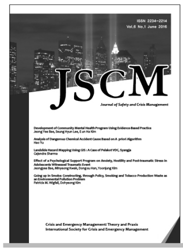


J. Saf. Crisis Manag. Vol.9 No.1, Jun. 2019. pp.1-6
pISSN 2234-2214 / eISSN 2671-5732
http://doi.org/10.14251.jscm.2019.1.1

Journal of Safety and Crisis Management

Role of Artificial Intelligence in Crisis and Emergency Management

Gajendra Sharma[1#], Jae Eun Lee[2]

[1]Department of Computer Science & Engineering, Kathmandu University, Dhulikhel, Kavre, Nepal
[2]Department of Public Administration, Chungbuk National University, 1 Chungdae-ro, Seowon-gu, Cheongju, Chungbuk, Korea

ABSTRACT

Artificial intelligence (AI) plays significant role in crisis and emergency management. AI not only can save lives during crisis an emergency, it can further help government officials to formulate strategies for increased safety and resiliency before a disaster strikes. In this paper the benefits of AI technologies in crisis response have been investigated. This study further discusses the role of artificial intelligence technologies such as robotics, ontology and semantic web, and multi-agent systems in crisis response. AI is behind many of the recent advances in technologies for crisis response and management.

Key words: artificial intelligence, crisis and emergency management, disaster risk

Introduction

Artificial intelligence (AI) technology tries to advance the efficiency of the management process during the crisis response through robotics sustaining urban search and rescue operations, enhancing information sharing using ontologies, providing customized query to crisis actors, and providing multi-agent systems for real time support and simulated environments (Massaguer, *et. al.*, 2006). From the point of view of information processing, the success of crisis response widely depends on gathering information from distributed sources, integrating it and making appropriate decisions. Such complexity makes it impossible for any single human or even a team to fulfill the roles adequately. Ontologies and semantic web are used to solve integrating problems, for example, ontologies are used in integrating heterogeneous information sources and semantic web services are used to provide customized queries to crisis responses. The World Wide Web Consortium and e-response project represent the visible effort in the way of building crisis response ontologies and getting the benefits of semantic web services (Disaster Management, 2019).

A multi-agent system provides the decisive solution to entire problems relating to interaction and coordination of response teams. Related multi-agent systems for crisis response involve a real-time support and simulation systems such as DrillSim, DEFACTO and WIPER. Robotics is a widely growing research area in crisis response. Multi-robot solutions had been used in a broad range of crisis response operations. In particular, robots are used in Urban Search and Rescue (USAR) operations. Urban Search and Rescue involves locating, rescuing, and medically stabilizing victims trapped in confined spaces. USAR workers have 48 hours to find trapped survivors in a collapsed structure otherwise the likelihood of finding

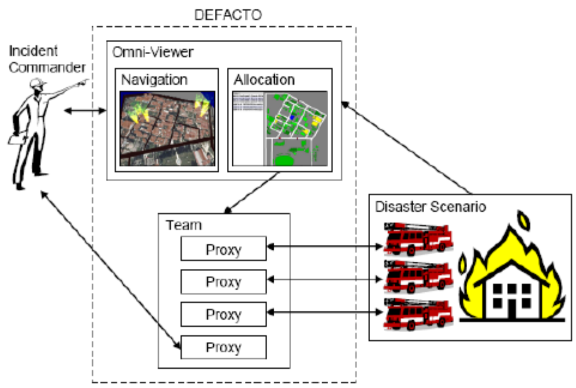
[#] Corresponding Author: Gajendra Sharma, E-mail. gajendra.sharma@ku.edu.np
Received: Jun. 20, 2019 / Revised: Jun. 30, 2019 / Accepted: Jun. 30, 2019

victims still alive is nearly zero. Greer and Jo (2002) summarized challenges that USAR team has to overcome into four areas: (1) efficient response (2) rescuers safety (3) environment disturbance and climatic conditions, and (4) inappropriate equipment and resources. Information management and processing in crisis response aimed to create digital representations for a common response operational picture. This common picture cannot be effective without overcoming the following challenges (Sharad, *et. al.*, 2004): (1) Diversity of information sources: information relevant to decision making may be dispersed from sensors where data is generated, to heterogeneous databases belonging to autonomous organizations. Besides this, critical information may span various modalities, e.g., voice conversations among crisis responders, cameras data, sensor data streams, Geographical Information Systems (GIS) oriented data and relational information in databases (2) Diversity of information users: different people/organizations have different needs and urgency levels regarding the same information. According to these challenges different types of data are used, but a common core set may be shared throughout. This common core set of information can be defined by ontology.

