice-centered 911 service does not meet the expectations of modern communications styles. However, in the near future anyone will be able to send a text message to emergency services through the existing 911 infrastructure. This is due to the U.S. Federal Communications Commission (FCC) tasking cellular service providers and 911 call centers or Public Service Answering Points (PSAPs) with developing the capability to receiving text messages in addition to telephone calls. Currently, text-to-911 is only available in certain markets where PSAPs have elected to accept emergency text messages from the public. (http://www.fcc.gov/text-to-911). This initiative is progressive in its orientation toward common communication trends. Today, in large-scale crisis events, there will be thousands of bystanders or victims trying to contact PSAPs via telephone. In larger disasters, this quickly overwhelms the current voice-based system. As we move toward the ability to text-to-911, we should expect a large influx of text messages to the PSAP. Being able to manage and utilize that data will be critical to informing the response management. Additionally, emergency managers should be able to leverage social media and other forms of technology-mediated communication to contribute to heightened situation awareness and greater success in managing and responding to crises.

During large events, Emergency Operations Centers (EOCs), are tasked with coordinating response, logistics and communications. The EOC becomes an incident-specific resource that needs to coordinate activities with and on the behalf of the incident commander. It operates as a resource to the incident command staff and often operates alongside the PSAP. We believe that Emergency Operations Centers (EOCs) will play a key role in information gathering, processing and delivering during these mass crises. There is a significant amount of work to be done in order to bring the EOC fully online (Militello, et al. 2007). EOCs are often publicly funded entities residing between municipal, county and state governments with cross-jurisdictional and heterogeneous responsibilities and funding sources. Despite holding a position of growing importance in terms of information management during crises, county and local EOCs often find themselves under funded, under staffed, and under developed, especially in regards to information technologically. Historically, crisis preparedness and response infrastructure has evolved in reaction to events given previous experiences in recent crises. This has resulted in often piecemeal development that is subject to a variety of bureaucratic pressures (Jensen and Waugh, 2014).

In this paper, we present the development and testing of system that aims to provide real-time data to emergency managers during a crisis event. On the one hand, the system is designed to accept, sort, triage and deliver hundreds of short text messages from citizens to the PSAP. On the other hand the system gathers, aggregates, processes and deliver data scraped from indirectly communicating populations engaged in a mass event to emergency managers. Both of these data sources can be served to emergency managers who can use them as data inputs to decisions affecting their operational situational awareness and the response to the crisis.

BACKGROUND

A number of events have forced emergency services to be re-configured radically since the 1970's. The phone number 911 was first instituted in the United States in 1968. This number allows residents to call a telephone center in order to request emergency services such as police, emergency medical services, or the fire department. In 1979, various agencies signed into existence by Eisenhower and Roosevelt were all collected under the name "Federal Emergency Management Agency." It was here that 911 began to become part of the public lexicon. By the 1980s, most municipalities had adopted 911 as their emergency backbone. However, telephone services themselves began to change. Cellular services grew in ubiquity. This resulted in a need to enhance 911. So, in 1996 after a number of incidents indicating a need to address growing cellular devices in circulation, the Federal Communications Commission (FCC) announced an enhanced 911 initiative (Reed, et al, 1998). This initiative specifically asked that cell phone and special mobile radio services incorporate 911 service by October 1997. By 2001, the e-911 initiative was also to include location services for all cell phones as well (Reed, et al. 1998). While the initiative was a success, events of the terrorist attacks of 2001 that resulted in radical shifts in emergency response.

In 2001, terrorists intentionally collided passenger jets into buildings in New York City, the Pentagon and intended to collide a fourth into another target, but failed. In response to this deliberate terrorist attack against the United States, there was a radical shift in what constituted disaster preparedness. FEMA was re-organized and placed under the Department of Homeland Security. In addition, further technological development also radically altered the way that citizens used communication devices. The FCC issued an order in August of 2014 requiring all carriers provide the ability of PSAPs to receive texts-to-911, if requested by the PSAP. The wireless carriers must be capable by the end of 2014 and respond to the PSAP request by June of 2015 (or 6 months from date of PSAP request, whichever is later). These changes, social, political and technological are driving forces in our need to provide improved 911 interaction.

