Engaging Communities in Public Safety via Social Media

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***Abstract*—The importance and effectiveness of community-based rescue efforts have become clear in recent emergency response operations of Hurricanes Harvey, Irma and Maria. Social media age has made it possible for the most physically disconnected residential areas to not only notify their loved ones of their safety by a single touch to update their status but also request help. In this paper, we propose a communication protocol and a Public Safety architecture over social media platforms like Twitter that allows a person in distress to send SOS messages to the Public Safety Network and for the response to be routed automatically to the closest dispatch unit or volunteer registered within the system. This allows distressed people to request help, like an "online 911" service, and lets the system take care of connecting both volunteers from the community as well as first responders to the victims. The proposed approach could enable communities to learn how to become part of the extended network of dispatch units by learning the skills necessary and registering with the Public Safety Network.**

***Index Terms*—Social media, public safety, communication, community, SOS**

I. Introduction

Communication is key to survival in any disaster scenario and social media is increasingly becoming a mainstream mode of communication. According to wersocial.org, approximately 3.3 billion people around the world use social media on mobile devices [1]. Recent disaster incidents showed several interesting uses of social media in terms of recording incidents and communicating with friends and community during and after a disaster. For example, social media was used for propagating information following the Haiti earthquake [2]. During the 2016 Pulse nightclub shooting in Orlando, Facebook was used by the nightclub to alert its followers to run out of the nightclub; and it was also used by the survivors to inform their loved ones that they were safe [3]. During Hurricanes Harvey and Irma, stranded people shared their locations with emergency officials over popular social media networks like Twitter, Facebook and Instagram, and also shared pictures to aid officials to gauge the severity of the situation [4]. Platforms like AIDR have shown that real-time disaster insights can be obtained through social media by using machine learning algorithms and crowd-sourcing for tweet classification [5].

Not only did we see the affected victims and emergency officials use social media, but also saw an increase amongst volunteers in the use of social media to locate stranded people requesting help. In Texas last year, a fleet of volunteer boat owners, Cajun Navy [6], participated in Hurricane Harvey rescue efforts by using apps like Zello [7], a walkie-talkie like app that works on WiFi or cellular data network and allows rescuers to talk over private channels to coordinate their efforts. There are several challenges that arise with such efforts, including coordination with officials from multiple agencies, lack of overall prioritization of efforts, and incomplete feedback loops [2], [8].

We propose to use social media apps not just for rescuers and volunteers but also to provide a service similar to the legacy 911 call service. According to the National Center for Disaster Preparedness at Columbia University, disasters often impact 911 service availability and social media can help people stay in touch [4]. Sometimes the 911 network fails due to other reasons. For example, the Verizon outage in June 2018 and the AT&T outage in March 2017 prevented cellphone users from dialing 911 [9], [10].

In the US, about 240 million 911 calls are made yearly, while there are 5,783 911 call centers according to December 2017 statistics [11]. The traditional 911 service suffers from scalability issues, especially in the case of major disasters with a huge influx of callers and a limited number of 911 call-takers, resulting in prolonged call wait times for callers who may not get connected until it is too late. Scalability is one of the challenges our proposed framework will tackle.

Another infamous issue is the need for reliable communication networks and information systems [12], which was a harsh awakening in the aftermath of Hurricane Katrina in 2005. Katrina opened our eyes to several issues that challenged officials in their search and rescue efforts, such as failure of infrastructure, delay in restoring landline networks, unavailability of a common framework for different agencies like FEMA, local police, Red Cross to communicate and share information rapidly and accurately. FEMA could not respond to all the victims in time, primarily due to inefficiencies in getting approvals through the various government workflows. Help from local communities was needed, but there was no system for victims to seek this help. We provide a framework that allows victims to request help, allows local communities to initiate rescue efforts much earlier than waiting for FEMA to arrive, and facilitates communication between the victims and response teams from the community or otherwise. Specific contributions include: a) Smart Public Safety Framework (SPSF) using social media as a communication platform, b) Twitter-based SOS protocol, and c) future research opportunities.

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II. Smart Public Safety Framework

We propose a Smart Public Safety Framework (SPSF) using social media as a communication medium in order to:

- *Scale the efficiency* of PS response and rescue where a purely centralized PS handling approach does not suffice and community engagement is necessary,
- *Reduce infrastructure dependency* for PS and disaster response communications, and
- *Engage communities* in helping victims and the PS officials in a safe and reliable manner.