A multi-agent system (MAS) is a system composed of multiple interacting intelligent software agents. Multi-agent systems can be used to solve problems which are difficult for an individual agent to solve such as crisis response, and modeling social structures. In the meantime, multi-agent architecture is the essence of response systems. The original idea comes out from agent characteristics in MAS, such as autonomy, local view of environment, and capability of learning, planning, coordination and decentralized decision making. Taking into consideration the amount of information that owes on Twitter, it is challenging for emergency managers and other stakeholders to investigate each individual tweet in real-time to look for useful information. As a result, the goal is to leverage different machine learning techniques such as information classification and extraction to perform the job automatically.

Literature Review

Demonstrating Effective Flexible Agent Coordination of Teams through Omnipresence (DEFACTO) incorporates state of the art AI, 3D visualization and human-interaction reasoning into a unique high fidelity system for training responders. By providing the responders interaction with the coordinating agent team in a complex environment, the responder can gain experience and draw valuable lessons that will be applicable in the real world. The DEFACTO system achieves this via <Figure 1>.



<Figure 1> DEFACTO system

Finding tactical and actionable information in real time within a rapidly growing stack of information is challenging for many reasons. For example, performing information extraction on short bursts of text (e.g., on 140-character tweets) is considerably more difficult than performing the same task on large documents such as blog posts news articles. Furthermore, study has shown that pre-trained classifiers extensively drop in classification accuracy when used in different but similar disasters (Imran, *et. al.*, 2013). This requires learning and training new classifiers using fresh training data every time a disaster strikes.

During disasters, social media provide real-time or low-latency situational awareness information that can enable crisis responders to be more effective in their relief efforts. However, different emergency response agencies are interested in different types of messages.

Role of machine intelligence

Traditional information processing cannot be employed in this model, as disaster responders cannot wait to collect information and then curate and classify it online. Instead, responders and other stakeholders require real-time insight and intelligence as the disaster unfolds.

Role of human intelligence

When attempting to perform non-trivial tasks, machines alone are not capable of great accuracy. Human intervention is needed to verify, teach, and/or correct the machine output. Use of human intelligence is the gap for the tasks that cannot be automated, for example, providing initial training, correcting or validating the machine's output are among the types of human interventions.

Combined intelligence

Relying solely on humans to investigate each individual message is challenging due to the scale of information posted on Twitter which goes beyond the processing capacity of humans.

Nowadays a wealth of technologies is available to crisis managers and first-responders. We are living in an era where drones, sensors and robots can provide accurate information in real time about damaged buildings and landscapes, thus making rescue efforts safer and less time consuming. Augmented and virtual reality technologies are used to enhance training with more realistic environments (Sebillo, *et. al.*, 2016; Julie, *et. al.*, 2019). Serious games are used to increase awareness of roles and responsibilities all stakeholders participating in crisis management (Di Loreto, *et. al.*, 2012). Computer simulation can provide decision makers with predictive tools for evacuations that sensibly model human behaviours.

The most used sources of information for fast and agile crisis information are social media as information is rapidly disseminated, can reach a large amount of audience and covers a wide variety of topics (Mazumdar, 2016). A Machine Learning algorithm works by having a set of example to learn from that are inputted into a model. The model is created by selecting a set of variables or factors that are used to make a prediction when a new data is presented to the model. A Machine Learning algorithm has also a learner component that looks at differences between the judgment of the model and the actual outcome or truth to adjust the parameters and in turn the model (Barocas, *et. al.*, 2016).

