

CrisisTracker: Crowdsourced social media curation for disaster awareness

J. Rogstadius
M. Vukovic
C. A. Teixeira
V. Kostakos
E. Karapanos
J. A. Laredo

Victims, volunteers, and relief organizations are increasingly using social media to report and act on large-scale events, as witnessed in the extensive coverage of the 2010–2012 Arab Spring uprisings and 2011 Japanese tsunami and nuclear disasters. Twitter® feeds consist of short messages, often in a nonstandard local language, requiring novel techniques to extract relevant situation awareness data. Existing approaches to mining social media are aimed at searching for specific information, or identifying aggregate trends, rather than providing narratives. We present CrisisTracker, an online system that in real time efficiently captures distributed situation awareness reports based on social media activity during large-scale events, such as natural disasters. CrisisTracker automatically tracks sets of keywords on Twitter and constructs stories by clustering related tweets on the basis of their lexical similarity. It integrates crowdsourcing techniques, enabling users to verify and analyze stories. We report our experiences from an 8-day CrisisTracker pilot deployment during 2012 focused on the Syrian civil war, which processed, on average, 446,000 tweets daily and reduced them to consumable stories through analytics and crowdsourcing. We discuss the effectiveness of CrisisTracker based on the usage and feedback from 48 domain experts and volunteer curators.

Introduction

Social media refers to online communication between users, often in the form of blogs, content communities, and social networking sites [1], and it is becoming a prevalent mechanism of interaction [2]. Advances in social media and the adoption of mobile devices are transforming how we experience and share news.

Twitter** [3] is a microblogging service that enables its users to send and receive short messages, called tweets, of up to 140 characters through the web, instant messaging, or SMS (short message service) interfaces. More than 140 million people use Twitter [4] as part of socializing, activism, and other non-crisis activities [5]. Characteristic to Twitter is a high level of redundancy of the content, both

because of users who re-share and optionally modify posts authored by others (called re-tweeting) and because of users who independently report the same event. Duplication drives how information spreads through the service, and previous research has indicated that 29% to 47% of crisis-related tweets are re-tweets and that 60% to 75% of all tweets are near duplicates of at least one other tweet [6].

Victims, responders, and volunteers increasingly use Twitter to share and access situation-awareness reports and to provide help during a wide range of disasters, such as wildfires and floods [7–10], accidents [11], and terrorist attacks [12]. Furthermore, relief organizations use Twitter to provide a means for emergency contact and to recruit volunteers [13]. Although Twitter can suffer from strong sample bias on a local scale, larger-scale patterns can accurately match those obtained through traditional data-collection methods [14, 15].

Digital Object Identifier: 10.1147/JRD.2013.2260692

© Copyright 2013 by International Business Machines Corporation. Copying in printed form for private use is permitted without payment of royalty provided that (1) each reproduction is done without alteration and (2) the Journal reference and IBM copyright notice are included on the first page. The title and abstract, but no other portions, of this paper may be copied by any means or distributed royalty free without further permission by computer-based and other information-service systems. Permission to republish any other portion of this paper must be obtained from the Editor.

0018-8646/13 © 2013 IBM

Twitter is a promising channel to explore for situation awareness because of the availability of open application programming interfaces (APIs) that give access to almost all of the communication in real time. Unlike traditional communication technologies such as cell phones, Twitter communication is largely public and can be monitored, and members of the disaster-affected population can be employed as a sensor network. Even in cases where data connectivity is limited to a subset of the affected population, important information spreads locally by word of mouth. Once the information reaches those able to share it online, it can, in theory, be sensed remotely, as was observed, for instance, during the devastating Haiti earthquake in 2009 [16].

Despite its popularity during crises, Twitter is very challenging to monitor during large-scale disasters because of very high message volumes and lack of essential metadata. Although geotagging is supported, only approximately 1% of tweets are in practice geotagged, and tags refer to the user rather than the message subject. Other disaster-related metadata such as higher-level report categories and named entities are unavailable. The 140 characters are also insufficient for most algorithms that build latent topic models, and the use of local languages with relaxed rules for spelling and grammar reduces performance of standard automation techniques such as named entity extraction. Finally, because the data is streaming, the corpus of data relevant to any single story is constantly changing, which many established techniques for text mining were not designed for. We propose to overcome these challenges by combining scalable automated techniques for event detection with crowdsourced human-based computation for further interpretation [17].

Human-based computation is a technique in which a computational process performs its function by outsourcing certain steps to humans. This is often done in a crowdsourced manner, where the computation is performed by a distributed group of people. The technique is practical for handling computational problems that are easy to solve for humans, but challenging for computers, such as image labeling [18], knowledge management [19], and solving business problems [20]. The performance of crowds largely depends on incentives [21] such as money [22], gameplay elements [18], [23], social capital [24], and public good [19]. Intrinsically motivated volunteers have been shown to be more likely than paid crowds to produce high-quality results [21]. With computationally challenging data and availability of motivated crowds, crowd-sourced human computation becomes an attractive approach for disaster information management. Yet, existing solutions offer insufficient support for dedicated crowds to cope with the torrent of information from social media during mass disasters [25].

In this paper, we present CrisisTracker [6], a web-based platform that integrates automated real-time analysis with crowdsourcing, to annotate rapid streams of unstructured

tweets with metadata and group related content, with the goal of increasing situational awareness during disaster. Although previous work has relied on crowdsourcing (e.g., via SMS) [26], or automated analysis [27–29], little prior work has considered integrating the two. CrisisTracker aims to support the first two levels in Endsley’s model of situation awareness [30], according to which fundamental perception of events is improved by event detection and ranking, and comprehension is improved by relating events to one another.

In the next section, we place CrisisTracker in the context of existing social media applications for disaster awareness. We then describe the system architecture of CrisisTracker and present the deployment of CrisisTracker during the 2012 Syrian civil war, demonstrating the effectiveness and usability of the system.

Related work

Social media is used throughout the emergency management cycle to detect potential hazards, to gain situation awareness, to engage and mobilize local and government organizations, and to engage volunteers at the disaster recovery stage. Users of social media at disaster time include victims, volunteers, and relief agencies. Existing systems, compared in **Table 1**, can be loosely grouped into disaster management [31, 32], crowd-enabled reporting [26], and automated information extraction [27–29, 33].

Sahana [31] and VirtualAgility WorkCenter [32] support the emergency disaster management process with information and inventory management and collaboration support for response organizations. Such systems often integrate raw social media feeds but lack capabilities for distilling useful reports and reducing information overload when activity is exceptionally high.

Crowd-reporting systems such as Ushahidi [26] enable curation and geo-visualization of manually submitted reports from a wide range of sources. Because Ushahidi relies on users in all information-processing stages, its effectiveness depends entirely on the size, coordination, and motivation of crowds. The majority of the most successful deployments have been by the volunteer-based Standby Task Force (SBTF) [34], which has set up dedicated teams for media monitoring, translation, verification, and geo-location. This team structure is further supported by task management extensions to the platform [35] and adapts well to needs of specific disasters but is difficult to scale to match information inflow rates during the largest events [25].

