Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2013 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

6-18-2013

Integrating Social Media with Ontologies for Real-Time Crowd Monitoring and Decision Support in Mass Gatherings

Pari Delir Haghighi
Monash University, pari.delirhaghighi@monash.edu

Frada Burstein
Monash University, frada.burstein@monash.edu

He Li
Monash University, hli98@student.monash.edu

Chao Wang
Monash University, showmethemails@gmail.com

INTEGRATING SOCIAL MEDIA WITH ONTOLOGIES FOR REAL-TIME CROWD MONITORING AND DECISION SUPPORT IN MASS GATHERINGS

Pari Delir Haghighi, Caulfield School of IT, Monash University, Australia, pari.delirhaghighi@monash.edu

Frada Burstein, Caulfield School of IT, Monash University, Australia, frada.burstein@monash.edu

He Li, Caulfield School of IT, Monash University, Australia, hli98@student.monash.edu

Chao Wang, Caulfield School of IT, Monash University, Australia, showmethemails@gmail.com

Abstract

Situation awareness plays an essential role in making real-time decisions in mass gatherings. In the last few years, social media data analysis has been proved to be an effective approach to enable and enhance situation awareness. Mass gathering events are dynamic and critical environments where thousands of people attend. During the event, there is a potential for injuries and other health hazards, and thus it is critical for emergency medical services to access real-time and situational awareness information, especially concerning the nature of the crowd. It has been well recognized in the literature that crowd mood and behaviour can have a direct impact on the crowd safety and patient presentation rates. We describe a mobile social media-enabled crowd monitoring architecture that aims to improve emergency management decision-making by analysing the data from social networks in real-time. The proposed architecture incorporates a crowd behaviour classification model, which facilitates real-time situation awareness and provides a better understanding of analysis results. Awareness and perception of crowd mood and behaviour during the event can significantly improve prediction of patient presentation rates; leading to timely and effective medical care provision. The implementation and evaluation of the proposed framework on an Android mobile phone is described.

Keywords: Social Media, Decision Support Systems, Ontology, Mass Gatherings, Medical Emergency Management.

1 INTRODUTION

Mass gathering environments are typically very dynamic and unpredictable. At these events, there is a potential for incidents including injuries and other health hazards (Arbon 2001). Medical emergency management in mass gatherings is a complex process that can be divided into three main stages: 1) pre-event, 2) during-the-event, and 3) post-event (Delir Haghighi et al. 2013). The pre-event phase generally involves planning and preparation for the event. At the during-the-event stage in order to achieve timely response and treatment in mass gatherings, it is imperative to provide emergency services and medical teams with real-time information and maintain high situation awareness. Situation awareness can refer to access to any information related to the venue, emergency services, patient presentation rates, availability of medical equipment and other necessary resources, as well as crowd behaviour. Situation awareness can significantly assist participating teams in the field with better prediction of patient presentation and medical workload and result in timely medical care provision.

In the last few years, social media analytics have been widely and successfully used to provide useful information about occurring situations (Yin et al. 2012). Social networking platforms, such as Twitter and Facebook, have recently become tightly integrated into people's daily life and everyday communication patterns. More and more people are likely to use social media platforms to publish how they feel, what they do or what they see, etc. Furthermore, with the current advances in mobile technologies and communication, people could get access to social media everywhere and anytime using their mobile phones or tablets. According to Ankeny (2011), almost 55% of Twitter's active users use a mobile device to tweet.

Recently, government agencies have also recognized the potential and importance of using social media as a useful source of information, particularly during emergencies and disaster situations (Ehnis and Bunker 2012). Social media analysis enables situation awareness in emergency management and improves real-time decision making (Vieweg et al. 2010). The applications of social media for emergency and disaster management include providing information of pre-incident activities, 'near real-time notice' about the occurrence of an incident, early reports about the impacts of the incident and measuring and monitoring community response to the emergency warnings (CSIRO 2013).

In the context of mass gatherings, crowd mood and behaviour are considered important factors for making decisions in emergency management (Zeits et al 2009). While current crowd monitoring systems provide useful information about crowd behaviour (Sharif et al. 2008; Abuarafah et al. 2012; Zhan et al. 2008; Song et al. 2012), their data analysis techniques are not underpinned by a solid crowd modelling approach. In our crowd monitoring approach, we use a rich and reliable crowd model that is created through studying the related literature and provides a better understanding of crowd analysis results. Social media data like the Facebook comments and tweets (Krüger et al. 2012) are good indication of a crowd's mood and behaviour but this data needs to be mapped to an accepted and standard crowd model to provide useful knowledge. For example, tweets that contain words such as 'attacking', 'fighting' and 'violent' can indicate a '*violent crowd*' (Berlonghi 1995). On the other hand, positive comments such as 'nice day', 'pleasant', 'watching game', 'great event' can describe a '*cohesive/spectator crowd*' type (Berlonghi 1995). Such data can be captured and processed online to monitor crowd behaviour and detect early signs of an incident.

In this paper, we propose a mobile social media-enabled crowd monitoring architecture that aims to improve decision making in mass gatherings by providing real-time situational information about crowd mood and behaviour based on the data captured from social networks. This architecture incorporates a novel crowd behaviour classification model that identifies the main categories of crowd types (Belonghi 1995) and populates them with synonyms and related words. To support informal language (e.g. emoticons) of social media, the proposed model also includes three aspects of sentiment analysis (i.e. positive, neutral and negative) and maps them to the crowd type categories and also to the level of emergency and medical workload (low, medium and high). This model is fully aligned with Domain Ontology for Mass Gatherings (DO4MG) proposed by Delir Haghighi et al. (2010). The use of the ontology presents further advantages of avoiding inconsistencies and discrepancies in terminology used by various stakeholders involved in emergency management. It supports standardisation and semantics across the whole cycle of mass gathering management. The other contribution of our work is to provide real-time crowd monitoring during the event compared to other existing evaluation methods for crowd assessment that are performed offline (post-event) (Hutton et al. 2009).