Emergency Operations Centers

An Emergency Operations Center (EOC) is a facility that houses communications capabilities and staff that support the response to a disaster. The size and complexity of the EOC usually is directly related to the size and complexity of the hazards that may impact the particular community. The most important role for the staff in the EOC is to ensure information about the incident is communicated to the command staff, to the responders and to the public. This requires resources, appropriate policies and procedures, and an experienced staff. It is important that the information be accurate, meaningful, and timely regardless of the intended audience. If the staff in the EOC cannot obtain accurate information in a timely manner they cannot perform their primary functions. Typically the staff is responsible for collecting, verifying, analyzing, and disseminating information that will help decision makers. The EOC may also be responsible for sourcing and ordering resources, developing long-term plans, addressing inter-agency policy issues, tracking overall costs, and addressing human resources related issues. Responders in the field manage life-saving, property conservation, and incident stabilization activities. The EOC supports that effort by coordinating resources required for recovery actions, coordinating the opening of shelters and relocation centers, starts the process to obtain financial assistance, communicates timeframes for re-opening of businesses, and virtually all of the coordination required by the incident commander and operational units. None of this can be done without accurate and timely information.

The challenge for the EOC staff is to leverage all of the sources of information available. Increasingly this includes technologies such as text, video, images, and social media. Whether this is in the form of social media or from messages sent to PSAPs, it is important that the data is captured, analyzed, and distributed, as appropriate. Currently there is little in the way of automated systems designed to specifically assist the staff in the EOC analyze large volumes of raw text data. It is often difficult just to make sure that this data is actually from inside the impacted geographic area. There are some services that can assist in tracking and analyzing discrete data, but there does not seem to be any software or services on the market that can evaluate large quantities of data in an emergency situation, determine the relevance, geospatially locate the data, and assign the data for further analysis or response.

At this time only the largest of the metropolitan areas have the means to not only capture the data from social media, but to process the data and integrate it into their decision-making. Most of them do this by using large numbers of staff to manually review data that may or may not have been passed through some type of script to pre-sort the data. Many EOCs, especially those in rural county-level EM functions, have very limited permanent staff and there is no standard means for collecting and processing social media data. The lack of standards and the lack of automation to help manage the potential volumes of data prohibit many from even attempting to use social media or text messaging during emergencies.

PROXY-CRISES EVENTS

Since actual disasters are of low frequency and are unpredictable, it is difficult to build and test any alert system. Artificial data, scenarios and laboratory experiments, or the analysis of past data, can only deliver limited quality needed for an alert system—the ability to detect and alter the unexpected. We feel that the similarities between a natural or manmade disaster and a large-scale planned event with smaller crises can offer a chance for researchers to test elements of an alert system either real-time, or in near real-time.

A proxy event for a disaster would allow us to evaluate methods, processes, or procedures for their suitability for use in disasters. To be a good proxy event the event must approximate the conditions that would be seen during a disaster, for the methods, processes, or procedures being tested. During most disasters communications is difficult because of the increased volume of communications and the stress on the human and physical resources. The volume of people trying to communicate with emergency services and official sources will likely overwhelm the current infrastructure, methods, and processes for handling the incoming communications.

In our research, we have developed the opportunity to test our alert system during two large planned events, football games and a dance marathon.

Football

Most large universities in the U.S. host football games during the fall. In the BIG 10 conference, stadiums seat anywhere from 50,000 to 110,000 fans during each game (Gall, 2013). Tailgating parties for each of these games can begin days before the event with impromptu trailer parks and campgrounds forming in the surrounding town and parking lots surrounding the stadium. During sold out games, additional tailgaters significantly increases the total number of participants in game-day activities beyond stadium attendance numbers.