TweetTracker [27] is a system that parses a Twitter feed to extract and rank popular hashtags, user mentions, and URLs and provides time filters, a map for geotagged tweets, and a word cloud of popular terms. Yin et al. [28] went further by developing a system for use in emergencies that detects trending words and phrases within a Twitter stream to enable drill-down (i.e., study) to increasingly detailed

Table 1 Feature comparison of related state-of-the-art systems, at the time of the writing of this paper. (● supported; ○ partly supported; ○ not supported.)

	Sahana [31]	VirtualAgility [32]	Ushahidi [26]	TweetTracker [27]	Yin et al. [28]	Twitcident [29]	NewsBrief [33,36]	CrisisTracker
Full-featured crisis management tool	●	●	○	○	○	○	○	○
Easily handles new event types and languages	●	●	●	○	●	○	○	●
Full 4W metadata (who, what, when, where)	●	●	●	○	○	●	●	●
User-controlled information management	●	●	●	○	○	○	○	●
De-duplication of redundant reports	○	●	○	○	●	○	●	●
Scalable real-time overview of social media	○	○	○	●	●	●	○	●

content through a series of word clouds. The system also incorporates pre-trained language-specific classifiers to detect messages containing specific information (e.g., reports of infrastructure damage) and a map for geotagged tweets.

Likewise, Twitcident [29] is a Twitter filtering and analysis system that improves situation awareness during small-scale crisis response, such as at music festivals and factory fires. It gathers geotagged tweets only and employs classification algorithms to extract messages about very specific events.

Despite extensive research into automated classifiers for short contextual strings, classification and information extraction has proven to be significantly more difficult than for well-formed news articles and blog posts. As in [28] and [29], classifiers tend to be language specific, and new training data is needed for each new desired label. This restricts their use in the mass disaster space, where report language is not known beforehand and unsupported report types or distinctions between subtypes may be sought in new disasters. For instance, reports of violence and looting may be grouped into one category in a post-earthquake setting, whereas several violence-related report categories may be of interest during the mapping of a civil war.

EMM NewsBrief [33, 36] automatically mines and clusters mainstream news media from predetermined sources in a wide range of languages, with new summaries produced every ten minutes. It also relies on rule-based classifiers for metadata, but substantial investment has been made to create such rules over a decade. Despite this great investment, it has not been extended to handle social media.

To our knowledge, no currently available system enables any of the mentioned communities to use timely social media as a structured information source during mass disasters. CrisisTracker accomplishes this by combining language-independent fast and scalable algorithms for data collection and event detection, with accurate and adaptable

crowd curation. Rather than displaying only raw tweets and high-level statistical metrics (e.g., word clouds and line graphs), the system also provides an intermediary level of natural-language narratives that retain details within reports. CrisisTracker is intended for use during mass disasters and conflicts when responders or observers lack resources to sufficiently monitor events on the ground or when physical access to local communities is restricted for some reason.

System architecture

This section describes CrisisTracker's information processing pipeline (**Figure 1**), which consists of data collection, story detection, crowd curation, and information consumption. Crowd curation is made possible by decoupling the information itself (stories) from how the information has been shared in the social network (tweets). CrisisTracker is free and open source and is available at <https://github.com/JakobRogstadius/CrisisTracker>.

Data collection

Tweets are collected through the streaming API of Twitter. This allows a system administrator to define filters in the form of words, geographic bounding boxes, and user accounts for which all matching new tweets will be returned as a stream. The Twitter API returns messages tagged with any geographic region that partially overlaps with specified bounding boxes. As regions can be very large, we perform an additional filtering pass to discard such messages and keep only those explicitly tagged with a coordinate within bounding boxes of interest (assuming no other filter is matched). The tracking filters are constrained by the API, and the system cannot yet suggest keywords or user accounts to track. Generally, approximately 1% of all tweets are geotagged, and it is infeasible to manually

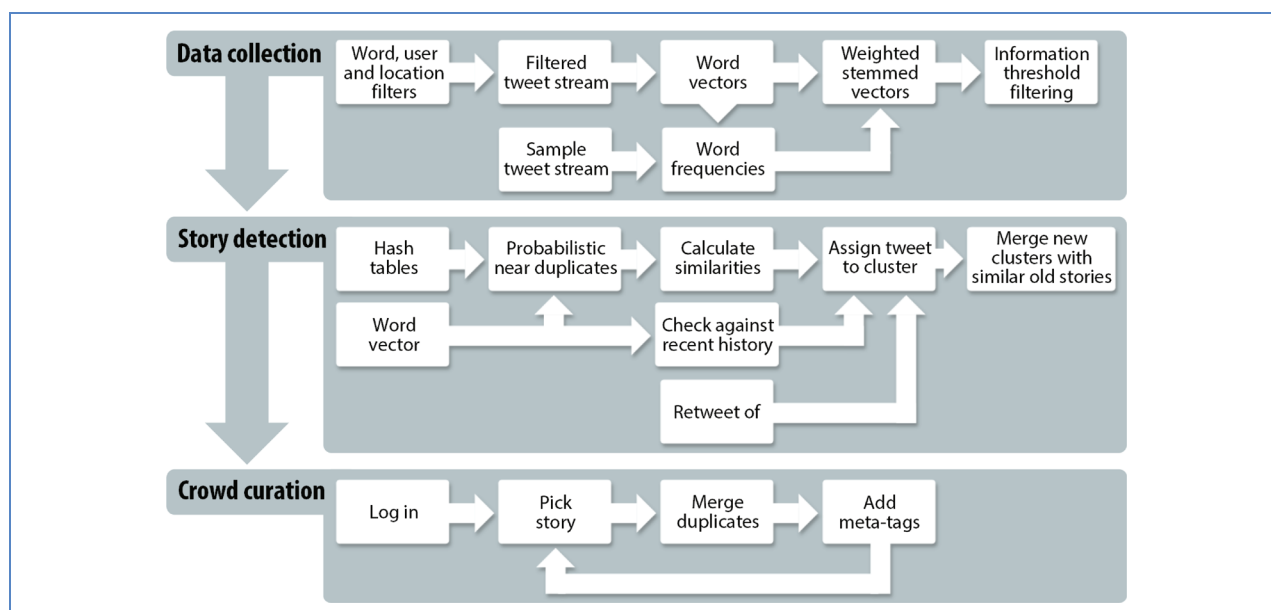


Figure 1

The information processing pipeline in CrisisTracker, consisting of three modules. Word frequencies from the data collection module are used for similarity calculations in both the story-detection and the crowd-curation module. The phrase “stemmed” in the figure refers to the process of reducing words to their basic word stems (e.g., “toys” is converted to “toy”).

select user accounts to cover truly large-scale events; thus, good keyword filters are the primary way to obtain high information recall in the system.

CrisisTracker also discards messages that have fewer than two words after stop-word removal and a very low sum of global word weights (approximated inverse document frequencies). In practice, discarded messages are mostly limited to short geotagged messages without any context (e.g., “@username Thanks!”).

Depending on the filters used to collect tweets, the sample will be more or less focused on actionable reports from a particular geographic region. CrisisTracker does not yet integrate algorithms to classify the content of individual messages or to identify sources local to the event. Instead, the system improves signal through ranking and filtering of stories, as explained below.