The proposed crowd monitoring approach provides emergency teams and commanders with up-to-date information about the occurring situations (i.e. crowd mood and behaviour) and their trends, and enables them to allocate resources in a more effective and efficient manner. The social media-enabled crowd monitoring architecture has been implemented as a prototype on an Android mobile phone and evaluated in terms of accuracy and processing time.

The rest of this paper is organized as follows. In Section 2, we discuss different stages of mass gathering management, and the role of the ontology to improve data integration and management across different phases. This section also discusses the crowd factor and its descriptors in mass gatherings. Section 3 describes the mobile social media-enabled architecture. The two main components of the architecture which include social media analyser and crowd behaviour model are detailed in this section. Section 5 discusses the implementation and evaluation of the proposed architecture based on accuracy and processing time. Finally, Section 6 concludes the paper.

2 MASS GATHERING MANAGEMENT

Mass gathering can be defined as an event in which at least 1,000 people attend for an extended period of time (Boatright, 2004). Examples include music concerts, sporting events, cultural gatherings, parades and etc. Due to the crowd size, type, density and mood, as well as other environmental factors, mass gatherings potentially increase the degree of vulnerability of those attending the event and the likelihood of life-threatening situations (Arbon 2001). During the mass gathering events, the emergency medical teams need to make complex and time-critical decisions. These decisions can relate to timely treatment of injured or ill spectators, providing more advanced levels of medical care, which requires rapid evacuation of patients to nearby hospitals, and requests for external and additional resources (Zeitz 2007; Morimura 2004). Making such emergency decisions during the event can be facilitated by appropriate decision support systems that cater for mass gathering emergency problems. Examples of such systems include situation-aware and mobile DSS (Delir Haghighi et al. 2010) that provide emergency teams with real-time information about the occurring situations on the move.

Organizing a successful mass gathering is complex process and includes several stages and a variety of tasks which require participation of different agencies and services. According to the mass gathering literature (Arbon 2001; Milsten et al. 2002; Zeitz et al. 2007; Calabro 1996; WHO 2008), the event activities can be categorized into three phases as shown in Figure 1.

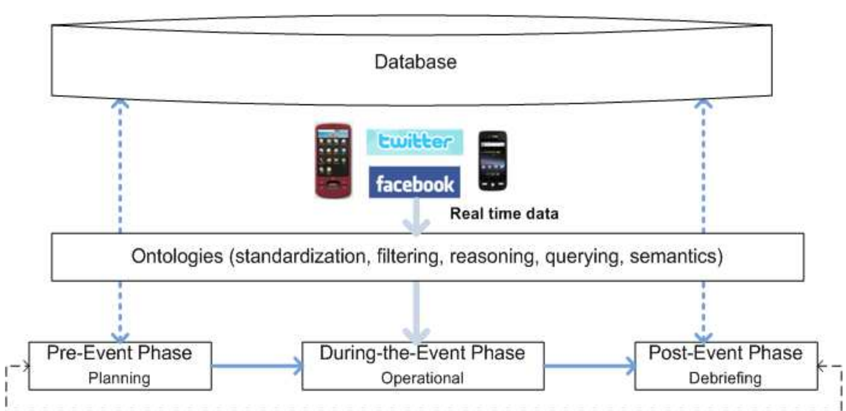

Figure 1. Mass gathering management phases (adapted from (Delir Haghighi et al. 2013).

The pre-event (planning) phase includes tasks such as defining the event, visiting the site and estimation of workload. The during-the-event (operational) stage involves real-time interaction and communication between emergency services, and monitoring the event and crowd. In this phase, real-time decisions are made. The post-event (debriefing) concentrates on recording event data, auditing, evaluation and debriefing are performed.

As Figure 1 shows, the activities in the pre-event and post-event phases such as planning or debriefing mainly require static data which is stored and recorded in a database. On the other hand, during the event, most of the tasks rely on real-time data. This stage can significantly benefit from real-time decisions support systems. This paper focuses on the second, during the event stage of emergency management in mass gatherings. At that stage, situation awareness (i.e. access to real-time information about the event and crowd) is highly imperative.

Social media information today is one of the main sources of real-time data that reflects a crowd's thoughts and feelings (Yang et al. 2009). Capturing and analysis of social media information during the mass gatherings can provide a sound understanding of crowd mood and behaviour, and significantly enhance situation awareness and real-time decision making.

Management and integration of all the mass gathering data is a challenging task, and is necessary to maintain data consistency across different stages of mass gatherings. Using a common ontology in all the stages facilitates consistency in data entry, management, filtering and integration in a standard and unified manner across all the activities. Ontologies as a conceptual model provide a formal representation of concepts and their relationships within a certain domain that can be used for knowledge sharing (Gruber 1995). The following subsection provides more details about the DO4MG (Domain Ontology for Mass Gatherings) which was proposed by Delir Haghighi et al. (2010) and adopted in this research. Integrating the data from social media with a domain ontology is a novel task and a challenge which is addressed in this paper.

2.1 The Domain Ontology for Mass Gatherings

Delir Haghighi et al. (2010) introduced a domain ontology, named DO4MG (Domain Ontology for Mass Gatherings) to improve decision making in the field of medical emergency management by providing a unified and common vocabulary of mass gatherings. The ontology also provides a consistent and comprehensive view on the problem domain that can be used by all concerned stakeholders and can be applied to all the phases and tasks of mass gatherings.

The core of DO4MG ontology is the concept of Mass Gathering. There are five main key concepts, in the DO4MG ontology, which define every mass gathering event. These include CrowdFeatures, EventVenue, GatheringType, EnvironmentalFactors and MassGatheringPlan. The second level of the ontology includes 40 subclasses, i.e. "children" or "leaf classes", which are broken into further subclasses. The total number of classes considering all the levels is 234.

The CrowdFeatures include CrowdCatalyst, CrowdMood, CrowdBehaviour, CrowdType, Fitness, CrowdDemographics and CrowdSize (as shown Figure 2). The term 'Crowd Catalyst' is described as factors that "contribute to or trigger a crowd from being one that is managed to one that needs to be controlled" (Belonghi 1995, p. 245). Crowd type and its eleven subclasses are defined based on the classification proposed by Berlonghi (1995). Crowd mood is described according to the study by Zeitz et al. (2009) and Hutton et al. (2009).