We envision an SPSF web system that can be used by PS officials, Public Safety Network (PSN) and Public Safety Call Handlers to track and view requests from end users automatically sourced through social media streams; analyze and triage requests; track and view volunteers' skills and training; assign requests to dispatch teams; and more. We will use the term Requester to refer to the person sending an SOS message via any of the social media platforms. We will use PS officials, PSN and PS Call Handlers interchangeably to refer to the infrastructure or people who respond to victims or emergencies. The PSN includes a) PS Call Handlers who respond to distress signals and b) Dispatch Units or Response Teams that accept the job and rush to the emergency locations. Dispatch Units are comprised of both officials of Police, Emergency Medical Service and Fire Department as well as volunteers from the community registered with the SPSF system. This framework could also have a smartphone app that volunteers can use to easily check in to the SPSF web system with location updates, add their latest relevant skills (e.g. bilingual), certifications (e.g. CPR, CFR-D) and training (e.g. lifeguard, mountain rescue, first aid), and view any feedback and comments from other PS officials or requesters.

Our proposed SPSF system architecture, shown in Figure 1, includes the following key components:

A. Pubic Safety Bot

The primary purpose of the Public Safety Bot (PSB) is to ingest social media streams in real-time, monitor for distress signals and alert the PS Call Handler. This would be accomplished by tracking an agreed-upon hashtag, e.g. #SOS that has been communicated to the public. There are many tools available to track messages and conversations around hashtags (e.g. Hootsuite) and each social media platform also has its own API for ingesting streams (e.g. Twitter Streaming API). If the request includes the emergency type, the PSB will flag it for the Handler. The PS Call Handler then engages with the Requester to confirm the flagged emergency or present enumerated options to Requester for a simple numeric selection to determine the cause of this request. The PSB can also be configured to initiate a series of predefined questions as per PS Call Handling procedure to save time for the handler if they are busy with another request. The PSB can work with an AI translator service to overcome language barriers between non-English speakers and call-takers. This is a clear advantage of using a social media based framework, as traditional 911 service does not have such on-the-fly translation capability.

B. Victim Triangulation

Location information is key for the success of any rescue operation. In the best-case scenario, a single, geo-tagged tweet from a victim that includes either an emergency code (if the public is familiar with emergency codes) or a picture of the emergency may be sufficient for the dispatcher to quickly assess the situation and send help. However, in reality, less than 3% of tweets are geo-tagged [13]. For the first responders to reach the distress signal origin, there is a need to triangulate the messages' location.

In the case of traditional 911 service, when a victim dials 911 from a landline, the Public Safety Answering Point (PSAP) is able to send first responders to the address registered with the landline number. When you dial from a cell phone, the call reaches the closest PSAP, but the mobile phones are not registered with specific addresses. However, the cell towers receiving the signal from the victim's mobile phone can triangulate the victim's location, and provide it to the PSAP agent. In most cases, the PSAP agent would still confirm the location of the victim or emergency. In the proposed online SOS service, pinpointing the requester's location is even more difficult as most users do not enable geo-tagging.

Aside from the obvious method of the PSAP asking the distressed caller directly about their address, researchers at Penn State propose *social triangulation* [14] where, by compiling which organizations and people one follows and looking solely at local organizations, they can determine what communities or localities a person belongs to. Another method is to analyze users' content and search for keywords, for example, some IBM researchers developed an algorithm using statistical and heuristic classifiers to predict the location of a Twitter user by analyzing the tweet content [15]. Although social triangulation can be helpful for public safety officials to send tailored and targeted messages to people based on their memberships to specific communities, this method may not work for pinpointing the location of a specific user in real-time during an emergency. Similarly, the content analysis method does not reach the granularity of location identification needed for rescue and response operations.

More work needs to be done for pinpointing an online SOS Requester. Perhaps one approach is to use AI to analyze SOS Requester's feeds on different social media platforms to discern their exact location. But this is time-consuming, it would involve determining the user's handles in various social media platforms, skimming the messages and pictures, then running some context analysis or image analysis on recent content to co-relate the background of photos, for example. In order to save time, should public safety officials run this analysis on people with social media presence beforehand? This raises socio-ethical concerns. But perhaps actions like these are necessary for preparedness, e.g., a proactive analysis on messages being exchanged before riots start can help officials respond in time to prevent catastrophe [16].