Story detection using locality-sensitive hashing

Incoming tweets are compared with previously collected tweets using a “bag-of-words” approach, meaning that the textual content of tweets is treated as a weighted set of unsorted words and that tweets are more similar the more words they have in common. A cosine similarity metric is then used to group messages that are highly similar. Clustering is performed using an extended version of an algorithm previously applied to Twitter corpuses [37] based on Locality-sensitive hashing [38], a probabilistic technique

using hash functions that quickly detects near duplicates in a stream of feature vectors. The time range in which duplicates can be detected for any incoming message depends on the rate at which similar messages have been received, and we refer to [37] for details.

Petrovic et al. [37] used an initial computation pass to calculate global word statistics (inverse document frequencies) in their offline corpus. In an online setting, word frequencies cannot be assumed to be constant over time, e.g., due to local changes in the tracked event and global activity in different time zones. The algorithm was therefore extended in two important ways. First, word statistics are collected on the basis of both the filtered stream and the Twitter sample stream, a 1% sample of all posted tweets. The word distributions are then approximated with a simple IIR (infinite impulse response) filter with exponential decay and a four-day half-time. Words that have a global frequency greater than 90% of the maximum frequency are labeled as stop-words unless they are tracking keywords. Words that have been seen less than three times are ignored. The second extension is to replace the oldest hash function hourly with a new function created from the current dictionary. The new hash table is then populated with the items from the removed table.

Furthermore, the original thread-based clustering algorithm offers high precision [37] such that clusters typically contain only highly similar tweets. However,

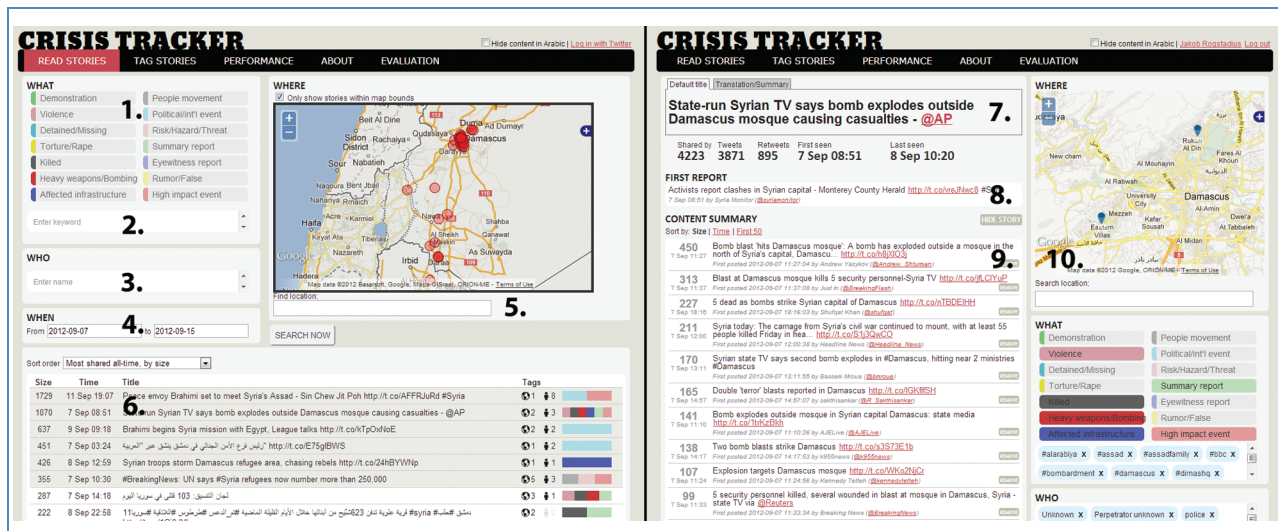


Figure 2

CrisisTracker and user interfaces. Left: User interface for exploring stories, with filters for category (1), keywords (2), named entities (3), time (4), and location (5), with matching stories below (6). Right: A single story, with title (7), first tweet (8), grouped alternate versions (9), and human-curated tags (10).

after implementation, we found that the recall of the algorithm was relatively low, such that the set of tweets that discuss a particular event was often split across several clusters. In CrisisTracker, all new clusters are therefore compared with the current clusters to check for overlap. We refer to such a cluster of clusters as a *story*, and as the next section explains, this method also enables human intervention in the clustering process. Initial informal evaluation suggests that our approach greatly improves recall without substantially reducing precision, but accurate measurement of cluster recall for Twitter-scale corpuses is a research problem in itself. We, therefore, leave the specific cluster evaluation for future work and instead focus in this paper on evaluating the general ability of CrisisTracker to improve situation awareness and support decision-making.

A limitation of any bag-of-words-based event detection technique is that clusters do not necessarily correspond to events, as tweets can potentially have high textual similarity and be grouped together without discussing the same event. We have observed this with sensor-based feeds that publish regular updates about weather and earthquakes. In addition, because the system would quickly run out of storage space if all content was retained, increasingly larger stories and all their content are deleted with increasing age, unless they have been tagged by a human. Stories consisting of a single tweet are kept for approximately one day.

Crowd curation and metadata creation

The purpose of clustering the tweet stream into stories is to facilitate crowd curation. De-duplication (ideally)

eliminates redundant work, directly reduces the number of items to process per time unit, enables size-based ranking of stories, and groups together reports that mention the same event but contain different details necessary for piecing together a complete narrative.

Search and filtering requires metadata for stories. Some of this metadata is extracted automatically, such as time of the event (timestamp of first tweet), keywords, popular versions of the report, and number of unique users who mention the story (referred to as story “size”). Story size enables CrisisTracker to estimate how important the message is to the community that has shared it [6, 9]. Users of the system can rank stories by their size among all Twitter users or among the 5,000 users most frequently tweeting about the disaster. In our experience, the top-5,000 option better brings out stories with detailed incremental updates to the situation, whereas the full rank more frequently includes summary articles, jokes, and opinions. Because metadata is assigned per-story, it also covers future tweets in the same story.

Curators are directed toward recent and extensively shared stories but can self-select which stories to work on. The first curation step is to further improve the clustering, by optionally merging the story with possible duplicate stories that are textually similar but fall below the threshold for automated merging. Misclassified content can also be removed from stories, which are then annotated (Figure 2) with geographic location, deployment-specific report categories (e.g., infrastructure damage or violence), and named entities. Stories deemed irrelevant (e.g., a cooking

recipe named after a location) can be hidden, which prevents them from appearing in search results. A Twitter account is required to log in to CrisisTracker as a curator, and as demonstrated by the SBTF, curators can be recruited globally on a volunteer basis or locally if post-disaster infrastructure permits.

Information consumption

Disaster responders, and others interested in the information, can filter stories by time, location, report category, and named entities. An information management officer at the United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA) explained in a private conversation that these are the basic dimensions along which responsibilities are typically assigned within the responder command structure, i.e., by location and/or type of event or intervention. Therefore, systems should support filtering along the same dimensions. Figure 2 presents the interfaces for exploring stories and for reading and curating a single story. The interface for curators to select work items is not shown.

CrisisTracker field trial

To evaluate how CrisisTracker supports its users, we conducted a field trial that focused on the 2012 civil war in Syria. Syria has a population of roughly 21 million, high Twitter adoption, and tweets in both English and Arabic; thus, the conflict includes many of the characteristic challenges of social media information management during international crises. The evaluation had two main purposes: to measure curators' processing capacity and to understand how real-time access to structured social media reports can support analysts and decision-makers in disaster management organizations.