DO4MG was developed in Protege[1] which provides several options to create synonyms. We extended crowd-related subclasses through using annotations and labels (i.e. synonyms) and provided a definition and a reference for the source of the concept (e.g. CrowdType_Spectator). Figure 2 shows the list of synonyms under the label that have been used to represent 'Spectator'. These synonyms play an important role in enabling semantic search and reasoning. They can also be utilised as a 'bag of words' for improving social media analysis in real-time crowd monitoring.

[1] http://protege.stanford.edu/

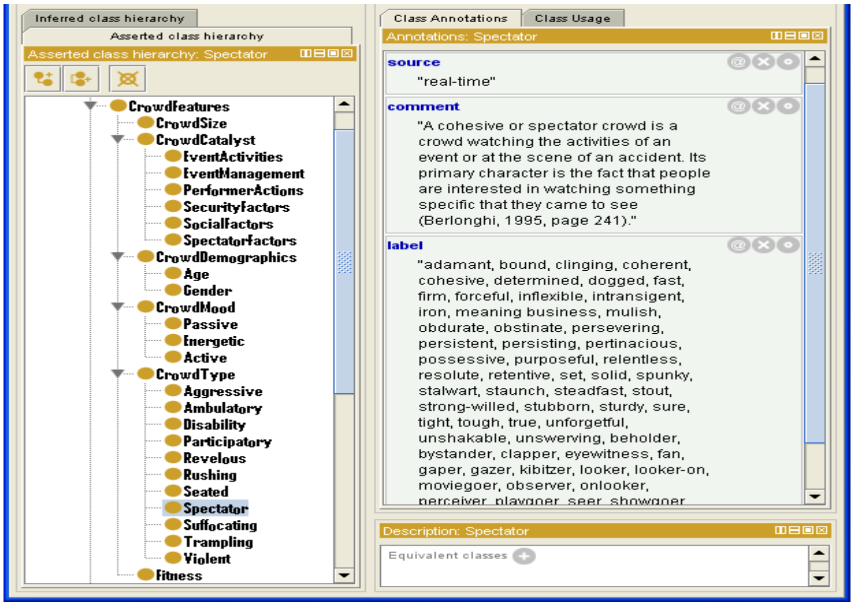

Figure 2. Extended concept of Crowd Features and its subclasses

The next subsection presents an overview of the concepts of crowd mood, behaviour and type that are used for crowd modelling.

2.2 Crowd Modelling in Mass Gatherings

There is an on-going need to better understand the drivers of patients seeking healthcare services in mass gatherings. Arbon (2001) categorised these drivers and factors into three domains of biomedical, psychosocial and environmental. The biomedical domain focuses on the number and type of patients, and the environmental domain concentrates on factors such as temperature or terrain. The psychosocial domain is concerned with psychological and social factors including crowd type, mood and behaviour.

Most of the studies have focused on exploring the key drivers of the biomedical and environmental domains (Arbon 2001, Zeitz 2009, Milsten 2002; 2003). However, there is limited research on understanding psychological elements; particularly crowd features or using such knowledge for improving predication of workload in mass gatherings in real time.

The relationship between the crowd mood and patient presentation rate has been identified by many researchers (Morimura 2004). It is imperative to monitor and observe the crowd mood and behaviour during the event and make effective decisions accordingly (Berlonghi 1995). In doing so, the first step is to define crowd type, behaviour and mood and distinguish between them.

Zeitz et al. (2009; pg 33) define crowd type as "an environmental descriptor of the demographics of a crowd" and crowd behaviour as "the demonstrable factor that requires assessment and monitoring to underpin management actions". They describe crowd mood as "more of a psychosocial descriptor of crowd". Crowd mood can be classified into *passive*, *active* and *energetic* based on the degree of physical movements and contact, talking and participation. Berlonghi (1995) categorizes crowd type into categories of ambulatory, disability/limited movement, cohesive/spectator, expressive/revellous, participatory, aggressive/hostile, demonstrator, escaping/trampling, dense/suffocating, rushing/looting, and violent. Inspired by the above categorizations, Hutton et al. 2009 developed an offline assessment tool to measure and monitor crowd behaviour. This tool aims to assess the psycho-social elements of a mass gathering by assigning scores to the different classes of crowd type, mood and behaviour using the data collected during the event.

2.3 Crowd Monitoring Approaches

Traditional crowd monitoring was limited to the observations of emergency team members who were geographically dispersed across the event venue (Wirz et al. 2012). With the advent of new technologies, a variety of more sophisticated approaches were introduced. The most widely used systems include video surveillance, image processing and closed-circuit television systems (Regazzoni et al. 1993; Davies et al. 1995; Song et al. 2012). Sharif et al. (2008) performed crowd behaviour monitoring based on escalator exits, mainly estimating sudden changes and abnormal motion variations in a set of interest points. A technique proposed by Abuarafah et al. (2012) performs monitoring and estimating of the crowd density in real-time using infrared thermal video sequences. Zhan, et al. (2008) presented a survey on crowd analysis methods employed in computer vision research and discusses perspectives from other research disciplines.

Recent advances in mobile technologies and developments in social media networking enable to improve crowd monitoring further by capturing and analysing real-time and rich information on the move. Wirz et al. (2012) introduce a pedestrian-behaviour model to infer and visualize crowd conditions from pedestrians' GPS location traces in terms of crowd density, crowd turbulence, crowd velocity and crowd pressure. Wakamiya et al. (2012) combine Web-based social network and the real-world location tagging in an integrated way, and monitor crowd's experiences through the location-based social network such as Twitter by collecting and analysing crowd's numerous micro life logs.

While the above-mentioned systems are able to provide useful information about crowd behaviour, their analysis has to be adapted to suit an acceptable crowd model. The analysis of social media based on an existing and valid crowd model can improve the interpretation of the results and make them more useful to the range of stakeholders, i.e. emergency teams. Using a common crowd model along with a unified domain ontology not only provides the benefits of maintaining consistency in data integration, but also across different phases of mass gathering management.