Alcohol consumption at these events is often significant and in itself is a major contributing factor for the volume of calls to stadium guest services, as well as police, emergency medical services. While many of these communications go through the 911/PSAP, there also may be local specific contact numbers at the stadium for guest services. Many stadiums utilize incoming text messages as an alternative to reach guest services. Calls that come into guest services and the PSAP amount to an extraordinarily large volume of communications that must be managed by a finite staff. Predictable events like football games create an excellent proxy for testing procedures meant to aid in the large volumes of diverse calls coming into a PSAP or EOC. The addition of text messaging allows us to further test these systems as next gen 911 becomes more common.

Large-scale University Dance Marathon

In addition to football games, there are other events that can serve as test beds for possible PSAP or EOC initiatives. For example, The Pennsylvania State University also holds a three-day Dance Marathon that raises money and provides emotional support to children and families effected by cancer. It is the largest student-run philanthropy in the world by involvement and by revenue. In 2014, the Dance Marathon raised over $13 Million in 46 hours. The Dance Marathon hosts 700 dancers with more than 15,000 organizers supported by over 375 student organizations. During the three-day event the normally small town gains 10’s of thousands of participants, visitors and dancers.

This event provides researchers with a different venue that is interesting for testing communications methods. This event spans 48 hours and is highly focused on the university student population as participants and visitors. Text messaging, the use of the anonymous social media YikYak and others like it allow for a multi-faceted test to occur with and throughout a diverse variety of communications channels. A dance marathon at a university attracts the appropriate demographic to fully incorporate these media into our tests as well. We anticipate that this group of social-media focused millennials will generate a large volume of communications across multiple social media modes during this event. This would allow for the testing of methods, processes, and procedures for sorting, categorizing, and otherwise managing the information to create situation awareness. It is likely there will also be opportunities to test two-way communications methods, processes, and procedures during an event of this type.

RESEARCH DESIGN

In this paper we present the development and testing of a two-fold system that aims to provide real-time data to emergency managers during a crisis event (see Tapia et al. 2011; Tapia, Moore, and Johnson 2013; Tapia and Moore 2014). On the one hand, the system is designed to accept, sort, triage and deliver hundreds of direct text messages from populations engaged in a crisis to emergency management staff who can respond. On the other hand the system will gather, aggregate, process and deliver data scraped from indirectly people using Twitter or other social media to talk about the crisis. Both of these data sources will be served to emergency managers who can use them as data inputs to decisions affecting their operational situational awareness and the response to the crisis.

We employ ***TAMEE - Text Analytics for Monitoring Extreme Events*** to gather both forms of text. The TAMEE system was developed to be used to aggregate Twitter Tweets that have been captured and saved to a MySQL database. These tweets are then displayed using frequency analysis tools. TAMEE provides tools to identify major themes, important contributors and links to important external content. In this work, we modify the back-end of TAMEE and focus the analysis on text messages that could be sent to a 911 Center.

Our goal is to create a system to allow an analyst to quickly aggregate and analyze the messages. We will create a set of identifiers (or features), provide weights, incorporate these into an analytical framework and use the results of the analysis as input to a scalable computation model. Our work will develop algorithms that can estimate content and intensity of messages in a high-volume streaming text comprised of short messages. As a by-product, this project will also create an evaluation benchmark that can be used by other researchers to test their algorithms.

TAMEE - Text Analytics for Monitoring Extreme Events

The TAMEE system was developed to be used to aggregate Twitter tweets that have been captured and saved to a MySQL database. These tweets are then displayed using frequency analysis tools. TAMEE provides tools to identify major themes, important contributors and links to important external content. Information overload quickly becomes an issue in extracting knowledge from data in a stream of tweets, even those that have already been selected that contain specific keywords. Noise makes difficult for emergency managers to gain actionable information from the vast, real-time information that Twitter and other social media provide. TAMEE makes use of frequency analysis of the words in tweets during extreme events using a novel set of analytic tools.