We recruited 44 unpaid volunteer curators to participate in the eight-day field trial. Half participated for a single day only, three participated every day, and on average, 13 unique participants were active each day. Volunteers were either recruited through the SBTF or independently recruited. Approximately two-thirds had previous experience from online disaster volunteering and one-third regularly participated in onsite disaster response. Curators were given detailed instructions on how to use the system to organize and annotate stories and could interact with one another and with the researchers through a dedicated persistent text chat.

At the end of the trial, 22 volunteer curators responded to an open-ended questionnaire regarding their experiences with the platform. Further semi-structured interviews were held with five of these curators. Interview questions followed up on the free-text answers from the questionnaire and focused on usability, workflows, motivation, perceived value of the work, and platform extensions.

Seven domain experts with extensive experience from the disaster management domain were also recruited to explore the curated stories in CrisisTracker during the

field trial week and assess the value of the system. Their expertise included disaster management at different levels, GIS (geographic information system) analysis, information management, and media monitoring. Two of the experts were actively following the Syrian conflict beyond the scope of our study, and three experts also participated as volunteer curators. Semi-structured interviews were held with all seven experts with questions relating to 1) their past use of social media reports during crisis, 2) their knowledge of the Syrian conflict, 3) their experiences using CrisisTracker, 4) potential applications of CrisisTracker during past events, and 5) the ability of CrisisTracker to support different users and use cases. Transcripts from interviews, plus chat logs, survey answers, emails, and other communications, were content-analyzed through inductive ("bottom-up") coding, clustering, and interpretation by one researcher [39].

To collect tweets, we defined a bounding box covering Syria, and together with an analyst familiar with the conflict, we selected 50 keywords in English and Arabic to track:

syria, assad, hama, damascus, aleppo, homs, bashar, #fsa, daraa, #siria, #syriarevo, #syrie, #syrian, #syrias, idlib, #realsyria, latakia, houla, latakia, rastan, deraa, #syr, hamah, tartus, harasta, zabadani, darayya, baniyas, babaamr, darayaa, raqqah, yayladagi, basharcrimes, suweida, latakiah, معركة دمشق الكبرى , #اللاذقية, #الثورة السورية, #سوريا_تحرر, #إدلب, #طرطوس, #سوري , #جيش_تويتر, #حلب, #حملة, #الجيش_السوري_الحر, #بشار . شق, حمص, #الجيش_الحر

The words referred mainly to major place names and popular hashtags. We worked with an analyst to define 14 relevant report categories to be applied by the human curators, e.g., "demonstration," "eyewitness report," and "people movement." Approximately 3.5 million tweets were collected during the evaluation week, but the system had been operational for several months before the volunteers began working, and older stories could be retrieved through searches.

Only a few participants spoke Arabic, and curators were encouraged to use machine-translation features built in to some web browsers to read stories and linked articles and add metadata based on the translated content. The platform supports inclusion of manually translated summaries to stories, which Arabic speakers in some cases provided in English. An option to hide Arabic stories also existed for users who found the Arabic content too tiring or difficult to work with.

Results

Clustering reduces workload

Clustering the incoming tweets into unique stories greatly reduced the rate at which new items needed to be processed.

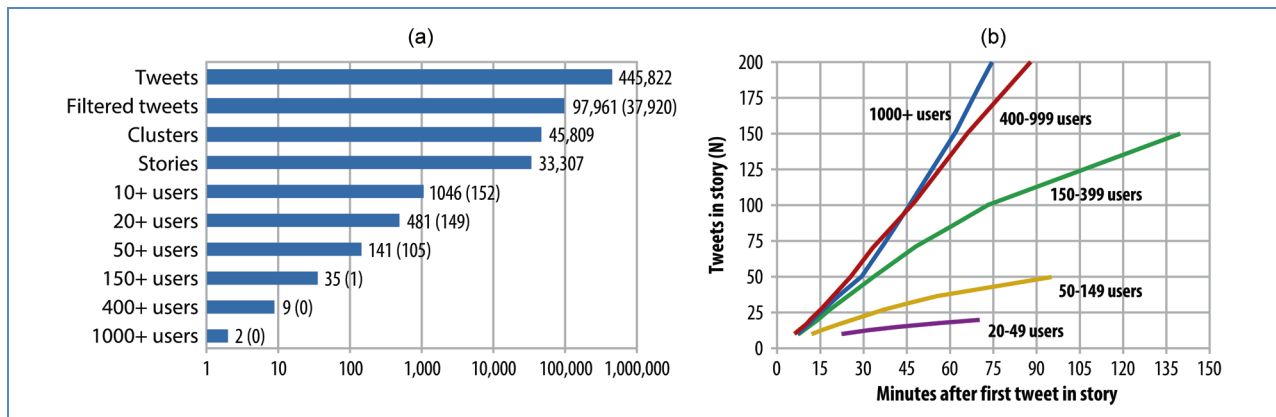


Figure 3

Tweets and stories. (a) Information pieces to process per day, and reduction in information inflow rate from each processing step. “ $N+$ users” refers to stories containing tweets from at least N unique users. Numbers in parentheses indicate additional items produced by the 58 spammer accounts. (b) Median time for stories to gain N tweets: growth rate of stories. If stories are filtered by size, events with an impact can realistically be detected approximately 30 minutes after the first tweet.

The system collected on average 446,000 tweets per day (minimum of 400,783 and maximum of 560,193). Seventy percent of tweets were immediately discarded, almost exclusively because the geographic bounding box covering Syria overlapped with parts of Turkey, causing geotagged tweets from throughout Turkey to be returned by the API. The remaining messages were then clustered into approximately 33,000 daily stories, of which 1,200 stories contained tweets from at least 5 users and 246 stories from at least 50 users.

Although size-based story ranking has been shown to generally improve the signal-to-noise ratio [6, 8], high levels of spam were initially found among the top stories. These spam stories mainly originated from a group of 58 highly active spammer accounts. Once these accounts were blocked, the number of daily stories shared by at least 50 users dropped to 141. Focusing on these top stories thus reduced the workload by 3 orders of magnitude, with several new top stories per hour. **Figure 3(a)** summarizes how each processing step contributes to making the workload manageable.

Scalability of crowd curation

On its own, CrisisTracker collects and clusters tweets into ranked stories and supports search and filtering based on time and keywords. Human curation is required for filtering based on location, category, and named entity, which primarily helps find events with less impact (and thus events that are less mentioned). Curators spent on average 4.5 minutes per story, with a heavy skew toward shorter times (median 2.3 minutes). Each work session lasted on average 28.5 minutes (median 20.8), with work sessions defined as periods of user activity separated by at least 15 minutes

of idle time. A total of 3,600 tags were added to 820 stories (1,775 before merging), and together the curated stories contained 616,009 tweets.

