Introducing an AI-based Response Framework for Mass Casualty Management

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Abstract

Advances made in Artificial Intelligence over the last couple of years have revealed certain limitations to traditional Mass Casualty Management (MCM).

This paper introduces a MCM response framework using state-of-the-art OR-based models of existing AI solutions aimed to optimize each stage (extrication, triage, and transportation) of the response phase during a Mass Casualty Incident (MCI).

Keywords: Mass Causality Management, AI-based solutions, extrication, triage, and transportation.

1. Introduction

An MCI refers to a multiple-casualty situation in which Emergency Medical Services (EMS) resources, such as personnel and equipment, are overloaded. This occurs when the number of casualties is often much higher than the available resources in a particular area [1]. MCI events often result from transportation accidents, terrorism, fires, or natural disasters.

MCM is a widely used model for managing victims in MCIs. It often employs a multi-sectional approach for managing the strong connection between triage, field stabilization, and evacuation [2]. There are two key components to this approach: (1) a command post that coordinates the incorporated links between the field and health care facilities, (2) levels of special knowledge attributed to responders (e.g., policeman, firefighter, search and rescue, pre-hospital team).

2. Key Components in MCM

An optimal MCM should consider the four phases of the disaster cycle: mitigation, planning, response, and recovery [1].

In the first phase, some of the devastating effects of disasters can be reduced by acting before the actual event happens. In the second phase, realistic disaster planning and practicing are finally revised. The response consists of a series of necessary procedures from notification of an MCI, searching, rescuing, and sending casualties to hospitals. Finally, the recovery phase rebuilds and reconstructs the infrastructure while taking some actions to reduce future disasters.

This paper focuses on the response phase, more specifically on extrication, triage, and transportation. It is a sequential process from collecting and classifying victims to sending them to appropriate hospitals. Extrication is the process that prioritizes patients based on the severity of their conditions for further actions, such as immediate movement or treatment. Triage aims to provide the most efficient aid to as many casualties as possible and prioritizes treatment and transportation of victims. This requires a dynamic balance between needs (types and number of injuries) and resources (infrastructure, equipment, and competent personnel ability).

During this stage, patients are triaged and transported based on different variables, such as the number of victims, the type of incident, the available resources, and the existing infrastructure capability. Thus, triaging errors may lead to worse outcomes in later processes and an increasing number of fatalities.

The patients are typically tagged as red (critical cases - major life-threatening injuries), yellow (urgent cases, non-threatening injuries), green (non-urgent cases), and black (unlikely survival).

3. AI-based Decision Support Systems for MCM

Recently, AI is applied to build decision-support tools used in the various phases of MCM models [4-7]. The AI-based decision support tools aim to assist in resource management for disaster response with a broad range of objectives and decision variables.

One usage is, e.g., in the search and rescue phase, where Mishra et al. [8] proposed a state-of-the-art detection method based on computer vision and developed a large dataset for searching and rescuing in natural disasters using drone surveillance; Perry et al. [9] introduced a triage method based on computer vision to provide real-time casualties information at the disaster scene for the MCI commander and the EMS dispatch.

Moreover, effective decisions regarding the evacuation of mass casualty patients to hospitals should involve the assessment of the facility capacity, such as the availability of beds and the ability to deal with the patient overload. Information regarding real-time hospital bed capacity is key to controlling the flow of patients from an MCI. In this case, it allows for evidence-based decision making regarding the evacuation of patients.

Various decision support models are proposed for resource management in disaster response [3]. Several factors should be considered for integration into the triage process, such as available resources and the scale of the disaster.

There are three categories of AI-based solutions for MCM models [3]: traditional optimization-based decision support, AI-based optimization, AI-based transportation congestion detection. However, these solutions are often proposed to address issues of different components in the MCM response framework. There is no MCM response framework supported by AI-based solutions for almost all its components, including the MCI area, triage stage, and transportation stage, to the best of the authors' knowledge. Therefore, this paper introduces an MCM response framework with extended support from recent AI-based solutions.

4. Proposed Response Framework for MCM

The recent developments of AI-based support tools for MCM can be employed in one MCM model. The proposed framework aims to inherit the advantages of different AI-based solutions that have been proposed for MCM separately. The overview of the proposed framework is described in Figure 1. In the following, the AI-based solutions for the components of the response framework are discussed.

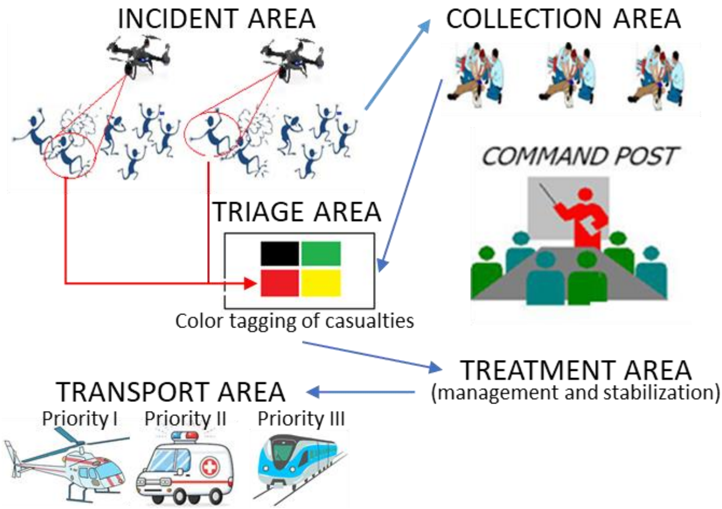

Figure 1. Response framework for an optimal MCM

(1) Search and rescue at the incident site: the task can be performed by applying the detection method introduced by Mishra et al. [8] or the triage method of Perry et al. [9]. In these methods, the AI-based detection models can analyze the video captured by drone surveillances to search for casualties. However, the AI-based triage method et al. [9] can be further used in the triage area.

(2) Search and rescue in natural disasters (i.e., floods): in this scenario, the victims are distributed in a large region. The search and rescue teams collect the casualties based on their requests. An optimization-based model proposed by Yan et al. [6] can be applied. In this model, the Support Vector Machine (SVM) and Reinforcement Learning (RL) work together to estimate the density of the regions of victim requests. Every time a victim is aided, the RL algorithm updates the density of patient requests.

(3) Triage process: the category information of each victim produced by the AI-based triage method of Perry et al. [9] for search and rescue automatically tags them into appropriate triage areas. Casualties with life-threatening injuries could ignore the collection area and be sent directly to triage for the quick delivery to hospitals. Here, expert knowledge is needed for final confirmation.

(4) Transportation: many AI-based models are proposed for real-time traffic congestion detection, as reviewed in [3]. These models typically use deep learning methods, such as Convolutional Neural Networks (CNNs), to identify vehicles and estimate their density on a given road segment. Among the reviewed models, the one proposed by Du et al. [10] is very promising. Besides traffic information, the model incorporates several factors, such as weather conditions, flying attitude of drones or unmanned aerial vehicles (UAVs), and vehicle category, to improve the detection accuracy.

5. Conclusion

AI is employed to address many phases in MCM, predominantly components in the MCM response phase. AI-based solutions, however, are often applied to address problems separately in MCM models. This paper introduces an MCM response framework in which most of its components are supported by robust AI-based models proposed in recent years.

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