3 SOCIAL MEDIA-ENABLED REAL-TIME CROWD MONITORING FOR MASS GATHERINGS

Kaplen and Haenlein (2010) define social media as a group of Internet-based applications that allows the creation and exchange of user-generated content through using Web 2.0 technologies. Twitter and Facebook are the most popular social networks. In the mass gathering events, when a large number of people gather it can be assumed that considerable numbers of these attendees will use social media technologies, such as Twitter, to publish personal messages during the event. This data can be utilized to enhance situation aware decision support systems, which includes crowd monitoring capabilities. Using up-to-date reliable data can improve the medical emergency management, and reduce the risks to public safety.

As discussed earlier, in order to utilise the social media data, it is necessary to reconcile the informal language people use in their messages with the relevant concepts and descriptors of a formal ontology (i.e. DO4MG) and a crowd classification model. In the next subsections first we describe the two main components of the crowd monitoring architecture which include social media analyser and the crowd behaviour classification model, and then present an overview of the proposed architecture.

3.1 Social Media Analyser

One of the main benefits of social media analysis is providing situation awareness in emergency management and improving real-time decision making (Vieweg et al. 2010; Johansson et al. 2012). There is an abundance of studies about social media analysis where different analysis methods are used (Yin et al. 2012; Pak and Paroubek 2011). In order to extract useful information from the social media data, there is a need for machine learning and text classification methods (Sebastiani 2002). Automatic text classification methods like trend topic categorization (Lee et al. 2011) are widely used to measure trends on Twitter. Text classification methods could be divided into three categories:

Statistical Classification such as Naïve Bayesian classifier (Yin et al. 2012; Sofean et al. 2012), Geometrical/Functional Classification like Support Vector Machines (SVM) and Neural Classification.

Social media analysis can be performed for purposes of sentiment analysis or trending topics (Yang et al. 2009; Lee et al. 2011; Krüger et al. 2012). According to Liu (2010), the most well studied sub-problems of sentiment analysis is sentiment classification. There are three levels of classification. The first level is concerned with discovering whether one document contains any opinions at all, which is also referred to as “subjectivity classification” or “opinion identification”. And the other level aims to classify opinionated documents as expressing a positive, negative, or neutral opinion (Johansson et al. 2012). And the most advanced layer involves with classification of review opinions into a number of product feature classes (Yang et al. 2009).

In our implementation we have adopted the fast string searching algorithm proposed by Boyer and Moore (1977) to find one string of characters in the other one. We also used a “bag of words” approach for sentiment analysis which consists of the following parts:

- A list of positive words that generally used by people to express positive feelings;
- A list of negative words that generally used by people to express negative feelings;
- A list of emoticons that represents a positive meaning of a message;
    - Examples: :-) :) 8) =) :} >:D :-D :D
- A list of emoticons that represents a negative meaning of a message.
    - Examples: :(:-(>_< T_T :-C >:[:c

Based on the “bag of words”, we define a list of rules to perform sentiment analysis that determines the meaning and relevance of the messages for CrowdMonitor. These rules are listed in Table 1.

Sentiment label	**Rules**
Positive	If messages contain positive keywords If messages contain positive emoticons If messages contain double negatives (e.g. not bad)
Neutral	If messages contain neither positive nor negative keywords If messages contain neither positive nor negative emoticons
Negative	If messages contain negative keywords If messages contain negative emoticons If messages contain negative following positive keywords (e.g. not fine)

Table 1. Rules for sentiment analysis.

The strength of our approach, compared to the current state of the art, is its underlying crowd classification model discussed in the following subsection.

3.2 Real-Time Crowd Behaviour Modelling

While post-event evaluation methods for crowd assessment such as the crowd assessment tool introduced by Hutton et al. 2009 are very useful to understand the psychosocial domain of mass gatherings, they are performed offline (after the event) and do not support real-time crowd monitoring during the event. One of the major benefits of crowd monitoring is in fact to provide emergency teams with real-time situation awareness during the event for early detection of any incident.

Crowd mood depends on crowd type (Zeitz et al. 2009) and crowd behaviour is mainly determined by crowd type and mood (Hutton et al. 2009). Assessing and monitoring crowd type can also provide an understanding of crowd mood and behaviour. In our study, to develop a crowd classification model we have adopted the crowd type’s eleven categories proposed by Berlonghi (1995), and populated them with synonyms and related words. Due to the large size of this information, Table 2 shows the collected synonyms only for one of the crowd types (i.e. cohesive/spectator). The synonyms are collected from WordNet[2] and Thesaurus.com[3]. WordNet is a rich lexical database of English words that are gathered into a number of cognitive synonym sets, and Thesaurus.com is a large and widely used free online thesaurus.

Crowd Types	WordNet	Thesaurus.com
Cohesive/ spectator	well integrated, witnessviewer, watcher, looker, observer	adamant, bound, clinging, coherent, cohesive, determined, dogged, fast, firm, forceful, inflexible, intransigent, iron, meaning business, mulish, obdurate, obstinate, persevering, persistent, persisting, pertinacious, possessive, purposeful, relentless, resolute, retentive, set, solid, spunky, stalwart, staunch, steadfast, stout, strong-willed, stubborn, sturdy, sure, tight, tough, true, unforgetful, unshakable, unswerving/ beholder, bystander, clapper, eyewitness, fan, gaper, gazer, kibitzer, looker, looker-on, moviegoer, observer, onlooker, perceiver, playgoer, seer, showgoer, sports fan, standee, stander-by, theatergoer, viewer, watcher, witness

Table 2. An excerpt of the crowd classification model for the cohesive/ spectator type.

The crowd model and its contents can be fully mapped to the DO4MG ontology's subclasses and their labels (i.e. synonyms). Figure 2 and Table 2 provide an example to illustrate this point. The main purpose of our proposed model is to enable classification of a crowd's published comments/tweets at a mass gathering event against a set of pre-defined descriptors. This classification will enhance the social media analyser with identifying the polarity of social media information and detecting the crowd's current type which also is an indication of crowd mood and behaviour.