We consider this total volunteer output substantial when compared with most Ushahidi deployments. Data provided by CrowdGlobe [40] shows that of 871 Ushahidi instances [41] that were ever active (containing ten or more reports), only 67 (7.7%) contained more than 820 reports. Furthermore, 14 of 15 public instances with 500 to 1,100 reports received their reports over more than two months, compared with our eight-day effort. As curation tasks are similar in the two platforms, we mainly attribute the higher productivity of CrisisTracker curators to automated information gathering.

As is common in crowdsourcing, the work effort was unevenly distributed among the participants, and 25% of the curators performed 75% of the work. Among the 22 people who curated at least 10 stories each, the average time spent per person per story ranged between 1 and 13 minutes. Only in a handful of cases did curators work on the same stories or remove others’ tags.

Based on the reported usage statistics and the rates at which information was collected, we estimate that approximately 15 curators, each active for 30 minutes per day, would be sufficient to have full metadata for all the main events during a humanitarian crisis of this type and magnitude. Approximately 150 curators would be able to build and maintain a very detailed database of almost all reported events, at a resolution finer than city-level resolution. Workforce size can be greatly reduced if curators can be encouraged to spend more than 30 minutes per day. Feedback from volunteers also suggests that the per-curator effort would have been higher if the deployment

had been a request from a humanitarian organization, rather than an academic study.

Real-time overview

One of the domain-expert participants, an anonymous English and Arabic speaking representative of Syria Tracker [42], was actively monitoring ongoing events in Syria in parallel with using CrisisTracker. Syria Tracker had been monitoring the crisis for 18 months and had set up infrastructure to automatically mine Arabic news media. Syria Tracker also received daily eyewitness reports and manually monitored online social media. This participant was therefore in a unique position in which he could in real time compare the information made available through CrisisTracker with that independently collected.

From the start of this conflict, Twitter was an active communication channel, used mainly by the opposition, and more recently also by government supporters. Links to relevant images, videos, and news articles are also often posted on Twitter almost immediately following publication of the resource. Syria Tracker was well aware of this rich source but had not found any way to reliably monitor it in real-time. After using the system, the expert explained that CrisisTracker was the first of many tools he had tried that provided a subjective sense of a real-time overview of this “information storm,” in both English and Arabic.

Timely and rich reports

One of the concrete ways in which Syria Tracker used the system was to use reports that were trusted but brief, as well as single-sided eyewitness reports, submitted via email, and in CrisisTracker quickly seek out complementary pictures and videos as well as reports from the opposing side. This augmentation of eyewitness reports enriched their understanding of ongoing events hours and sometimes even days before mainstream media reported the news.

According to Syria Tracker, the tool improved sensitivity of information collection by detecting several important events (e.g., massacres, explosions, and gunfire) before they were reported by other sources. CrisisTracker also improved specificity, by quickly finding links to evidence such as images and videos. Early detection of events enabled focused manual monitoring of other sources to corroborate evidence and make early assessments of the truthfulness or severity of new claims. For instance, videos of missiles being fired with claims regarding time and place led to searches for corresponding impacts. During ongoing events such as urban skirmishes, CrisisTracker would also provide real-time updates, whereas eyewitness reports would arrive as high-quality summaries later during the day. Syria Tracker also valued the historical record of social media communication provided by the tool, as Twitter does not support searches more than a few days in the past.

Six of the seven interviewed experts in some way mentioned timeliness as a primary reason for using the system. An incident commander who actively used the platform over a time period of several days said, “I feel very confident that those reports will come out ahead of CNN and BBC and that they will have the central nuggets of who, what, when, where, why. For an incident commander, it is the difference between learning something in 2 to 3 hours versus learning it in 6 to 8.” A data analyst with a background in disaster response further added that the timeliness and ability to see how stories are evolving, was a “huge” benefit.

Figure 3(b) shows how quickly stories of different magnitude would be detected when monitoring all stories above a size threshold. Of 9,207 stories, each eventually containing tweets from 150 or more users, 10% would be detected within four minutes, 50% within 31 minutes, and 90% within 3.5 hours of the first report, with a size threshold set at 50 users (141 stories per hour).

On its own, Twitter is in fact so timely that some participants described how they had felt in the past so that “if you’re not on the Twitter stream, you quickly lose sight of the history. It becomes very much a snapshot, a moment-in-time assessment of what’s happening.” Since CrisisTracker retains a historical archive of all larger stories as the main event progresses, it becomes possible to go back in time and analyze both short-term and long-term trends.

A GIS expert who was also one of the most active curators described how seeing real-time commentary on related political events in Moscow, next to reports of events on the ground along with how many people were killed, gave her a sense of how the entire world was connected. She further described how “you can see over a period of time where people are moving, and how that relates to conflict areas. Water shortage or food—you can almost anticipate where needs are going to be.” As discussed later, reaching this level of understanding requires a significant time investment. However, we consider it promising that such insights can be gained from data largely derived from automated processing of freely available social media.

Discussion

Usage barriers

Arabic content proved frustrating for many non-Arabic speakers, who simply hid it and focused on stories in English. Others were concerned about the quality of machine translations, but it was noted that “obviously some reports seem just fine with little room for error, while others are just unusable.” Another volunteer said that “using Google Translate** [integrated in the browser] was very easy, and by being able to curate stories, especially those in Arabic, I felt more of a “direct” connection with what was going on.”

Interestingly, of the greatest obstacles proved to be geotagging of English reports, as translated location names often could not be found on the map or through search. Overall, our impression is that machine translation is tiring but relatively safe to use for curators, as the impact of mistranslation is limited to tagging errors that reduce the quality of search and filtering.

Many experts and volunteers were impressed with the overall intuitiveness and ease of use of the platform. A few users explicitly compared CrisisTracker with their experience using the Ushahidi platform, which they considered to be more tedious to work with and less intuitive. Participants with experience from both platforms particularly valued CrisisTracker's ability to relate stories to one another and its method of handling duplicate reports. However, the evaluation also identified several minor user-interface issues that led to breakdowns in user interaction and that should be resolved before the platform can be considered sufficiently mature for public use.

In rapid-onset disasters, ease of deployment (effectively, the deployment time) is a critical aspect of an information management system. Although anyone can download the CrisisTracker source code and set up an instance, further work is needed to simplify and automate the deployment process. Ideally, this would be accomplished through a system similar to the Crowdmap website [41], where new instances of the Ushahidi platform can be deployed on cloud servers through a web interface.

Many participants raised concerns that the complete openness of the system, combined with lack of "undo" functionality, leads to high sensitivity to vandalism, in the form of purposeful incorrect tagging, and the merging or hiding of stories. This is particularly an issue during conflict settings, and extensions need to be made to handle this, either by adding mechanisms for screening of curators or by implementing a version control and community moderation system similar to those on OpenStreetMap** [43] and Wikipedia** [44].

Using CrisisTracker to support decision-making

Our evaluation suggests that the greatest value of CrisisTracker, during complex and constantly changing large-scale events, is improved real-time situation awareness. This result is very similar to an evaluation study [45] of the Ushahidi deployment for the 2010 Haiti earthquake, which showed that improved situation awareness at an aggregate level was the greatest contribution of the crowdsourced map, in particular during the early days of the crisis when the situation on the ground was still unclear. Content analysis of tweets collected during natural disasters [46] indicates great availability of response-phase-related reports: hazards, interventions, fatalities, personal status, and damage. This agrees with our general perception of the content distribution for the Syrian conflict. Although one

disaster-manager participant in our study speculated that CrisisTracker would be of great value also in the recovery phase, the content analysis indicates that recovery-related tweets are scarce.

