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Multi-Agent System for Optimizing Victim Tagging in Human/Autonomous Responder Teams

Maria A. Cardei
University of Virginia
cbr8ru@virginia.edu

Afsaneh Doryab
University of Virginia
ad4ks@virginia.edu

I. Introduction

A mass casualty incident (MCI) is a situation in which casualties greatly outnumber available local resources, eventually overwhelming the local healthcare system within a short time frame [1]. When responders arrive at the scene of an MCI, one of their first tasks is to locate individuals and assess their injuries promptly, known as triage. After triaging victims, responders physically tag them with a color-coded label indicating their injury severity before identifying other victims. Fast and efficient victim tagging serves as a critical initial step in the MCI process, providing vital information that guides subsequent decisions. It enables the timely assessment of the total number of victims, their distribution based on the severity of injuries, and their respective locations throughout the MCI environment.

Most of the current work done to improve the emergency response to MCIs has a focus on improving resource allocation [2], responder coordination [3], [4], or transportation to treatment facilities [5] with human-only responders. There is a lack of research done in the on-scene or pre-hospitalization stage of an MCI response, specifically the task of tagging victims fast. This step is frequently assumed and overlooked in existing work. Our work aims to address this gap by designing and testing a novel multi-agent system (MAS) that models the victim tagging stage during an MCI. This system applies equally well to human or hybrid teams that include autonomous systems. We create and test five responder-team policies and compare them to determine the optimal strategy for a team of medical responders to tag victims quickly in an MCI. Our preliminary experiments simulate the scenario with 20 medical responders and 100 victims.

II. Method

We design a MAS where we model responders (human or robotic) and victims as two types of agents. We model agent behavior using finite-state machines. We consider discrete-time t, which starts from $t = 0$ and advances one unit until all victims are tagged by responders. At a time t, a victim v has the following attributes: (1) $v.x$ and $v.y$ coordinates in the 2D area A, (2) $v.healthState$ the state behavior [0,1], (3) $v.policy$ victim policy, (4) $v.isTagged$ whether v is tagged or not, i.e. 0 if v is not tagged and 1 otherwise, and (5) $v.tagger$ the responder who will tag them. For this study we assume that a victim's policy is idle and does not change over time ($v.policy$ = $idle$). Health status ($v.healthState$) can be defined using varying criteria, and our mechanism works independently of the criterion used. At a certain time t, a responder r has the following attributes: (1) $r.x$ and $r.y$ coordinates in the 2D area A, (2) $r.state$ the state behavior, (3) $r.policy$ responder policy, (4) $r.nextVictim$ next victim to be tagged, and (5) $r.triageTime$ is the time spent in the 'triage' state. The possible states of a responder are $r.state \in \{idle, move, triage\}$. A responder r_i starts in the $idle$ state, then transitions to the $move$ state as r_i moves towards $r_i.nextVictim$. When r_i reaches $r_i.nextVictim$, they transition to the $triage$ state and remains for $r_i.triageTime$ steps. Then r_i transitions to the $move$ state if another victim needs tagging, or the $idle$ state if all victims are tagged.

Responders select the next victim to be tagged until all are tagged. Their victim selection is based on the responder-team policy. In **Random Victim (Policy 0)**, responders select a random victim that has not been tagged yet and is not currently chosen by a responder. In **Nearest Victim (Policy 1)**, responders choose an untagged victim that is nearest to them and is not chosen by a responder. In **Nearest Victim with Rescheduling (Policy 2)**, responders do the same, with the option to choose a victim that has been chosen by a different responder. If this responder is closer to the victim, they choose the victim, and the other responder will be rescheduled. In **Critical Victim (Policy 3)**, responders choose to tag the nearest victim to them who is also critically injured. Once all critically injured victims have been tagged, then responders follow Policy 2. Critically injured is defined as having a $healthState < 0.5$. In **Grid Assignment (Policy 4)**, the area is evenly split up into sections based on the number of responders. Each responder tags victims nearest to them within their specific assignment until all victims in their respective sections are tagged.

III. Experimental Evaluation

Our MAS is implemented in an agent-based modeling framework where we run simulations to test and compare the responder-team policies. Figure 1(a) illustrates the simulation architecture. We use the Mesa open-source agent framework [7] for the MAS design. The model has continuous space, runs in discrete time steps, and utilizes a scheduler that activates agents randomly at each time step. Our preliminary experiments involve 20 responders and 100 victims in a rectangle-