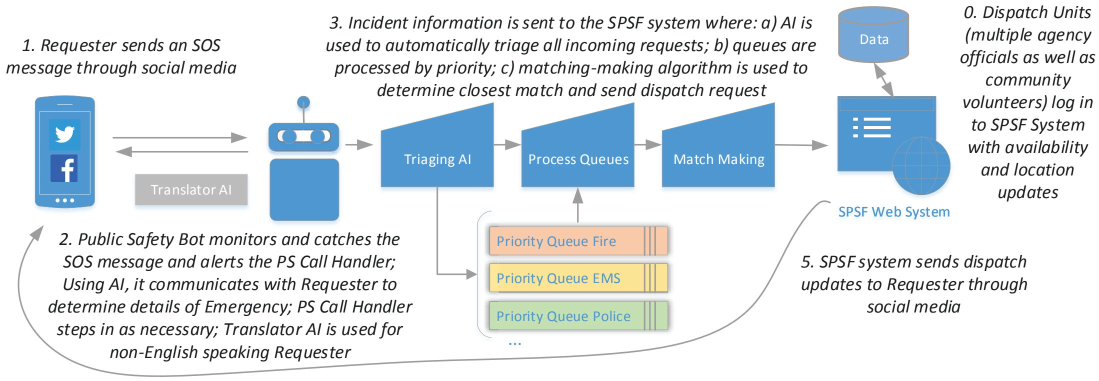

Fig. 1. Smart Public Safety Framework (SPSF)

C. Triaging Social Media SOS Messages

A drawback of using social media for SOS is that social media messages can be anonymous and it will be necessary to have AI techniques that can effectively filter out fake online SOS calls. Additionally, such triaging can help with overloading issues in the legacy 911 call service as most 911 call centers are manned by a limited number of PSAP agents. These agents have to prioritize calls as they receive them while minimizing the wait time of callers in order to process the most important calls first. The proposed PSB can ask the questions necessary to triage the request, discard fake ones, and flag requests with life-threatening emergencies. Today's social chatbots can have an engaging conversation with the user and gain the user's trust through empathetic exchange [17]. Studies show that machine learning algorithms have the potential to triage patients in the emergency department [18] and in some cases can be better at triaging decisions than humans [19]. The AI tool Corti can assist an emergency call-taker to identify if the caller is having a cardiac arrest in 95% cases (versus 73% by a human dispatcher) by recognizing patterns in breathing [20].

Traditional 911 service breaks down during large scale disasters, where PSAP is inundated with phone calls and some people cannot even get through. Augmenting the traditional network with a social media based SOS service should help alleviate the burden in disaster cases, but it may just as easily exacerbate the issue. By making it easy for people to send photos and videos with their SOS messages, the amount of traffic generated during a big disaster may end up affecting network availability and response time. This could be handled by using a mix of Internet-based social networks and device-to-device networks to extend connectivity by sharing device services like messaging and data [21].

D. Queue Processing and Matchmaking

This module is responsible for managing Priority Queues for incoming requests that have already been flagged with the emergency type. It automatically processes the incoming requests and adds them to their relevant queues i.e. fire, police, and medical. Each emergency queue can itself be prioritized and all queues can be processed in parallel as response teams are generally separate for these emergency types. Note that this is an advantage to manned PSAPs as calls are processed in the order they are received, there is no way to know that a high-emergency call is in the wait queue while a low-emergency call is being handled.

Resolution of PS response resource allocations to requests will need to be performed dynamically. Further, since response teams may be composed of community participants, the requesters may need to be consulted prior to making allocations of dispatch units and response teams to a particular request. One approach could be to allow the Requester to view ratings and reviews of dispatch units and choose who they would like to receive help from, if time permits. The app would query its database of volunteers/officials and find available units that are close-by and have completed similar requests in the past along with their user ratings for past requests.

E. Volunteer Management

Let us assume that volunteers would occasionally like to help out the PS response teams by offering their services, either in non-emergency PS requests or in high-emergency PS situations to augment the limited task force of the PS teams. We expect the volunteers to have skills and training needed to successfully accomplish requests assigned to them. The assumption is that either the volunteers have prior experience, e.g. as a firefighter, lifeguard, etc., or they will be offered some sort of training when they join the PS volunteer network to donate their time for improving public safety. Volunteers must be willing to share their location when they check-in to the SPSF system. We also propose a Volunteer Management module in the SPSF system where PS officials can view all volunteer activities, ratings/feedback received, time logged, training acquired, as well as feedback from other PS officials who may have worked with them on a job.