CrisisTracker also addresses two important limitations identified by the Ushahidi evaluation. First, CrisisTracker uses existing social media to access the voices of affected populations, rather than relying on independently submitted or manually collected reports. Second, while the vast majority of reports go uncured in both CrisisTracker and Ushahidi, CrisisTracker is able to direct curation efforts toward those reports that are discussed most in the core community and thus most likely to improve situation awareness.

Despite general praise for the good usability, intuitiveness, and ability of CrisisTracker to extract rich and timely information of important events, many participants made clear that gaining an accurate understanding of the information remains a time-consuming task. A high-level manager in a humanitarian organization explained that while much useful information is collected by the system, key points need to be distilled from the stories to make that information useable in time-sensitive situations.

The system is therefore not yet ready to be used directly as a decision-support tool by decision-makers who have very limited time to sit down, read, and analyze information. Rather, CrisisTracker is suitable for use by analysts and others who already work on filtering and aggregating information from different sources to produce maps and reports tailored for the decision-makers of the organization. The analysts we interviewed were very enthusiastic about the tool and only requested export functionality to be implemented, to enable comparison of social media reports with data from other sources.

Several participants, both curators and experts, expressed that they wanted CrisisTracker to help them assess the trustworthiness of stories in the platform. Discussions focused on the suggestion that assessment should be done on a source level, for instance, by inferring how credible a first report is based on the past record of that account or by highlighting the most trustworthy account that has shared a story. Others noted that different sources have different authority for different information, which greatly adds complexity to such calculations. For instance, a personal account with strong political bias may contribute little to international news but may still be authoritative regarding events in the particular suburb where they live. In other cases, an untrusted source may post a link to a highly trusted government website, or a trusted government account may post outdated information that is contradicted by citizen-generated video footage. A potentially feasible approach may be to allow curators to mark single accounts as having extremely high or low credibility and deriving source ratings from sharing patterns of past stories.

One participant noted that human curation itself may be misinterpreted as validation, which, if true, would be a serious risk in decision-making and could be an entry barrier for volunteer curators. This is something that future development will need to keep in mind and find ways to avoid.

Several of the more experienced disaster managers we interviewed or have spoken to at other times have noted that accuracy and timeliness will always remain a tradeoff. Verification requires both time and expertise, and a system that can deliver very quick reports in a consumable format does not need to always be correct to be valuable. One disaster management consultant estimated that even her trusted personal sources that she uses for verification may only be right in 80% of the cases. Several participants also reported that they felt the grouping by the system of complementary reports into stories helped build reliability and supported validation. We strongly believe that the rich and timely but unverified reports in CrisisTracker are most valuable when combined with other sources, for instance, to enrich brief-but-trusted eyewitness reports as demonstrated by Syria Tracker. We also believe the system is capable of providing rich historic narratives around specific points in time and space that can help explain interesting features in other datasets.

Managing a CrisisTracker deployment

When integrating crowdsourced human-based computation into disaster information management, crowd management has a direct impact on performance metrics such as precision, recall, and processing speed. Based on experiences from our evaluation, we propose that humanitarian organizations that want to deploy this class of systems assign a person the new role of crowd director.

First, the crowd director is responsible for recruiting curators, e.g., through the organization's own registered disaster volunteers or through an independent volunteer organization such as the Standby Task Force. As volunteering competes with other tasks in people's lives, it is of great importance during recruitment to motivate potential curators by clearly explaining how the work will create benefit and help a population in need. Volunteers will also be able to be effective more quickly if they receive basic background information regarding the disaster. Basic training materials regarding how to use CrisisTracker are already available.

Once work begins, the crowd director must continuously communicate decision-makers' information requirements to the crowd. This will enable the crowd to curate information that is of particularly high value. For instance, instructions can be to focus on reports relating to a particular town or report category or to spend more or less time on tracking down precise locations. Unlike information management systems that are completely automated,

interactive crowd management enables CrisisTracker to effectively function differently depending on the particular needs of each deployment. Rather than having to fine-tune or develop new processing algorithms for each new use case and content language, organizations can themselves maximize performance by providing directions and recruiting volunteers with relevant skills and experience.

Finally, insecure or inexperienced volunteers will ask for affirmation that their work is correctly performed. The crowd director must remain accessible to provide such feedback, which can be the difference between having a volunteer who only curates a single story and then stops, and one who confidently returns day after day during most of her spare time. Some intervention may also be required to improve accuracy of the assigned labels, by prompting volunteers who, despite their good intentions, make mistakes or too rushed classifications (e.g., placing geotags in the middle of cities when more specific information is available).

Conclusion

Situation awareness is one of the main precursors to appropriate decision-making [30]. Social media, in particular Twitter, has emerged as a new source of citizen-generated reports that can potentially offer a detailed real-time view of the situation on the ground during large-scale complex disasters. As physical access to affected areas can be restricted, and no response organization has resources to be everywhere, such inexpensive distributed sensing mechanisms are highly attractive during mass disasters and conflicts.

During crises affecting millions of people, it is not uncommon to see hundreds of thousands of social media messages being generated every hour, and information management tools are needed to effectively extract and organize relevant information in real time. However, social media messages have proven difficult to process using traditional natural language processing algorithms, and most success stories in the disaster space have relied on organized crowds of volunteers who process content manually. As this approach on its own has scalability issues, information overload has remained a serious barrier that obstructs integration of social media in decision-making during mass disasters.

In this study, we demonstrate how combining crowd curation with automated data collection and language-independent real-time text clustering can achieve scalability, accuracy, timeliness, and flexibility. Based on feedback and usage statistics collected from 48 participants during an 8-day evaluation deployment, focused on the 2012 Syrian civil war, we show that our proposed architecture produces the first system that enables a comprehensive real-time overview of Twitter during mass disasters. Stories (tweet clusters) in CrisisTracker contain

rich event descriptions, images, and video and can, in most cases, reliably be detected approximately 30 minutes after major events, placing them between immediate eyewitness reports and traditional media coverage. Although clustering helps assess the credibility of reports, the traditional disaster response practice of relying on multiple independent sources remains strongly recommended to avoid false leads.

Both expert and volunteer participants found the system to be intuitive and easy to use. Analysis is, however, time consuming, and we conclude that the current system is ready for use by analysts, but not directly by decision-makers. We also recommend that a new role, the crowd director, is assigned to bridge the gap between volunteer curators and organizations that want to deploy a system such as CrisisTracker.

Future work

Three extensions are needed to make CrisisTracker ready for live use by humanitarian organizations around the world. Functionality needs to be added to export data from the system into other products currently in use by relief organizations and volunteers. Mechanisms also need to be added that help prevent and reduce impact of vandalism. Finally, because time is a scarce resource particularly during rapid-onset disasters, the system needs to be made easier to deploy.

Future work will examine ways to improve the visualizations to support quicker and more accurate interpretation of real-time data, as well as deeper analysis of the relationships between locations, sources, named entities, and events. We also plan to integrate semi-supervised classification algorithms, which can learn from human curators and partly automate metadata creation. Furthermore, we want to add a high-level layer of collaborative interpretation and analysis that goes beyond current functionality for organizing and labeling content.