During the event, social media information collected from different platforms such as Twitter can be analysed and provide a good understanding and knowledge of crowd behaviour and detect any unusual pattern. However, the comments and terms used in social media can hardly match with the vocabulary that is provided in dictionaries or thesaurus (as listed in Table 2) because social media uses an informal language. Therefore, in our study we attempt to apply the sentiment analysis method which identifies three aspects of the crowd (i.e. positive, negative and neutral) and match them against the crowd types. Figure 3 shows the relationship of these aspects with other descriptors of crowd.

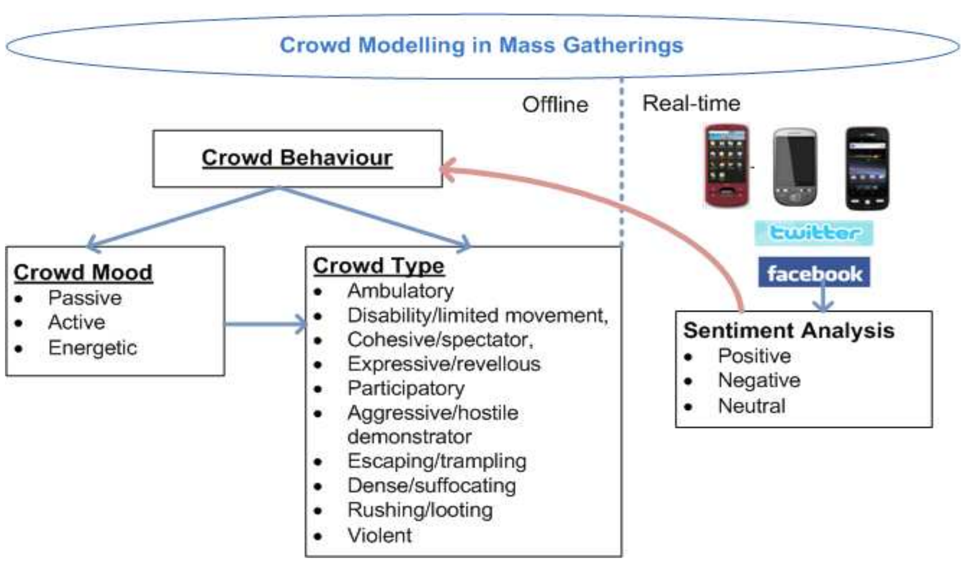

Figure 3. Use of sentiment analysis for crowd modelling.

[2] http://wordnet.princeton.edu/
[3] http://thesaurus.com/

To incorporate sentiment analysis in the crowd modelling approach, we map three aspects of sentiment analysis to the crowd type descriptors and medical workload in mass gatherings. Table 3 shows the details of our proposed mapping which are established based on the crowd type studies in the context of mass gatherings (Berlonghi 1995; Zeitz et al. 2009, Hutton et al. 2009).

Crowd Types	**Sentiment Analysis Aspects**	**Emergenc Level (Medical Workload)**
Ambulatory	Neutral	Medium
Disability/limited movement	Neutral	Medium
Cohesive/spectator	Positive	Low
Expressive	Positive	Low
Participatory	Positive	Low
Aggressive/hostile	Negative	High
Demonstrator	Neutral	Medium
Escaping/trampling	Negative	High
Dense/suffocating	Negative	High
Rushing/looting	Negative	High
Violent	Negative	High

Table 3. Mapping the results of sentiment analysis to the crowd type classes and workload.

3.3 Social Media-Enabled Crowd Monitoring Architecture

The proposed mobile social media-enabled crowd monitoring architecture consists of the client and server sides (see Figure 4). All interactions between the client system and server are achieved via web services and based on Service-Oriented Architecture (SOA).

The server side consists of Social Media (SM) Collector, Social Media (SM) Analyser, Report Generator, Crowd Behaviour Classification Model, and Web Service Manager. *SM Collector* periodically queries the social media platforms and retrieves related data posted by attendees. *SM Analyser* performs processing and data analysis on the collected information based on our proposed *Crowd behaviour Model* and the ontology (DO4MG). *Report Generator* uses social media analysis results to create a useful and summarised report about current crowd behaviour. The emergency staff use the client component to perform user registration, user query and information updates. The data about the clients (i.e. emergency and medical teams) are stored in *the database* on the server side. *Web Service Manager* is responsible for communicating with the client side, responding to client queries and publishing the crowd analysis results and reports.

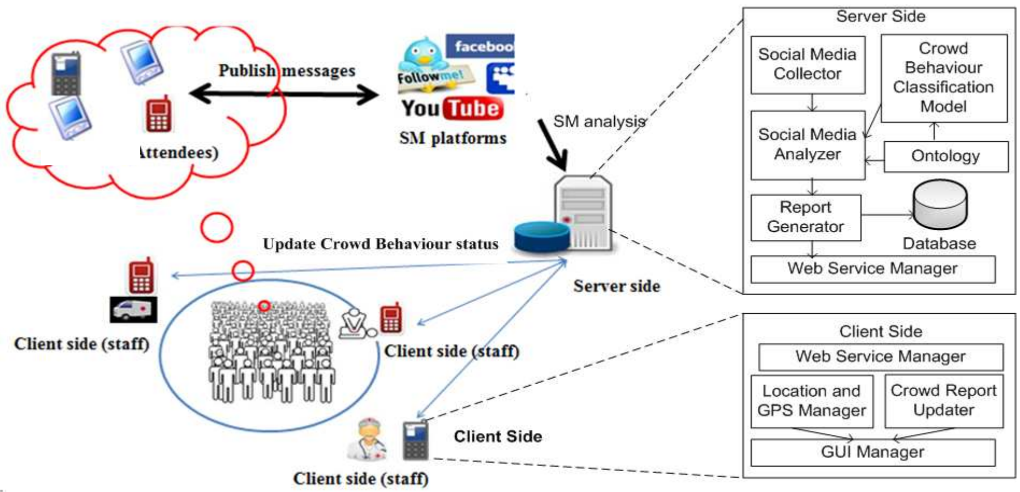

Figure 4. The architecture of real-time social media-enabled crowd monitoring.