TAMEE—Features and Capabilities

TAMEE is a collection of multiple software systems that strive to provide easy collection, analysis and recall on tweets pertaining to a certain subject. In the next sections, we describe the various aspects of the system as well as the collection and storage methods of the system. These include the Twitter Collection Agent, the Frequency Graph, the Word Cloud, the Tops Lists, the Raw Data Display, and Controls. See Figure 1 (below) for an overview of the interface.

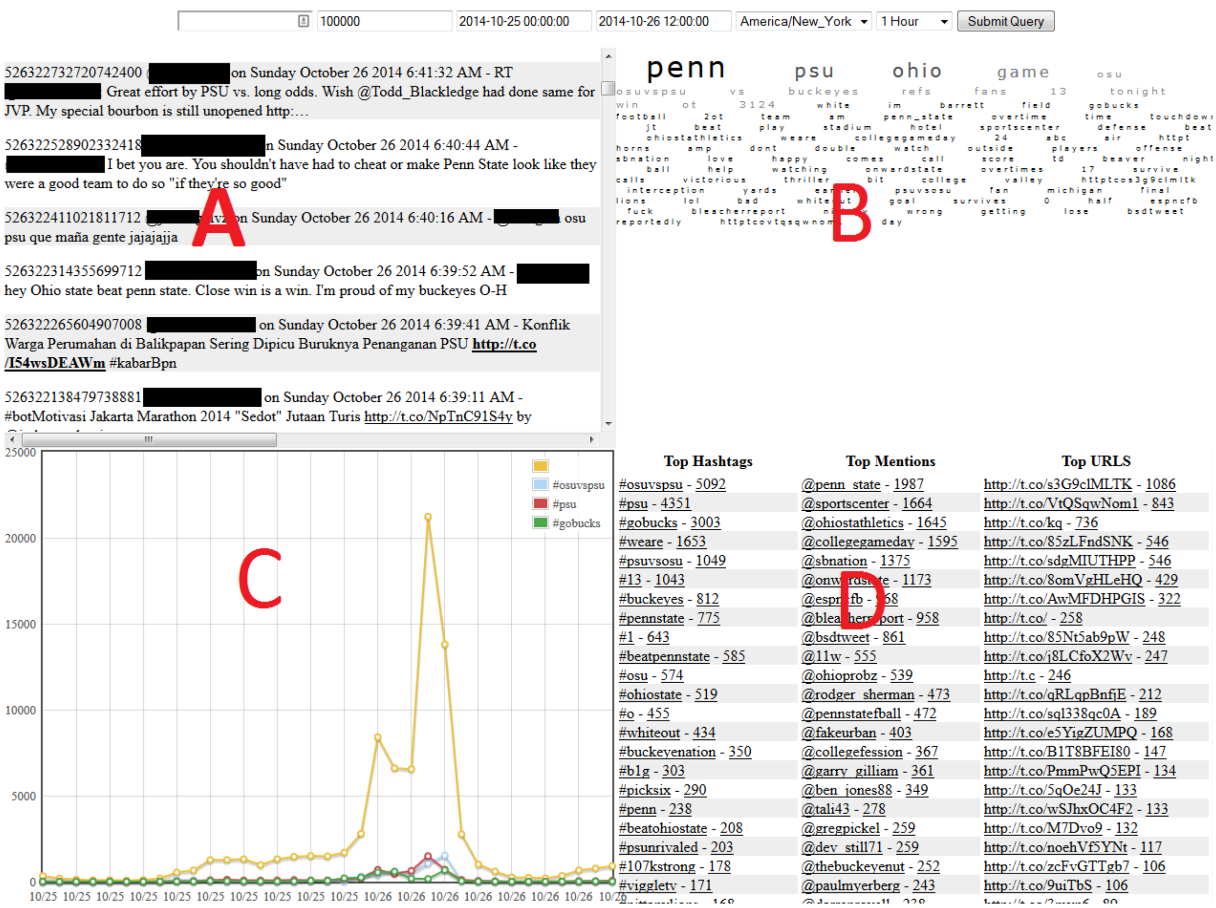

Figure 1. TAMEE's Display with (A) Tweet Feed, (B) Word Cloud, (C) Frequency Chart and (D) Tops Lists. Data from PSU vs. Ohio State Football game on 10/25/14