Acknowledgments

We express our sincere gratitude to all the curators and disaster-response experts who participated in this study. We thank Patrick Meier for promoting the evaluation as a Standby Task Force deployment and for his guidance in crowd management. We also thank Syria Tracker for its support in making the deployment realistic and safe, and for actively using the system in its daily monitoring of the conflict. We thank Rebecca Curzon and Vicki Kraeling for promoting the study with disaster practitioners. Finally, we thank Ko-Hsun Huang for key guidance in gathering, analysis, and interpretation of data. This work is supported by an IBM Open Collaboration Research Award and by the Portuguese Foundation for Science and Technology (grant CMU-PT/SE/0028/2008; Web Security and Privacy).

**Trademark, service mark, or registered trademark of Twitter, Inc., Google, Inc., OpenStreetMap Foundation, or Wikimedia Foundation in the United States, other countries, or both.

References

1. A. M. Kaplan and M. Haenlein, "Users of the world, unite! The challenges and opportunities of Social Media," *Bus. Horiz.*, vol. 53, no. 1, pp. 59–68, Jan./Feb. 2010.
2. *Social Networks/Blogs Now Account for One in Every Four and a Half Minutes Online* | Nielsen Wire. [Online]. Available: <http://blog.nielsen.com/nielsenwire/global/social-media-accounts-for-22-percent-of-time-online>
3. Twitter. [Online]. Available: <http://twitter.com>
4. *Twitter Turns Six*. [Online]. Available: <http://blog.twitter.com/2012/03/twitter-turns-six.html>
5. A. Java, X. Song, T. Finin, and B. Tseng, "Why we twitter: Understanding microblogging usage and communities," in *Proc. 9th WebKDD 1st SNA-KDD Workshop Web Mining Social Netw. Anal.*, San Jose, CA, USA, 2007, pp. 56–65.
6. J. Rogstadius, V. Kostakos, J. Laredo, and M. Vukovic, "A real-time social media aggregation tool: Reflections from five large-scale events," in *Proc. Workshop CSCW/Smart ECSCW*, Aarhus, Denmark, 2011.
7. S. Vieweg, A. Hughes, K. Starbird, and L. Palen, "Microblogging during two natural hazards events: What twitter may contribute to situational awareness," in *Proc. CHI*, Atlanta, GA, USA, 2010, pp. 1079–1088.
8. K. Starbird, L. Palen, A. Hughes, and S. Vieweg, "Chatter on the red: What hazards threat reveals about the social life of microblogged information," in *Proc. CSCW*, Savannah, GA, USA, 2010, pp. 241–250.
9. K. Starbird and L. Palen, "Pass it on?: Retweeting in mass emergency," in *Proc. ISCRAM*, Seattle, WA, USA, 2010, pp. 1–10.
10. J. Palmer. (2008, May). Emergency 2.0 is coming to a website near you. *New Sci.* [Online]. 198(2654), pp. 24–25. Available: <http://www.newscientist.com/article/mg19826545.900-emergency-20-is-coming-to-a-website-near-you.html>
11. I. Lamont, *A Plane Lands on the Hudson River, and Twitter Documents it All*. [Online]. Available: http://www.computerworld.com/s/article/9126181/Plane_lands_on_the_Hudson_and_Twitter_documents_it_all
12. S. Busari, *Tweeting the Terror: How Social Media Reacted to Mumbai*. [Online]. Available: <http://edition.cnn.com/2008/WORLD/asiapcf/11/27/mumbai.twitter/index.html>
13. P. Meier, *Behind the Scenes: The Digital Operations Center of the American Red Cross*. [Online]. Available: <http://irevolution.net/2012/04/17/red-cross-digital-ops/>
14. M. Graham, *What Can Twitter Tell Us About Hurricane Sandy Flooding? Visualised*. [Online]. Available: <http://www.guardian.co.uk/news/datablog/2012/oct/31/twitter-sandy-flooding>
15. M. Graham, A. Poorhuis, and M. Zook, *Digital Trails of the UK Floods—How Well Do Tweets Match Observations?* [Online]. Available: <http://www.guardian.co.uk/news/datablog/2012/nov/28/data-shadows-twitter-uk-floods-mapped>
16. *Disaster Relief 2.0: The Future of Information Sharing in Humanitarian Emergencies*, UN Found. Vodafone Found. Technol. Partner., Washington, DC, 2011, Harvard Humanitarian Initiative.
17. J. Rogstadius, V. Kostakos, J. Laredo, and M. Vukovic, "Towards real-time emergency response using crowd supported analysis of social media," in *Proc. Workshop Crowdsourcing Human Comput. CHI*, Vancouver, BC, Canada, 2011.
18. L. von Ahn and L. Dabbish, "Labeling images with a computer game," in *Proc. CHI*, Vienna, Austria, 2004, pp. 319–326.
19. S. Kuznetsov, "Motivations of contributors to Wikipedia," *ACM SIGCAS Comput. Soc.*, vol. 36, no. 2, Jun. 2006, Article 1.
20. M. Vukovic, "Crowdsourcing for enterprises," in *Proc. IEEE Congr. Services*, Los Angeles, CA, USA, 2009, pp. 686–692.