The client-side component runs on mobile phones of the emergency staff and enables them to register and access real-time information about crowd behaviour. The client side components include Location and GPS Manager, Crowd Report Updater, GUI Manager and Web Service Manager. *Location and GPS Manager* is responsible for updating the real-time coordinates of the registered members while they are on the move and passing this information to GUI Manager. *Crowd Report Updater* receives the reports and information from the server side on a periodic basis, adjusts them for displaying on a mobile screen, and interacts with GUI Manager to update the reports. *GUI Manager* is responsible to provide an interactive interface, on which the user can perform different functions such as registration, tracking the location of other team members on Google maps and reviewing the current report of crowd behaviour. *Web Service Manager* queries the server and receives the published information.

The following section discusses the implementation of evaluation of our proposed architecture.

4 IMPLEMENTATION AND EVALUATION

CrowdMonitor is a real-time decision support system for crowd monitoring in mass gatherings. It provides not only situational information about the emergency teams like location and status (busy or available) but also information about crowd behaviour and its corresponding emergency level (low, medium and high). The server component of CrowdMonitor was implemented and tested on a desktop machine with an Intel® Core™ i3 2.13GHz, storage 500GB, 4GB memory running Windows 7 64bit. The client component was developed and evaluated on a GPS-enabled Nexus S with Android version 4.04 Smartphone with 1 GHz single-core, 16 GB storage and 512 MB memory. Figure 5. shows the client interface for the emergency staff and the results of social media analysis. These features allow the emergency staff to predict possible emergency situations during the events and better prepare for them. The images (a) and (b) in Figure 5 show the location of emergency staff on a dynamic map (Google map). The image (c) shows an example of a posted message used in data analysis with its captured details, and the image (d) provides a general conclusion based on social media analysis results and presents the corresponding emergency level (i.e. Medium).

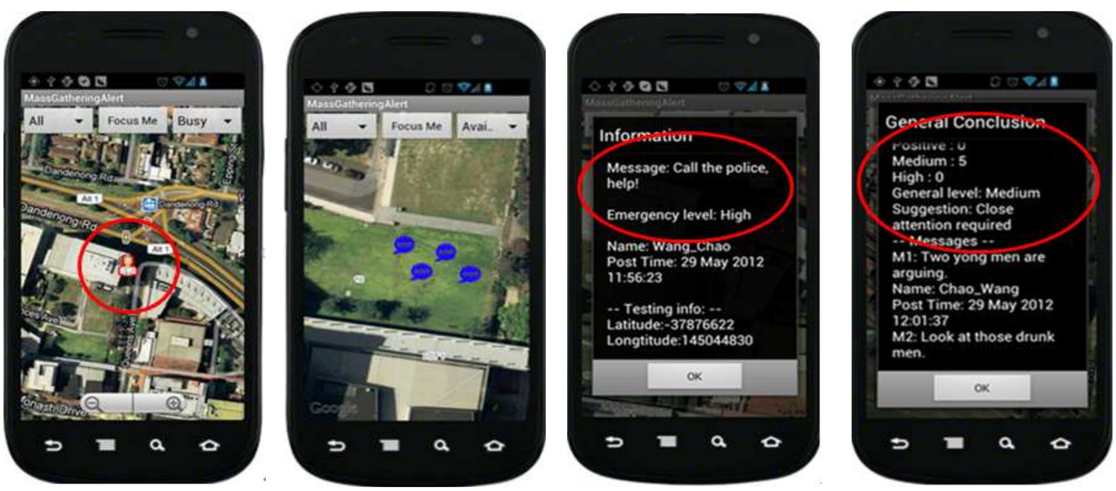

Figure 5. An overview of CrowdMonitor (a) and (b): Location of emergency staff on the map; (b) and (c)example of posted messages by attendees and social media analysis results.

CrowdMonitor is our preliminary implementation that mainly focuses on sentiment analysis but we are currently extending this prototype to fully incorporate the proposed crowd model and provide a report on crowd type categories.

4.1 Accuracy Evaluation

To validate accuracy of our social media analysis method, a comparative evaluation was conducted between the analyzer of CrowdMonitor and the open source code and corpus (i.e. Twitter Sentiment

Corpus) by Niek Sanders[4]. Sander's dataset contains 5513 Tweets and all messages are marked with one of the four sentimental labels (i.e. Positive, Neutral, Negative and Irrelevant). The 'Neutral' and 'Irrelevant' aspects are very similar and both represent borderline cases that are neither positive nor negative. In our evaluation, we considered both categories under the 'Neutral' label. First we tested our algorithm on the Sander's dataset and then compared the analysis results to the actual categorised labels to estimate the accuracy. As Table 4 shows the overall accuracy was 65.53%.

	Analysis results using our method			**Valid Accuracy for each label**
	Positive	**Netural**	**Negative**	
Actual Positive category	**73%**	17%	10%	73%
Actual Netural category	23%	**60.5%**	10.5%	60.5%
Actual Negative category	9%	12%	**79%**	79%
Overall Accuracy	**70.83%**			

Table 4. Accuracy of the CrowdMonitor analyzer.

We also compared our results with those produced by Sander's algorithm. Table 5 shows these results.

	Analysis results using Sander's method			**Valid Accuracy for each label**
	Positive	**Netural**	**Negative**	
Actual Positive category	**63%**	23%	14%	63%
Actual Netural category	9%	**87%**	4%	87%
Actual Negative category	21%	33%	**46%**	46%
Overall Accuracy	**65.33%**			

Table 5. *Accuracy of the Sander's method.*

As shown in Figure 6, Sander's method only performs better in processing and identifying the neutral category (87%) but considering both positive and negative categories it performs poorly with 63% accuracy for positive category and 46% for negative category. Overall, our approach outperforms the Sanders's algorithm in terms of accuracy (with 5.5%).