Twitter Collection Agent

The Twitter Collection Agent utilizes the open source scripts from 140dev.com to capture tweets containing specific keywords or in specific locations using the Twitter Stream API v1.1. The tweets are collected and expanded into a MySQL database. The data collected includes the Tweet Text, Poster's User Name, Unique Tweet ID, Geocoordinates (if the user provided them), and other metadata about the Tweet. The 140dev.com engine has been successful at capturing tweets from the Streaming API at rates of over 100,000 per hour on a single desktop workstation. Tweets can be captured if they match one of a set of keywords, or if they tweet was geo-located within one of several user-defined geofenced boundaries.

Frequency Chart

The Frequency Chart (Figure 1, Panel C) is a Flot graph that provides a visual representation of the temporal aspects of the current data collected. Flot is an open source JavaScript library used to create graphs and visualizations as well as update them in pure JavaScript. This chart gives analysts the ability to see spikes and other patterns including the number of tweets per time period that contain specific words or hashtags. The graph can be modified in order to represent various temporal flows including one hour, four hours, ten hours and twenty-four hour periods. For example, Figure 1 shows tweets captured during the Penn State/Ohio State Football game in October 2014. Data frequency is separated into one hour blocks. The data in the figure spikes during the 11PM hour, as this was near the end of the game which included two overtime periods.

From this basic visualization, an analyst can infer much about the time in which the data is collected regarding the subject. Flot is an open source JavaScript library that dynamically generates the graphics on the client side as the web page is loaded. The time/frequency calculations are done server side. This allows the chart to be context sensitive and it therefore can be generated after the user's input requests so that it is the most useful.

Word Cloud

Word clouds are a popular way in current social media to visualize the word distribution of various aspects of a corpus of text. TAMEE includes word clouds (Figure 1, Panel B) in order to allow users to quickly understand the key terms in a large volume of tweets at a glance. This also allows users to quickly see the top users (ones who are mentioned often in other tweets) that are driving conversations and cross reference this data with the top lists explained below. The size of the words are defined relative to the amount of times it appears in the text.

In the creation of the word cloud, all the select tweets are fed through a word cloud creation algorithm. Once all the text has been entered, relevant stop words from both English and Spanish are removed to cleanse the text of these common words (the, and, but, a) so they do not dominate the display. The resulting world cloud representation affords an intuitive way of looking at the large amount of text at a glance. From an analytic perspective, users can quickly identify unexpected words as they appear in volume. The word cloud generation algorithm is fairly efficient. Even given tens of thousands of tweets, the visualization is computed in near real time.

Tops Lists

The Tops Lists (Figure 1, Panel D) generates and displays various lists of the most used hashtags, mentions (of specific users) and URLs. This list displays the hashtag, mention or URL itself and a count of the total amount of times it appears in the raw data. If one were to click on the hashtag they would be taken to a Twitter search for that hashtag. A mention link refers to the mentioned user's Twitter page. The top URLs direct the user to the link of the page that was referenced in the tweet. Another feature of this part of the interface is the ability to click on the count and have that specific text highlighted in the Tweet stream. This is good if a user wants to see the specific context with which certain items are mentioned. These lists give the user an overall idea of what hashtags, users and URLs are related to the conversation. As a result, this allows users to find potential users to follow, links to relevant data and possibly learn of new hashtags to consider watching.