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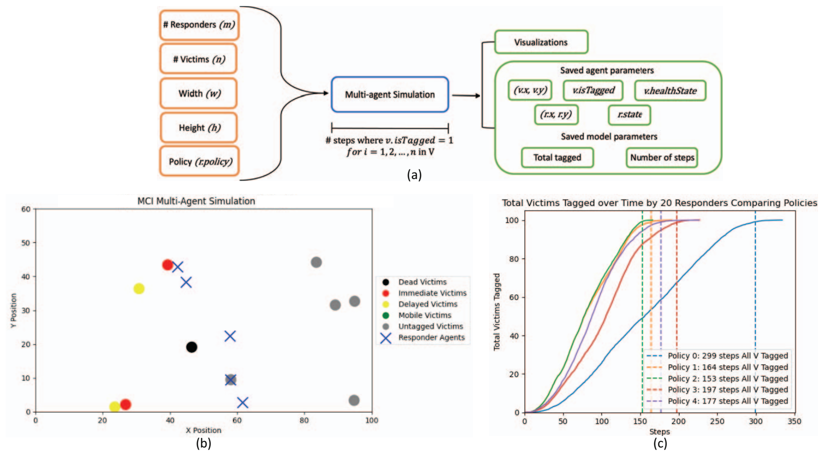

Fig. 1. (a) Architecture of the multi-agent simulation. (b) Simulation in progress for an MCI example. Responder agents enter the environment from $(r.x, r.y)$ = (0,0). $v.healthState$ values correspond to the START triage algorithm [6] where triage tag categories are black, red, yellow, or green. (c) Simulation results comparing policies for the amount of time steps it takes to tag 100 victims by 20 responders. Average results are reported along with averaged curves across 50 iterations.

shaped environment. Fifty iterations of each experiment are performed to gather average results.

The policies are evaluated by analyzing the number of time steps it takes for the responders to tag all victims. Figure 1(b) shows an example simulation, and 1(c) illustrates the results. Figure 1(c) demonstrates that Random Victim (Policy 0) is the least efficient, taking an average of 299 time steps to tag all victims, while Nearest Victim with Rescheduling (Policy 2) performs best with an average of 153 time steps to tag all victims. Visually it appears that Nearest Victim, Nearest Victim with Rescheduling, and Grid Assignment Policies (1, 2, and 4) have steeper curves, which indicates that these policies are more effective in tagging victims quicker. Additionally, the Policies 1 and 2 curves overlap from $t = 0$ until $t = 75$, where 50 victims have been tagged. This indicates that, for any number of victims up to 50, 20 responders tag a similar number of victims each time step. Other sections of the curves also overlap, such as Policies 1 and 4, at $t = 112$. This suggests that some policies could be similarly effective at specific time steps when there is a particular combination of victims and responders. The efficiency of several policies are relatively similar, which prompts the need for further analysis, as well as individual policy analysis. Additionally, it would be interesting to see whether these results stay consistent across varying numbers of responders and victims, as MCIs can involve a wide range of victim casualties.

IV. Conclusion

We developed an MAS of the victim-tagging process during an MCI response and tested five responder-team policies in a simulated environment with 100 victims and 20 responders to determine which policy results in responders tagging victims the fastest. The results indicate that Nearest Victim with Rescheduling (Policy 2) outperforms the rest, highlighting the importance of responder-team collaboration to employ rescheduling when necessary. Further experimentation should be done to explore each policy in depth and determine if the results hold consistent across all potential MCI scenarios. This would provide valuable insight for responder-teams to make quick and accurate corresponding decisions during an MCI.

V. Poster Description

The poster will contain a brief introduction and background information, and explain the proposed method and novel contributions. It will also illustrate the results and dive into analyses, conclusions, and future work. Figure 1 indicates poster contents well.

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References

[1] Renee L DeNolf and Chadi I. Kahwaji. Ems mass casualty management. *National Library of Medicine*, 2022.

[2] Glenn I. Hawe, Graham Coates, Duncan T. Wilson, and Roger S. Crouch. Agent-based simulation of emergency response to plan the allocation of resources for a hypothetical two-site major incident. In *Innovative Artificial Intelligence Solutions for Crisis Management*, volume 46, pages 336–345, 2015.

[3] Rafael A. Gonzalez. *A Framework For ICT-Supported Coordination in Crisis Response*. PhD thesis, Delft University of Technology, Delft, Netherlands, 2010.

[4] Rafael A. Gonzalez. Analysis and design of a multi-agent system for simulating a crisis response organization. In *Enterprises & Organizational Modeling and Simulation*, number 6, pages 1–15, 2009.

[5] Yu Wang, Louis K. Luangkesorn, and Larry Shuman. Modeling emergency medical response to a mass casualty incident using agent-based simulation. *Socio-Economic Planning Sciences*, 46(4):281–290, 2012.

[6] Los Angeles Fire Department. Start - simple triage and rapid treatment, 2005. Accessed: 2024-02-05.

[7] Jackie Kazil, David Masad, and Andrew Crooks. Utilizing python for agent-based modeling: The mesa framework. In Robert Thomson, Halil Bisgin, Christopher Dancy, Ayaz Hyder, and Muhammad Hussain, editors, *Social, Cultural, and Behavioral Modeling*, pages 308–317, Cham, 2020. Springer International Publishing.