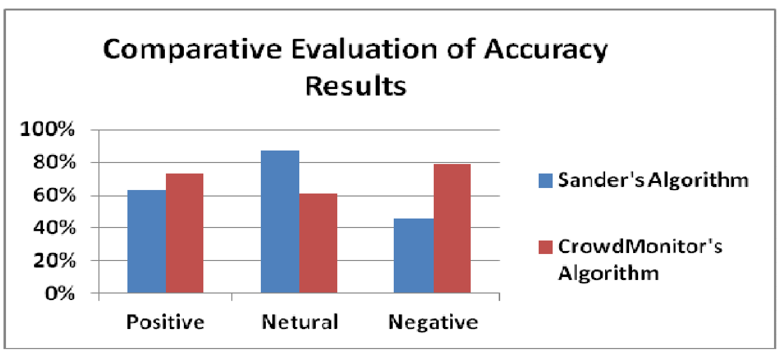

Figure 6. Use of sentiment analysis for crowd modelling.

4.2 Processing Time Evaluation

To support medical emergency services in mass gathering with real-time information, the crowd monitoring application should be able to analyse data with a short delay. We also evaluated our prototype in terms of processing time. Processing time here refers to the time that takes for social media analyser on the server side to process social media data and produce the results. This evaluation was performed with 8 different sizes of 'bag of words' and 20 different sizes of tweets. The reason was that the size of keywords and tweets being analysis can both affect the processing time. Table 6 depicts the results based on the size of keywords and messages in milliseconds (msec).

[4] http://www.sananalytics.com/lab/twitter-sentiment/

Keywords / Messages	25	50	75	100	125	150	175	200
5000	218	421	639	826	1076	1216	1357	1544
10000	390	780	1201	1528	1965	2277	2698	3057
15000	561	1138	1716	2262	2870	3447	3868	4368
20000	764	1497	2371	2964	3775	4461	5304	5990
25000	982	1887	2901	3915	4726	5709	6535	7410
30000	1138	2215	3463	4461	5584	6708	7924	8814
35000	1326	2620	4024	5413	6630	8002	9016	10202
40000	1513	2979	4539	5881	7332	9063	10670	11793
45000	1716	3416	5148	6786	8502	10202	11606	13166
50000	1918	3728	5631	7347	9469	11029	13197	14632
55000	2106	4180	6271	8236	10311	12433	14086	16146
60000	2340	4524	6708	8845	11154	13322	15662	17643
65000	2496	4882	7394	9843	12261	14726	16692	18985
70000	2730	5210	7909	10327	13072	15350	18423	20436
75000	2854	5725	8502	11310	14149	17128	19234	21918
80000	3135	5943	9157	11762	15007	17674	20888	23478
85000	3244	6458	9687	12745	16052	19390	21808	24788
90000	3432	6661	10030	13182	16894	19796	23680	26286
95000	2666	7191	10764	14274	18111	21450	24429	27658
100000	3775	7410	11310	14664	18657	22027	26317	29390

Table 6. Performance evaluation in terms of processing time (milliseconds).

As the size of keywords and messages increases, the processing time increases too. However, even with the last case where the number of tweets are 100,000 and the applied keywords consist of 200 words, the processing time is about 29 seconds which is considered small and unnoticable. In our future work, we intend to compare the processing time of our apparoach to the Sander's algorithm.

5 CONCLUSION

In this paper, we studied the requirements for situation-aware information systems for crowd monitoring and the opportunities created by social media data analysis. We introduced a real-time and mobile social media-enabled crowd monitoring architecture for decision support in mass gatherings that incorporates a novel crowd behaviour classification model and a social media analyser. The crowd behaviour model consists of a number of crowd descriptors extracted from the literature and populated with a list of synonyms. Since social media uses an informal language, we integrate this model with sentiment analysis and propose a mapping approach that matches these aspects to crowd types and also to the level of emergency and medical workload. The proposed crowd model is fully aligned with the Domain Ontology for Mass Gathering (DO4MG), introduced by Delir Haghighi et al (2010), which provides a common and standard representation of the knowledge domain of mass gatherings. It also facilitates maintaining consistency in data storage, management and integration.

The paper described the implementation and evaluation of the proposed architecture for a CrowdMonitor application that targets Android mobile phones. This implementation incorporates parts of the proposed crowd behaviour model, and demonstrates the feasibility of its use. We are currently working on integrating the entire crowd behaviour model including crowd type descriptors into our prototype. We intend to test and compare different social media analysis methods using our model with respect to accuracy, processing time and their support for mobile and real-time decision making and select the most appropriate method for our crowd monitoring application. However, even the preliminary implementation described in this paper illustrates how real-time data freely available through social media platforms can provide useful information and facilitate more dynamic response to sudden and unusual changes in emergency management. Such applications can improve decision making, response to emergencies, enable better and more effective use of resources, and at the end reduce the risks to human lives.

References

Ankeny, J. (2011). Twitter tops 100 M active users, with 55% active on mobile [Web Log Post]. Retrieved Feburary 3, 2013 from http://www.fiercemobilecontent.com/story/Twitter-tops-100m-active-users-55-active-mobile/2011-09-09

Abuarafah, A.G., Khozium, M.O., AbdRabou, E. (2012). Real-time Crowd Monitoring using Infrared Thermal Video Sequences. *Journal of American Science*, 8(3), 133-140.

Arbon P, Bridgewater F, Smith C. Mass gathering medicine: A predictive model for patient presentation rates. *Prehospital Disaster Medicine*, 6, 109-116.

Berlonghi, A.E. (1997) Understanding and planning for different spectator crowds, *Safety Science*, 18 (1995), 239-247.

Boyer, R. S., and Moore, J. S. (1977). A fast string searching algorithm. *Communications of the ACM Magazine*, 20(10), 762-772.

Calabro, J. Gohmer, E. Rivera-Rivera, D. Balcombe, J. Reich, Provision of Emergency Medical Care for Crowds, *American College of Emergency Physicians*, 1996.