These lists are generated via standard PHP string comparisons within the text so they are sensitive to spelling and grammar errors that are inherent in the raw data. However, Twitter has an autocomplete feature that assists users in the proper spelling of many links and mentions, so this minimizes some the problem. The time complexity of the generation of these lists grows fairly fast with the addition of more rows, but for the most part the algorithms are able to handle tens of thousands of Tweets very efficiently. The only drawback of this feature is that these lists may not be representative or helpful if the amount of text collected or requested is very small.

Tweet Text Display and Controls

TAMEE displays the raw text of the messages (Figure 1, Panel A) that match the search terms. The controls allows the user to fine tune the data they have collected to meet certain user specified criteria. Search term, tweet limit, starting date, ending date and time period are all available for the user to adjust. This allows users to select very small specific time frames, but at the same time also be able to select broad areas if they so choose.

Additionally, all the Tweets are displayed with the username of the user that posted it, the time it was posted and the actual text of the tweet. Coupled with the tops lists and the word cloud, this allows the user to dive into the raw text itself and be able to understand what the massive amount of data means at a glance. Tweets are displayed from the MySQL database in their raw form. Therefore, any shorthand, emoticons, misspellings and other intentional or unintentional grammatical errors in the original text are propagated forward. The messages are exactly as they are presented on Twitter.

TAMEE— Texting 911

In this section, we modified the back-end of TAMEE and focus the analysis on text messages that could possibly be sent to a 911 Center. While this is somewhat different than what TAMEE was designed to do, the affordances appear to be useful on text messages as well as tweets. We explored two potential sources of text-to-911 center data. The first is an actual PSAP in a relatively rural county, but the PSAP we chose does not currently have a capability to receive text messages. The second is a large university football stadium that has a publicly-available short-code text system. However, this stadium has not experienced any large-scale disaster incidents in which the text system was used extensively.

Adapting to Text Messages

We acquired the text messages from a stadium's guest services texting platform to explore whether TAMEE's facilities could be helpful in analyzing text messages instead of Twitter Tweets. A total of 645 messages were imported into the database and spanned four different major football games over a two-month period. While this text volume is extremely small as compared to Twitter over a similar period, we believe that this is analogous to a number of 911 calls that might be delivered over a text messaging interface under normal (non-crisis) conditions.

As expected, the frequency chart shows when the events (games) occur. Some messages were sent to the system between games as different stadium operations personnel tested the system.

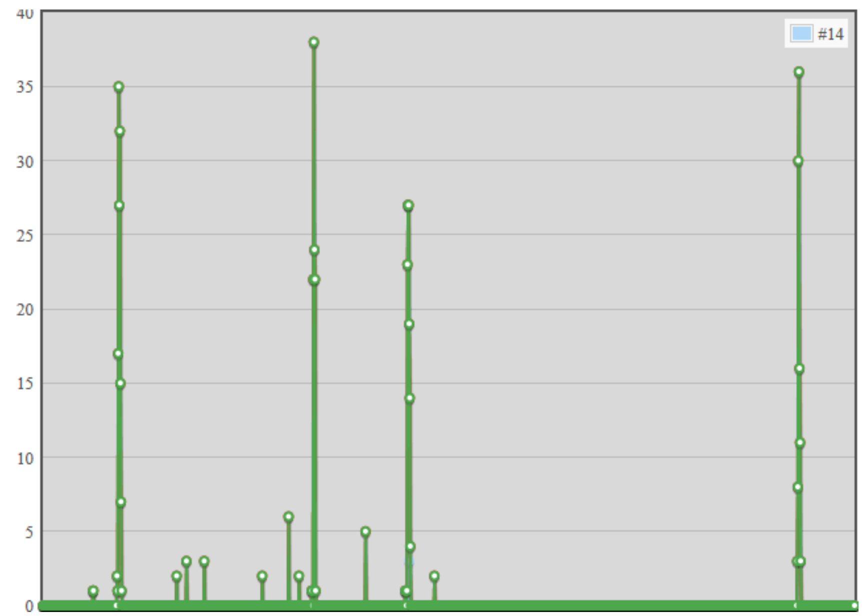

Figure 2. Text message frequency in TAMEE over a two month period

Additionally, the frequency chart shows key words in relation to the overall frequency. In the figure below, we see the frequency of the word "drunk" in relationship to all other text messages.