Connection between Artificial Intelligence and Emergency Management

AI combines the data-crunching prowess of today's high-speed computers with sophisticated mathematical algorithms to quickly analyze large volumes of information for valuable insights. Used to improve everything from medical diagnoses to product marketing campaigns, AI provides emergency management (EM) professionals more detailed situational awareness, such as comprehensive block level damage assessment within few minutes after an earthquake. The proprietary algorithms that strengthen Seismic Concern consider the design and age of buildings, how they fared in previous earthquakes and even surrounding soil conditions that impact risk levels. The platform then analyzes other critical factors, such as population density, to create heat maps showing the most vulnerable areas (Artificial Intelligence, 2017).

This information helps EM professionals and others who support the emergency operations center decide how to prioritize responses and utilize scarce resources. In the hours and days after a disaster, the algorithms continuously update and improve ongoing resource deployments as field reports, social media posts and communications from the EM ecosystem stream into the platform. While seismic concern is a critical tool for when disaster strikes, it can also enhance training for future responses. By creating realistic simulations based on geophysical data for tabletop exercises and full-scale drills, seismic concern keeps teams sharp and helps them identify any gaps in their response plans. The scenarios also provide EM professionals information they can take to local businesses, hospitals and schools to assist them improve emergency strategies and increase community safety (Artificial Intelligence, 2017).

As government officials search for new resources to make their jurisdictions safer in the aftermath of a large-scale emergency, a growing number of executives are considering AI environment. They enhance public safety and EM effectiveness with advanced technology that helps EM professionals better utilize precious resources while disasters unfold. Leading platforms like seismic concern also help government to prepare for future disasters. By investigating the potential of AI, agencies can take an important step to reduce casualties mitigate physical damages and increase community's resiliency to risk.

In order to respond to disasters and crises, decision-makers have to work quickly, coordinate actions and make decisions that cover large areas affected by a multitude of different factors and aspects. During a crisis, decision makers are working in conditions of "ill-defined goals and ill-structured tasks, uncertainty, shifting and competing goals, dynamic and continually changing conditions, action-feedback loops (real-time reactions), time stress, high stakes, multiple players, organizational goals and norms" (Klein, *et. al.*, 2010). AI approaches are indisputably good candidates, as they have already proven successful in other information-intensive, knowledge-critical domains including business and engineering.

A Scenario

An EM team decides to use social media to understand the events related to the terrorist attack in Istanbul. They use a system that collects social media data legally and in line with the terms and conditions of Twitter. The Twitter data they gather will be fully identifiable. The system gathers data using hashtags such as: #Turkey #Istanbul #ISIS #IS. The system will:

- perform sentiment analysis
- perform social network analysis
- create a network visualization
- starts following users that post relevant content

The aim is to understand how sentiment about the events emerges over time amongst different networks of Twitter user and identify specific users that show extreme emotions and can be, for the content and the sentiment shared, and their social network position, be identified as threats.

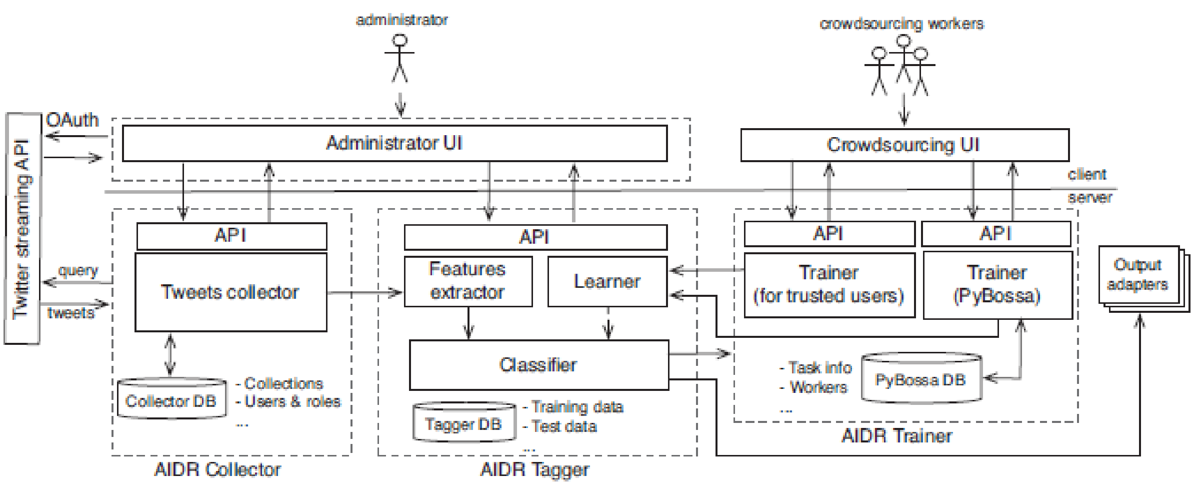
A celebrated recent AI is Google's AlphaGo Zero (Silver, *et. al.*, 2017), which, being only instructed with the rules of the game of Go, was able to learn over the span of three days how to conquer its predecessor that had earlier defeated the world champion. Go has been considered the most demanding game for AI to play because of the vast number of possible moves and the complexity of patterns involved. However, like all games of complete information, Go is an ideal use case for AI, the domain of the problem is precisely defined by explicit rules and the objectives of the opponent are identified.