Christian Ehnis , Deborah Bunker (2012), Social Media in Disaster Response: Queensland Police Service - Public Engagement During the 2011 Floods, *23rd Australasian Conference on Information Systems*, 3-5 Dec 2012, Geelong

CSIRO, Detecting emergencies using social media, 10 October 2012, http://www.csiro.au/en/Outcomes/ICT-and-Services/emergency-situation-awareness.aspx

Davies, A.C., Yin, J.H, Velastin, S.A. (1995). Crowd monitoring using image processing, *Electronics & Communication Engineering Journal*, 7(1), 37-47.

Delir Haghighi, P. Burstein, F., Zaslavsky, F., Arbon, P. (2013), Development and evaluation of ontology for intelligent decision support in medical emergency management for mass gatherings, *Decision Support Systems*, 54, 1192–1204.

Delir Haghighi, P., Burstein, F., Al-Taiar, H., Arbon, P., Krishnaswamy, S. (2010), Ontology-based service-oriented architecture for emergency management in mass gatherings, *Proceedings of IEEE International Conference on Service-Oriented Computing and Applications*, Perth, Australia, 1-7.

Gruber, T.R. Toward Principles for the Design of Ontologies Used for Knowledge Sharing. *International Journal of Human and Computer Studies*, 43 (1995) 907-928.

Johansson, F., Brynielsson, J., Quijano, M.N. (2012). Estimating Citizen Alertness in Crises Using Social Media Monitoring and Analysis. *Intelligence and Security Informatics Conference (EISIC)*, 2012 European, 189-196.

Kaplen, A.M., Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of *Social Media. Business Horizons*, 53(1), 59–68.

Krüger, N., Stieglitz, S, and Potthoff, T. (2012), Brand Communication In Twitter – A Case Study On Adidass. *In Proceedings of PACIS 2012*. Hochiminh City, Vietnam, Paper 161.

Lee, C., Yang, H., Chien, T., Wen,W. (2011). A Novel Approach for Event Detection by Mining Spatio-temporal Information on Microblogs, *International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 2011, 254-259, July 2011.

Liu, B. (2010). Sentiment Analysis and Subjectivity. In N. Indurkhya and F. J. Damerau(Eds.), *Handbook of Natural Language Processing*.

Milsten AM, Maguire BJ, Bissell RA, Seaman KG: Mass-gathering medical care: A review of the literature. *Prehospital Disaster Medicine*, 17(3),151–162.

Milsten, A.M, Seaman, K.G., Liu P., Bissell, R., & Maguire, B. (2003). Variables influencing medical usage rates, injury patterns, and levels of care for mass gatherings. *Prehospital Disaster Medicine* 18, 334–346.

Morimura N, et al. (2004) Analysis of patient load data related from the 2002 FIFA World Cup Korea/Japan. *Prehospital Disaster Medicine*, 19(3), 278–284.

Pak, A., Paroubek, P. (2011) Twitter for Sentiment Analysis: When Language Resources are Not Available. 22nd Workshop on Database and Expert Systems Applications (DEXA), 111-115.

Regazzoni, C.S., Tesei, A., Murino, V. (1993). A real-time vision system for crowding monitoring. *In Proceedings of the IECON '93*, 3, 15-19.

Sebastiani, F. (2002). Machine learning in automated text categorization. *ACM Computing Surveys*, 34, 1-47.

Sharif, M.H., Ihaddadene, N., Djeraba, C. (2008). Crowd behaviour monitoring on the escalator exits. *11th International Conference on Computer and Information Technology*, p.194-200, Dec. 2008.

Sofean, M., Denecke, K., Stewart, A., Smith, M. (2012). Medical case-driven classification of microblogs: characteristics and annotation. *In Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium (IHI '12).* ACM, New York, NY, USA, 513-522.

Song, H., Liu, X., Zhang, X., Hu, J. (2012). Real-Time Monitoring for Crowd Counting Using Video Surveillance and GIS, *2nd International Conference on Remote Sensing, Environment and Transportation Engineering (RSETE),* 1-4 June 2012.

Vieweg, S., Hughes,A.L., Starbird,K., and Palen, L. (2010). Microblogging during two natural hazards events: what twitter may contribute to situational awareness. *In Proceedings of the 28th international conference on Human factors in computing systems*, 1079-1088. *ACM, 2010.* New York, NY, USA.

Wakamiya, S., Lee, R., and Sumiya, K. (2012). Crowd-sourced urban life monitoring: urban area characterization based crowd behavioral patterns from Twitter. *In Proceedings of ICUIMC '12*. (Lee, S. et al. Eds.), ACM, Article 26, New York, NY, USA.

WHO (World Health Organization), Communicable disease alert and response for mass gatherings, June 2008. Retrieved March, 2013 from http://www.who.int/csr/Mass_gatherings2.pdf.

Wirz, M., Franke, T., Roggen, D., Mitleton-Kelly, E., Lukowicz, P., Troster, G. (2012).Inferring Crowd Conditions from Pedestrians' Location Traces for Real-Time Crowd Monitoring during City-Scale Mass Gatherings, *21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE),* 367-372, June 2012.

Yang, C., Wong, Y. C. and Wei, C.P. (2009). Classifying web review opinions for consumer product analysis. *The 11th International Conference on Electronic Commerce (ICEC '09).* ACM, New York, NY, USA.

Yin, J., Lampert, A., Cameron, M., Robinson, B., Power, R. (2012) Using Social Media to Enhance Emergency Situation Awareness. *IEEE Intelligent Systems*, vol.9, 52-59.

Zeitz K, Tan H, Zeitz, C. Crowd Behaviour at Mass Gatherings – A literature review. *Prehospital Disaster Medicine* 2009; 24, 32-38.

Zeitz K, Bolton S, Dippy R, et al. Measuring emergency services workloads at mass gathering events. *Australian Journal of Emergency Management*, 22(4),24-30.

Zhan, B., Monekosso, D. N., Remagnino, P., Velastin, S.A., Xu, L.Q. (2008). Crowd analysis: A survey. *Machine Vision and Application*. October 2008, 19 (5-6), 345-357.