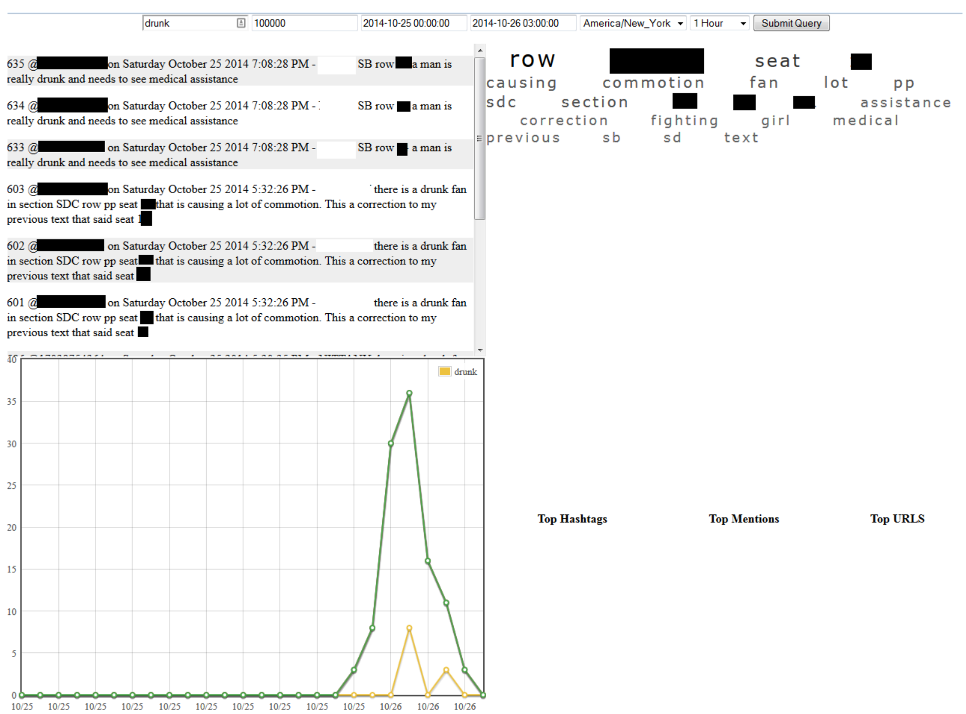

Figure 3. Analyzing text messages looking for "drunk" as a keyword

This representation roughly matches the 1:1 to 5:1 text message to incident frequency that we would expect to see in normal (non-crisis) conditions. As we have seen with TAMEE's capabilities, as people text instead of calling, we should be able give the emergency manager the capability to interpret the data in aggregate. As has been seen in other incidents, the cell phone towers' capacities have been overloaded and people cannot make outbound calls during crises, but text messaging seems to still work. The 911 center's job of dispatching resources to incidents would likely have been exceeded and regional PSAPs are picking up the overflow of call and text reports. In our scenario, we can imagine that our EOC has been established as the incident command post to deal with a large crisis. Representatives from police, fire, EMS, hazmat and local government would be able to use the PSAP Texting Data to get a handle on the size and scope of the incident while the PSAP operators handle individual calls.

One of the functions of Emergency Management is to get a handle on the size and scope of the incident. We imagine that the Emergency Manager could have direct access to the 911 center's text messaging data and could use TAMEE to get a better feeling for the number and nature of the reports that are coming in. However the EM knows that the PSAP employees are completely overwhelmed trying to answer every text and determine where limited resources are needed. The EM could looking at the incoming feed of the 911 text messages rather than the incident and response statistics that are generally after the incident is over.