System Overview

The purpose of Artificial Intelligence for Disaster Response (AIDR) is to filter and categorize messages posted to social media during humanitarian crises in real time. AIDR collects crisis-related messages from Twitter, asks a crowd to label a sub-set of those messages, and trains an automatic classifier based on the labels. It also improves the classifier as more labels become available. AIDR users begin by creating a collection process by entering a set of keywords or a geographical region that will be used to filter the Twitter stream. The user can monitor the collection status using dashboard. A crowd of annotators provide training examples: a system-selected message and a human-assigned label, which are used to train classifiers for incoming items. As a final point, an output of messages sorted into categories is generated, which can be collected and used to create crisis maps and other types of reports.

Architecture and Implementation

The general architecture of AIDR is shown in <Figure 2>. AIDR is a free software environment that can be run as an online application. It comprises three core components; collector, tagger, and trainer. The collector performs edge adaptation (Turaga, *et. al.*, 2010) and is responsible for data collection. For example, in current setup it collects messages from Twitter using the Twitter streaming application programming interface (API). The collected tweets are then passed to the tagger for further processing. The tagger is responsible for the classification of each individual tweet. The tagger is comprised of three modules: feature extractor, learner, and classifier. The output of AIDR can be accessed through output adapters, which are exposed as an API. To illustrate real-time classified items on a map or any other visualization widget, one can use AIDR's live stream output adapter. In addition, to fulfill



<Figure 2> AIDR architecture showing Collector, Trainer, and Tagger various visualization demands, AIDR includes APIs to retrieve the items.

AIDR includes a client-side and three server-side applications. The client-side application has been developed using the Sencha ExtJS framework, and the server-side implementation is developed using Java and the Springs 3.0 framework for the main application. We use PyBossa for the crowd sourcing processing purposes, and REDIS for communication. AIDR is an open-source platform, and its source code is available at this repository.

Recommendations from this study

Following recommendations can be made from this study:

1. A more human centered approach is needed if crisis-warning applications are to be used effectively and with a good response from the population
2. AI has an important role to play in crisis technologies
3. Human behaviour and in particular social cohesion plays a critical role in managing crisis situations
4. Evacuation should not only be studied in currently operational buildings, but software is for architects in the design phase.
5. AI should make increasing inroads into risk management, heading towards the establishment of an integrated AI risk management with knowledge of risk, positions, counterparties, the humans making risk decisions and all aspects of day-to-day risk.

AI for policy makers

㉮ AI could be instructed to scan for vulnerabilities meeting generic criteria

㉯ It could scan the literature for new research, advising senior policy makers of promising new ideas

㉰ It might be able to replace some applied research.AI could even take over much of the model writing function, guided by high-level theories

㉱ It could provide recommendations to the policy authority, based on its theoretical understanding of the system and provide conditional forecasts of its own behaviour.

In order to do many of these things it will have to justify and explain its reasoning, which remains a significant challenge.

Conclusion

AI offers powerful tools for the development of crisis response and management systems. The technologies of robotics, ontology and semantic web, and multi-agent systems can be useful to solve the problems of crisis response. Social media like Twitter receive an overwhelming amount of situational awareness information. For emergency response, real-time disaster insights are important. The success of any AI is directly tied to the proprietary data management and analytical capabilities engineered into the underlying algorithms. But effectiveness also hinges on other key technology components for enhancing EM team success.