F. Community Credibility

There are many ways of building credibility in service-seeking platforms like Home Advisor and Quora where the work or answer-seeker posts a request, it gets answered by multiple people and a job professional or final answer is selected. In the SPSF framework, following an appropriate time after an incident has been handled, the PS volunteer/official will also be able to receive feedback from the Requester. Requester can provide quantitative feedback, in the form of a 0-5 star rating or qualitative feedback in the form of comments back to the SPSF system. Comments can be private or public, with private comments only viewable within the SPSF system and public comments displayed as reviews on the official's/volunteer's public profile. In addition to ratings and reviews, the PS volunteer/official will be able to receive endorsements from their peers for the skills they have based on any work they have done before or after joining the SPSF. All this data essentially builds credibility of volunteers and is also fed into the matchmaking process as described in Section II-D to find the most suitable skilled response team for a request, or to allow the Requester to make a selection of the volunteer/official they would like to work with as they will be able to see public reviews from past Requesters on services provided. The question is, can we build enough credibility through this framework to allow public to trust strangers with their lives during times of disasters?

III. A Twitter-Based SOS Protocol

In terms of communications, SPSF will allow a victim to conveniently contact PSN via social media instead of just relying on the traditional 911 call service. A high-level description of SPSF communication protocol between victims and PS Call Handlers is as follows:

1) PSB monitors channel for distress messages;
2) Requester posts an SOS message on channel; content may also include voice, picture, and/or video;
3) Translator AI auto-detects the language, interprets and translates the messages between the PSB and Requester;
4) PS Call Handler/PSB asks about the nature of the emergency (as a simple selection list) or confirms what can be determined from the content;
5) Requester responds with emergency details, e.g. fire, chemical hazard, accident, intruder, or shooting;
6) PS Call Handler/PSB checks if geo-tags are available, and if not, requests exact location of the Requester;
7) If requested, Requester provides location and other information requested by PS Call Handler/PSB;
8) Triaging AI automatically categorizes and prioritizes requests if deemed legitimate;
9) Match-making AI determines most apt Dispatch Unit and sends emergency code and location information;
10) Dispatch Unit accepts the task and provides ETA;
11) PS Call Handler/PSB assures Requester that help is on the way and provides ETA when available;
12) Dispatch Unit provides updates via SPSF system to the PSN to quickly disperse information;
13) Dispatch Unit executes Incident Action Plan;
14) Dispatch Unit checks out;
15) Requester has opportunity to provide feedback later.

A. Twitter-Based 911 Call Protocol

We specifically focus on Twitter, and propose to use Twitter for Business for the Public Safety (PS) officials. The Direct Messages (DMs) feature in Twitter can be used to send a message privately to a particular user or business, if enabled by the account owner. This allows an affected person to discreetly send an SOS message to the Public Safety team. The DM feature has evolved over the years and now allows anyone to send DMs to a business without the need to follow the business. The Twitter-based SPSF communication protocol between an SOS requester, PS Call Handlers and Dispatch Units within the SPSF system is depicted in Figure 2.