21. J. Rogstadius, V. Kostakos, A. Kittur, B. Smus, J. Laredo, and M. Vukovic, "An assessment of intrinsic and extrinsic motivation on task performance in crowdsourcing markets," in *Proc. AAAI Conf. Weblogs Social Media*, Barcelona, Spain, 2011, vol. 11, pp. 321–328.
22. N. Kaufmann, T. Schulze, and D. Veit, "More than fun and money. Worker motivation in crowdsourcing—A study on mechanical turk," presented at the Proc. Americas Conf. Information Systems (AMCIS), Detroit, MI, USA, 2011, paper 340.
23. S. Cooper, F. Khatib, A. Treuille, J. Barbero, J. Lee, M. Beenen, A. Leaver-Fay, D. Baker, and Z. Popović, "Predicting protein structures with a multiplayer online game," *Nature*, vol. 466, no. 7307, pp. 756–760, Aug. 2010.
24. D. Raban, "The incentive structure in an online information market," *J. Amer. Soc. Inf. Sci. Technol.*, vol. 59, no. 14, pp. 2284–2295, Dec. 2008.
25. P. Meier, *Some Thoughts on Real-Time Awareness for Tech@State*. [Online]. Available: <http://irevolution.net/2012/02/02/real-time-awareness/>
26. Ushahidi. [Online]. Available: <http://www.ushahidi.com/>
27. S. Kumar, G. Barbier, M. A. Abbasi, and H. Liu, "TweetTracker: An analysis tool for humanitarian and disaster relief," presented at the Demonstration Paper 5th Int. Assoc. Adv. Artif. Intell. (AAAI) Conf. Weblogs Social Media, Barcelona, Spain, 2011.
28. J. Yin, A. Lampert, M. Cameron, B. Robinson, and R. Power, "Using social media to enhance emergency situation awareness," *IEEE Intell. Syst.*, vol. 27, no. 6, pp. 52–59, Nov./Dec. 2012.
29. F. Abel, C. Hauff, G. J. Houben, R. Stronkman, and K. Tao, "Semantics + Filtering + Search = Twitcident. Exploring information in social web streams," in *Proc. Int. Conf. Hypertext Social Media*, Milwaukee, WI, USA, 2012, pp. 285–294.
30. M. Endsley, "Theoretical underpinnings of situation awareness: A critical review," in *Situation Awareness: Analysis and Measurement*. Evanston, IL, USA: Routledge, 2000, pp. 3–32.
31. Sahana Softw. Found. [Online]. Available: <http://sahanafoundation.org/>
32. VirtualAgility WorkCenter. [Online]. Available: <http://www.virtualagility.com/>
33. C. Best, E. van der Goot, K. Blackler, T. Garcia, and D. Hornby, "Europe media monitor—System description," Eur. Commiss., Brussels, Belgium, Rep. No. EUR 22173 EN, 2005.
34. *Introducing the Standby Task Force*. [Online]. Available: <http://blog.standbytaskforce.com/about/introducing-the-standby-task-force/>
35. *The Rogue Genius Micro-Tasking System*. [Online]. Available: <http://roguegenius.com/>
36. EMM NewsBrief. [Online]. Available: <http://press.jrc.it>
37. S. Petrovic, M. Osborne, and V. Lavrenko, "Streaming first story detection with application to twitter," in *Proc. Human Lang. Technol.—Annu. Conf. North Amer. Chapter Assoc. Comput. Linguist.*, Los Angeles, CA, USA, 2010, pp. 181–189.
38. M. Charikar, "Similarity estimation techniques from rounding algorithms," in *Proc. 34th Annu. ACM Symp. Theory Comput.*, Montreal, QC, Canada, 2002, pp. 380–388.
39. H. Hsieh and S. Shannon, "Three approaches to qualitative content analysis," *Qual. Health Res.*, vol. 15, no. 9, pp. 1277–1288, Nov. 2005.
40. CrowdGlobe. [Online]. Available: <http://crowdglobe.net/>
41. Crowdmap. [Online]. Available: <https://crowdmap.com/>
42. Syria Tracker. [Online]. Available: <https://syriatracker.crowdmap.com/>
43. OpenStreetMap. [Online]. Available: <http://www.openstreetmap.org/>
44. Wikipedia. [Online]. Available: <http://www.wikipedia.org/>
45. N. Morrow, N. Mock, A. Papendieck, and N. Koemich, "Independent evaluation of the Ushahidi Haiti project," Ushahidi, Nairobi, Kenya, 2011, Development Information Systems International. [Online]. Available: <http://www.alnap.org/pool/files/1282.pdf>
46. S. Vieweg, "Situational awareness in mass emergency: A behavioral and linguistic analysis of microblogged communications," Ph.D. dissertation, Univ. Colorado, Boulder, CO, USA, 2012.

Received November 15, 2012; accepted for publication December 13, 2012

Jakob Rogstadius *Madeira Interactive Technologies Institute, Caminho da Penteada, 9020-105 Funchal, Portugal (jakob@m-iti.org)*. Mr. Rogstadius is a Ph.D. candidate at the Madeira Interactive Technologies Institute, Research Associate at Qatar Computing Research Institute, and lead developer of CrisisTracker. He received an M.Sc. degree in media technology and engineering from Linköping University in 2009 and has previously worked in information visualization research and decision-support systems development in industry and academia.

Maja Vukovic *IBM Research Division, Thomas J. Watson Research Center, Yorktown Heights, NY 10598 USA (maja@us.ibm.com)*. Dr. Vukovic is a Research Staff Member in the Services Delivery Department at the IBM T. J. Watson Research Center. She received a dual B.Sc. degree in mathematics and computer science from University of Auckland in 1998, an M.Sc. degree in computer science from International University in Germany in 2000, and a Ph.D. degree in computer science from the University of Cambridge in 2006. She worked as a Research Scientist at the MercedesBenz Research Lab in Palo Alto, California, on remote vehicle customization and telematics systems. At IBM, Dr. Vukovic is working on enterprise crowdsourcing and identity-access management systems. She is author or coauthor of more than 50 technical papers and has organized several workshops on crowdsourcing and social media for disaster management. Dr. Vukovic is a senior member of the Institute of Electrical and Electronics Engineers (IEEE).

Claudio A. Teixeira *Madeira Interactive Technologies Institute, Caminho da Penteada, 9020-105 Funchal, Portugal (claudio.teixeira@m-iti.org)*. Mr. Teixeira is a Research Assistant at the Madeira Interactive Technologies Institute. He received a B.Sc. degree in informatics engineering from University of Madeira in 2010 and is currently finishing his M.S. degree in informatics engineering from the University of Madeira.

Vassilis Kostakos *Department of Computer Science and Engineering, University of Oulu, Oulu 90570, Finland (vassilis@ee.oulu.fi)*. Dr. Kostakos is Professor of Computer Engineering in the Department of Computer Science and Engineering at the University of Oulu. He received B.Sc. and Ph.D. degrees in computer science from the University of Bath in 2001 and 2004, respectively. In 2010, he became a fellow of the Academy of Finland Distinguished Professor Program, and in 2012, he received a Marie Curie Career Integration Grant. He conducts research on human-computer interaction, ubiquitous computing, and social media. He is a member of the Association for Computing Machinery (ACM).

Evangelos Karapanos *Madeira Interactive Technologies Institute, Caminho da Penteada, 9020-105 Funchal, Portugal (ekarapanos@uma.pt)*. Dr. Karapanos is an Assistant Professor at Madeira Interactive Technologies Institute where he also acts as the academic director of the Carnegie Mellon | Portugal Professional Masters of Human-Computer Interaction. Dr. Karapanos holds a Ph.D. degree (*cum laude*) from Eindhoven University of Technology on methods and tools for user-experience evaluation. His work has been published in, among others venues, the Association for Computing Machinery Special Interest Group on Computer-Human Interaction (ACM SIGCHI) *Conference on Human Factors in Computing* and in the *International Journal of Human-Computer Studies*. He also published the book *Modeling Users' Experiences with Interactive Systems* (Springer) in 2012. He has been a visiting researcher at Philips Research, Philips Consumer Lifestyle, and the Human-Computer Interaction Institute at Carnegie Mellon University. Dr. Karapanos is a member of the Association for Computing Machinery.

Jim A. Laredo *IBM Research Division, Thomas J. Watson Research Center, Yorktown Heights, NY 10598 USA (laredoj@us.ibm.com).* Mr. Laredo has more than 20 years of experience in the Information Technology Industry, including the areas of transaction processing (Transarc Corporation), business process management (Vitria Technology), software as a service, and cloud computing and systems management (IBM). He has been building systems and services for customers in financial services, telecommunications, insurance services, and manufacturing. Mr. Laredo has spent the last ten years at IBM, eight of which were at the T. J Watson Research Center in New York. In particular, he has spent the last three years working in the area of enterprise crowdsourcing, seeking innovative techniques that make use of people's knowledge to scale business-process management across the organizations of the enterprise. Mr. Laredo has an engineering degree from Universidad Simon Bolivar, Caracas Venezuela, and an M.Sc. degree in computer science from the University of Toronto.