Acknowledgments

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2017S1A5B8059946).

References

Artificial Intelligence: A Game Changer for Emergency Response. The Power of Artificial Intelligence When it Matters the Most, Available online at: www.oneconcern.com/aboutus. Accessed on March, 20. 2019.

Barocas, S. and A. D. Selbst. 2016. Big Data's Disparate Impact. *California Law Review*. 104: 671-732.

Daniel, Massaguer, Vidhya Balasubramanian, Sharad Mehrotra, and Nalini Venkatasubramanian. 2006. Multi-Agent Simulation of Disaster Response. *AAMAS'06* May 8-12 2006, Japan.

David, Greer, M. C. Kerrow Phillip, and Jo Abrantes. 2002. Robots in Urban Search and Rescue Operations. *Proceedings of 2002 ACRA, Aukland(November).* 25-30.

Di Loreto, I., S. Mora, and M. Divitini. 2012. Collaborative Serious Games for Crisis Management: An Overview. In *Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE), 2012 IEEE 21st. International Workshop.* IEEE. 352-357.

Disaster Management. http://esw.w3.org/topic/DisasterManagement. Accessed on March, 20. 2019.

Imran, M., S. M. Elbassuoni, C. Castillo, F. Diaz, and P. Meier. 2013. Extracting Information Nuggets from Disaster-Related Messages in Social Media. *Proceeding of ISCRAM, Baden-Baden, Germany.*

Julie, D., N. Elsa, and T. Murray. 2019. ICT and Artificial Intelligence for Crisis and Emergency Management. *Proceedings of the 52nd Hawaii International Conference on System Sciences*. 626-628.

Klein, G., R. Calderwood, and A. Clinton-Cirocco. 2010. Rapid Decision Making on the Fire Ground: The Original Study Plus a Postscript. *Journal of Cognitive Engineering and Decision Making*. 4(3): 186-209.

Mazumdar, S., V. Lanfranchi, N. Ireson, S. Wrigley, C. Bagnasco, U. Wehn, R. McDonagh, M. Ferri, S. McCarthy, H. Huwald, and F. Ciravegna. 2016. Citizens Observatories for Effective Earth Observations: The WeSenseIt Approach. *Environmental Scientist*. 25(2): 56-61.

Sebillo, M., G. Vitiello, L. Paolino, and A. Ginige. 2016. Training Emergency Responders through Augmented Reality Mobile Interfaces. *Multimedia Tools and Applications*. *75*(16): 9609-9622.

Sharad, Mehrotra, C. Butts, Dmitri V. Kalashnikov, Nalini Venkatasubramanian, Ramesh Rao, *et. al*. 2004. Project Rescue: Challenges in Responding to the Unexpected. *SPIE*. 5304: 179-192.

Silver, D., J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai, A. Bolton, Y. Chen, T. Lillicrap, F. Hui, L. Sifre, G. van den Driessche, T. Graepel, and D. Hassabis. 2017. Mastering the Game of Go without Human Knowledge. *Nature*. 550: 354-359. www.nature.com/nature/journal/v550/n7676/full/nature24270.html.

Turaga, D., H. Andrade, B. Gedik, C. Venkatramani, O. Verscheure, J. D. Harris, J. Cox, W. Szewczyk, and P. Jones. 2010. Design Principles for Developing Stream Processing Applications. *Software: Practice and Experience*. 40(12): 1073-1104.

Gajendra Sharma(gajendra.sharma@ku.edu.np)

He received Ph.D. in information systems engineering from Harbin Institute of Technology, China. He did his postdoctorate from Dalian University of Technology, China. He is Professor of the Department of Computer Science and Engineering at Kathmandu University, Nepal. He worked as Associate Professor at Liaoning University of Technology, China from 2011-014. His interesting areas of research are crisis & emergency management, information systems and technology, and policy implementation.

Jae Eun Lee(jeunlee@chungbuk.ac.kr)

He received his B.A., M.A., Ph.D. from Yonsei University, Korea in 2000. He is Professor of the Department of Public Administration and Director of National Crisisonomy Institute at Chungbuk National University, in which he has taught since 2000. His interesting areas of research and education are crisisonomy, disastronomy, emergency management, organizational studies, and policy implementation.