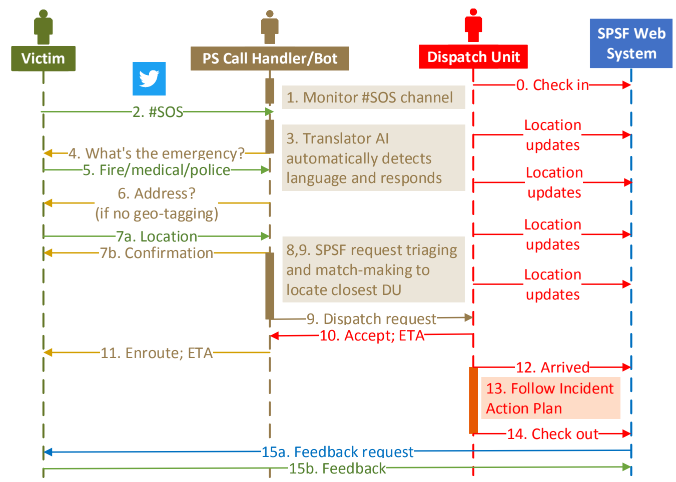

Fig. 2. SPSF's protocol for SOS message exchange via Twitter

B. Delay Analysis

A key question is whether or not the Twitter-based SOS protocol will incur shorter delay in responding and rescuing victims compared to the traditional 911 service. In Figure 3, t_1 refers to the time it takes for the victim to send an SOS tweet to the SPSF channel, t_2 refers to the streaming time from Twitter servers to the SPSF web system for analysis and action, delay t_3 denotes the communication between PSB and victim to determine location and the nature of emergency and t_4 represents the time for triaging incoming requests. The SPSF system makes the determination of which dispatch unit or volunteer to dispatch based on proximity of the available units, the type of emergency and the current queue. The delay t_5 is the amount of time it takes for the SPSF system to contact a suitable dispatch unit or volunteer and receive confirmation from them when they have accepted the assignment. If this request is not accepted or no response is received after a certain time, then the SPSF system would contact the next best available dispatch unit or volunteer. Sometimes, the information received from the victim is not sufficient to make a determination of the issue or automatically assign a dispatch unit. Let's assume t_5' to be the delay when a PS agent has to step in to handle the situation and respond to the victim while locating the appropriate dispatch unit. Let t_6 denote the travel time for dispatch/volunteer unit to reach the victim. Total end-to-end worst-case delay will be $t_{max} = \sum_{i=0}^{6} t_i + t'_5$.

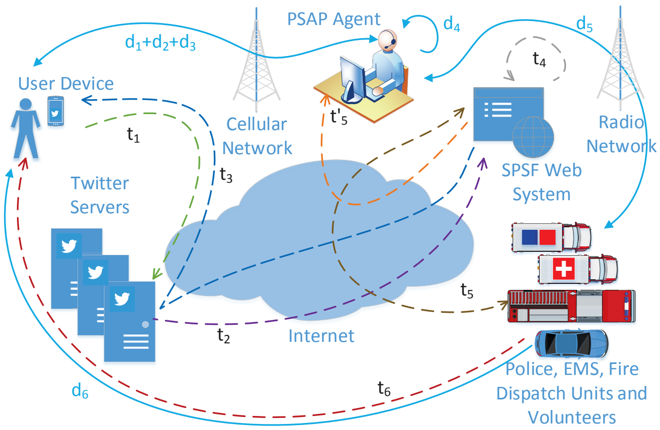

Fig. 3. SPSF vs. traditional 911, delay in various communication segments

In the traditional 911 scenario, we assume the victim will call 911 using their cellphone (80% 911 calls come through wireless endpoints [11]). Let d_1 be the time it takes the victim to dial the number and d_2 be the time it takes the PSAP agent to answer the call. This depends on the number of agents, the current calls being answered, and the number of incoming calls. It takes the PSAP agent d_3 time to gather information about the nature and location of the emergency from the victim. Let d_4 be the time it takes the PSAP agent to triage the situation and find a dispatch unit that has the necessary capabilities to handle the emergency and is the closest to the victim's location. Let d_5 be the time it takes for a dispatch unit to be assigned. The dispatch unit then reaches the victim in time d_6. Total end-to-end delay in the traditional 911 scenario will be $d = \sum_{j=0}^{6} d_j$.

Response time guidelines from the National Fire Protection Association Standard 1710 require a turnout time of 80 seconds for fire and 1 minute for EMS emergencies with 4 minutes or less for the first unit to arrive and 8 minutes for all units for 90% of incidents [22]. We can also assume that the time it takes for the victim to dial 911 or text SOS is the same, i.e., $t_1 \approx d_1$. The SPSF system has built-in automation for answering an SOS call via a bot, and can handle an SOS tweet immediately irrespective of how many PSAP agents are staffed at the PSAP or how many other calls are being serviced at the same time. The Twitter stream being received from the Twitter server at the SPSF system is near real-time, so we can assume $t_2 \approx 0$. Yet, when there are large number of callers, the call-wait time for a PSAP agent in the traditional 911 service d_2 will grow large [23]. Thus, $t_2 << d_2$ when the number of callers is large.

Another key difference between traditional 911 and SPSF lies in the performance of AI-based bot in handling the SOS request. The time it takes for the trained PSB to ask questions of the victim as compared to the PSAP agent can be assumed to be similar. So, we can assume $t_3 \approx d_3$. The time for SPSF AI to triage the situation successfully (i.e., with strong confidence) and locate an appropriate dispatch unit (t_4+t_5) is less than the time it takes an agent d_4. Let ρ be the probability that SPSF's Triaging AI is successful in triaging with a strong enough confidence, then a human PSAP agent will have to step in $1-\rho$ times. We can assume that the time for PSAP agent to locate a dispatch unit is comparable in both cases, i.e., $d_5 = t'_5$. Lastly, the travel time for the dispatch unit to reach the victim's location is the same in both cases $d_6 = t_6$. Based on this, the average delay for SPSF can be written as $t_{avg} = \rho(t_{max} - t'_5) + (1-\rho)t_{max} = t_{max} - \rho t'_5$. Thus, as long as ρ is positive, it holds that $t_{avg} < t_{max} \leq d$. Improvements in AI will increase ρ. As $\rho \rightarrow 1$, the delay performance of SPSF will improve too. The efficacy of this AI-based approach depends on the naturalness of the chatbot [24], accuracy of the AI-based triaging [19], and potential in the medical and emergency response fields [20], [25]. Some of these challenges are highlighted in the next section.