DISCUSSION

In this paper we report on the development and testing of our protocols and software in two circumstances. We have conducted two pilot tests, one using Twitter and another using incoming SMS text messages, both inside the EOC during large football events. We have two additional field tests planned for Spring 2015 – one at the dance marathon, and the other for the spring scrimmage football game.

During the first pilot test we analyzed Twitter tweets with a set of keywords that relate to the football team and university's name. The tweets were gathered and processed using TAMEE. The processed and visualized data was then put in front of the emergency manager and several assistant students who evaluated and triaged the messages and made decisions about the immediacy and impact of the tweet and whether it indicated that there was a likely large scale event or problem. If there was, the EM funneled the information to the appropriate person (police, fire, EMS) for action.

We learned that since most Twitter tweets are not geotagged, most tweets were not coming from our campus. Even though we had the right keywords, tweets were about the game and the team, not from the stadium. Since the university is a large, public institution with a large fan-base, the amount of noise in the system was much greater than was expected. Most students and fans in attendance at the game don't apparently tweet with the school's name (or one of our other keywords) as one of the words in the tweet.

During the second pilot test we acquired the text messages from the stadium and facility operations. We put this data into TAMEE to determine if TAMEE was suitable for text messages as well as it was for Twitter Tweets. We found that the low frequency of messages was not detrimental to the usability of TAMEE. We expect that if there were a much larger volume of incoming text messages, such as in a disaster or large-scale emergency, that switching perspective from individual message response to viewing the messages in aggregate would be helpful for the EM and incident commander.

While it was not part of the second pilot test, we seek to integrate the output of both the text messages and data from multiple social media platforms into one visualization in near real time. Twitter and Facebook are likely social media platforms that will be integrated, but we are also beginning to work with Yik Yak (www.yikyakapp.com) to gain access to their geo-located, but anonymous social media data. The goal of this phase of the research is to develop information communication technologies (ICTs) to allow for the processing, quick and efficient of information something akin to a common operational picture (COP). A COP, often seen in military operations, is a way to increase common situational awareness and an attempt to present actionable information to all levels of the crisis response.

CONCLUSIONS

During a mass crisis event the demand for direct communication with emergency services often rises past the ability of officers to respond. Typically during a mass event, telecommunication services, if still functioning, become saturated with callers intending to reach the 911 Center to report an incident. If a call can be placed, the 911 Center itself may be saturated and unable to receive the call. In that case the call is rerouted to nearby counties, which may have open 911 lines. Once these additional lines are saturated the caller will receive a busy signal or a message, which invites the caller to try again later. During a mass crisis event the inability to connect with emergency services could cause additional panic, frustration and put lives at additional risk.

To address this problem Next Generation 911 services are coming online. Sending a text uses a fraction of the bandwidth required to place a phone call. If telecommunication services are saturated, it is far more likely that a text will reach it intended target than a phone call. In addition, theoretically a dispatcher receiving a request for aid can respond to more than one texting individual at a time, unlike the one-caller-to-on-dispatcher model presently in use. As of today most 911 centers are still operating on a one-to-one model, even if they accept texts. Dispatcher overload may be reached quickly in a mass crisis event.

In mass crisis events Emergency Operations Centers are in a position to monitor, evaluate and triage incoming textual messages if they overflow the capacity of the 911 center. As we have noted above EOCs often fill the role of a communication hub during mass crisis events, receiving, processing and disseminating information between responders during a crisis. It is possible that as voice calls are supplemented or replaced by texts during mass events the EOC will play a role in analyzing this data as well as overflow capacity for the 911 Center. We believe that the role of the public EOC is changing partially because of the potential role change in relation to textual data and 911.

The problem with this model is that typically EOCs only come online when they are needed, i.e. during a mass crisis event. They are mostly staffed by volunteers and/or representatives of other emergency services, who are only together for occasional training and crisis events. Technologies, technical training and technical support are significantly limited.

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