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HUMAN-IN-THE-LOOP AGENT-BASED SIMULATION FOR IMPROVED AUTONOMOUS SURVEILLANCE USING UNMANNED VEHICLES

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ABSTRACT

The goal of this work is to propose a hardware-in-the-loop, human-in-the-loop agent-based simulation which incorporates the human crowd characteristics and behaviors captured by computer vision techniques, for an effective crowd control using unmanned vehicles (UVs). Three major functions needed in our autonomous surveillance system include: 1) detection, 2) modeling, and 3) tracking. The proposed simulation communicates with the crowd detection module in the UVs' onboard computer in real-time, developing plans for a number of simulated crowd-individuals based on the parameters extracted from real crowds. Next, the social-force-based crowd modeling is used in the simulation to interpolate waypoints for moving the simulated individuals to their planned destinations. Finally, these waypoints are sent to the tracking module for a more realistic prediction of crowd's future location for the UVs' path planning purposes. Preliminary results reveal significant improvements in performance measures for this human-in-the-loop simulation, which demonstrate the effectiveness of the proposed methodology.

1 INTRODUCTION

Crowd surveillance via cooperative unmanned vehicles (UVs) requires integration of a variety of hardware, software, and human components for performing autonomous missions. Implementation and testing of such system is a challenging and costly process as the scale of the system increases. Modeling and simulation of the real system is an alternative, which can highly reduce the mentioned challenges for the planning and decision making purposes. Detection of the real crowd using computer vision techniques and incorporating these information into the simulation can enhance the modeling and tracking performance at an acceptable added cost, while the computer vision algorithm could be validated or trained by the use of simulation. In this work we treat each moving crowd detected by the unmanned aerial vehicle (UAV) as a single target. we aim at improving the crowd tracking performance in a realistic manner through proposing a new human-in-the-loop simulation model based on data of real crowd movements, extracted in real-time from UAV at a low fidelity. Compared to our previous work (Khaleghi et al. 2014), where we presented a hardware-in-the-loop simulation with real UVs for the simulated crowds, in this work the real crowds act as passive components, whose behaviors are processed by UVs and then used as simulation modeling inputs in real-time. Our initial motivation stems from a significant drop observed in the system performance (i.e. crowd coverage rate), due to splitting event of a crowd in our previous work.

2 PROPOSED HUMAN-IN-THE-LOOP SIMULATION

After the UAV's detection algorithm presented in (Minaeian, Liu, and Son 2015) detects the first set of crowds with respect to time, it will send a message to the simulation module, containing every detected crowd's location and its geometric size (boundaries). This first message is used to activate the simulation module and initialize the location of a prefixed number of simulated individuals. The initial location of individual agent i $\left(x_i(t_0), y_i(t_0)\right)$ would then be a random position in the reported boundaries. The data are fed into the simulation every $\Delta t^{(\mathrm{D})}$, updating the simulated individuals' waypoints. In order to capture the crowd's movement trajectory as well as its dynamic (size, shape and velocity) in the simulation generation, we affine-transform the current crowd's boundary coordinates (at time t) to its next boundary coordinates (at time $t+\Delta t^{(\mathrm{D})}$) as reported by the detection algorithm. This way, we will take care of translation and scaling in the crowd's boundary and extrapolate the whole crowd's behavior for each single simulated individual. The individual agent i's next destination at time $t+\Delta t^{(\mathrm{D})}$ is then:

$$x_i\left(t+\Delta t^{(\mathrm{D})}\right) = x^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right) + \left(x_i(t) - x^{(\mathrm{LB})}(t)\right) * Xratio\left(t+\Delta t^{(\mathrm{D})}\right)$$

$$y_i\left(t+\Delta t^{(\mathrm{D})}\right) = y^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right) + \left(y_i(t) - y^{(\mathrm{LB})}(t)\right) * Yratio\left(t+\Delta t^{(\mathrm{D})}\right)$$

where $x^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right)$ and $y^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right)$ are the updated coordinates of the crowd's lower bound, and:

$$Xratio\left(t+\Delta t^{(\mathrm{D})}\right) = \frac{\left(x^{(\mathrm{UB})}\left(t+\Delta t^{(\mathrm{D})}\right) - x^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right)\right)}{\left(x^{(\mathrm{UB})}(t) - x^{(\mathrm{LB})}(t)\right)}; \quad Yratio\left(t+\Delta t^{(\mathrm{D})}\right) = \frac{\left(y^{(\mathrm{UB})}\left(t+\Delta t^{(\mathrm{D})}\right) - y^{(\mathrm{LB})}\left(t+\Delta t^{(\mathrm{D})}\right)\right)}{\left(y^{(\mathrm{UB})}(t) - y^{(\mathrm{LB})}(t)\right)}$$

These locations are then used as intermediate destinations of the simulated individuals. However, we still need to use some crowd modeling approach to guarantee collision-free trajectories. In the social force modeling module, the waypoints of each agent are calculated using the direction towards the intermediate destination (α_0) and a predefined comfortable walking speed (v_0). Moreover, to take into account the interactions among crowd's individuals, the direction and speed of each agent in the crowd is updated based on the two heuristics described in Moussaïd, Helbing, and Theraulaz (2011). Next, the Euclidian distance ($dist$) between the current location and intermediate destination of each simulated agent is computed, which is then used to calculate its comfortable walking speed as $v_0 = dist / \Delta t^{(\mathrm{D})}$. Finally, the tracking module proposed in our previous work (Khaleghi et al. 2014) predicts next-time location of the crowd.

3 EXPERIMENTS AND DISCUSSION

Figure 1 illustrates the comparison of the systems performance based on detection versus the human-in-the-loop simulation for a detected crowd. As expected, tracking based on the proposed simulation-based tracking outperforms the detection-based tracking (12% better on average) and its variation is significantly lower (90% less variant). These results along with many other tested scenarios (e.g. crowd splitting or joining), reveal the effectiveness of our proposed approach for an improved autonomous surveillance.

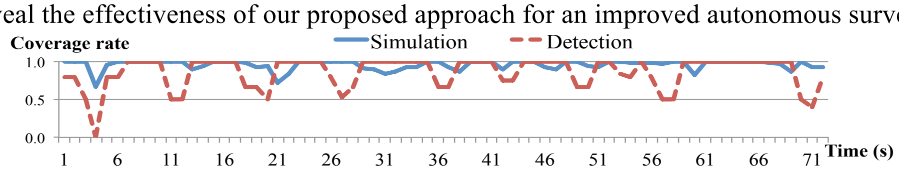

Figure 1: The comparison of coverage rate for one crowd considering the two methods

REFERENCES

Khaleghi, A. M., D. Xu, S. Minaeian, M. Li, Y. Yuan, J. Liu, Y.-J. Son, C. Vo, and J.-M. Lien. 2014. "A DDDAMS-based UAV and UGV Team Formation Approach for Surveillance and Crowd Control." In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 2907-2918. Piscataway, New Jersey: IEEE, Inc.

Minaeian, S., J. Liu, and Y.-J. Son. 2015. "Crowd Detection and Localization Using a Team of Cooperative UAV/UGVs." in *Proceedings of the 2015 Industrial and Systems Engineering Research Conference*, edited by S. Cetinkaya and J. K. Ryan.

Moussaïd, M., D. Helbing, and G. Theraulaz. 2011. "How Simple Rules Determine Pedestrian Behavior and Crowd Disasters." In *Proceedings of the National Academy of Sciences* 108(17):6884-6888.