IV. Challenges and Opportunities

The SPSF concept gives way to several questions and areas of research. The first question is whether AI-enabled social network-based chatbots can replace a PSAP [26]. While automation allows us to scale with limited personnel manning 911 call centers, whether AI can make better and quicker overall decisions than humans has yet to be proven [25], [27]. Currently, AI's potential is to assist the PSAP agents to make better decisions than machine or human alone [20]. Furthermore, during an emergency, a person wants to talk/chat with an agent they can trust. How would the requester feel about chatting with an AI bot? Will they trust the decisions being made? Research in social chatbots [17] shows that both emotional quotient and intelligent quotient should be part of the chatbot design to help the user develop trust in the chatbot. Perhaps using a combination of deep-learning based technologies like AWS Lex and AWS Polly, sophisticated natural language-based online 911 bots can be built. On the positive side, in addition to being scalable, these automated techniques allow for greater accessibility than legacy 911 service as they can be integrated with a real-time translation service like Google Translation API.

We also raise the importance of detecting the victim's location for a successful rescue and response operation, especially in the case of non-traditional framework. In the case of a 911 call, the caller's cellular service sends location information to the nearest PSAP. In the case of social media, it is not a given that the distress message will be geo-tagged. So, effective means of triangulation need to be developed to locate the person, assuming the victim is at the location of the emergency. More work needs to be done to see if social triangulation [14] methods are real-time enough for "online 911" scenario. In emergencies, a few minutes can mean the difference between life and death; each passing minute in a cardiac arrest decreases the probability of survival by 7-10%.

SPSF also provides a platform for volunteers to become available for request match-making based on volunteer skill-set and experience. It also provides a way for garnering feedback from community, thereby increasing volunteer credibility. More work needs to be done on how to rank volunteers and whether a point system or a certification system is needed. This leads us to the discussion on security.

All communication between the victim and the Public Safety Call Handler as well as between the victim and dispatch or volunteer units needs to be over secure private channels. To that end, Twitter is currently testing encryption for their Direct Messages and when available, this feature would be key for the proposed framework. Geo-tagging also has its own privacy concerns but location information is needed for rescue, whether provided directly by the user or through geo-tagging or through some means of triangulation. Sometimes the person reporting the emergency may not wish for their identity to be revealed. More work needs to be done to assess the viability of social media for such anonymous reporters.

We proposed an automatic Request Triaging AI in the SPSF framework to help filter out fake SOS messages which can be an issue inherent in the use of social media as messages can be anonymous. This is not an issue in the traditional 911 service, as with current equipment at PSAPs it is possible to get the identity of the caller and prank callers are penalized. The triaging AI module will need subject matter experts (SMEs) to ask followup questions to prioritize calls properly, e.g., the D.C. Fire and EMS Department has registered nurses at PSAPs to determine if a 911 medical call is a true medical emergency requiring an ambulance be dispatched [28]. The efficiency and effectiveness of the priority automation with SMEs in SPSF needs to be explored in the context of SOS messages.

We have proposed one simple approach in the SPSF Matchmaking module that finds the closest available dispatch unit with the right skills for the job and pings them for accepting the request. In reality, if a unit has already been dispatched but is headed to a low or medium priority emergency site and another high priority life-threatening request arrives at a close-by location, they should be redirected to handle the life-threatening situation. The matchmaking and queue processing modules need to intelligently make adjustments without frustrating the requester or response teams.

V. Concluding Remarks

In this paper, we have proposed a framework for "online 911" using social media platforms like Twitter. We have also proposed an automatic distress message handler that can handle and process messages at a much higher rate than traditional 911 service and is scalable. In addition, the proposed framework also encourages community/volunteer involvement and provides them a platform to engage with the Public Safety Network for emergency response. We outlined several research challenges and opportunities arising from the framework.

Acknowledgment

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