Swarm Intelligence in Evacuation Problems: a Review

Guido Guizzi[1], Francesco Gargiulo[1], Liberatina Carmela Santillo[1], and Hamido Fujita[2]

[1]University of Naples Federico II, Dipartimento di Ingegneria Chimica, dei Materiali e della Produzione Industriale
P.le Tecchio 80, 80125 Naples, Italy
[2]Intelligent Software Systems Laboratory, Iwate Prefectural University, 020-0193 Iwate, Japan
{g.guizzi,f.gargiulo,santillo}@unina.it,issam@soft.iwate-pu.ac.jp

Abstract. In this paper authors introduce swarm intelligence's algorithms (ACO and PSO) to determine the optimum path during an evacuation process. Different PSO algorithms are compared when applied to an evacuation process and results reveal important aspects, as following detailed.

Keywords: Evacuation, FSE, Swarm intelligence, ACO, PSO

1 Introduction

The management of the crowd plays a key role, in order to ensure that most people can reach a safe area. [1]. In literature we find several models to analyze the evacuation process characterized by the parameters and each has unique and specific features. The study of evacuation process is based on simulation models in which are considered the building characteristics, the fire characteristics and behavioral models (also called evacuation models), in which a key role is played by occupant characteristics and their interaction with fire[2]. The implementation of swarm-based systems, inspired behavior of social living beings, began from the early nineties[3]. From the early twenty-first century the study was aimed to understand how to assimilate human behavior during an emergency to animal behavior. This idea led to develop different methods to study the problem such as ACO (Ant Colony Optimization) and PSO (Particle Swarm Optimization). The aim of this work is to identify the most promising lines of research into the phenomenon and implement appropriate preventive action to safeguard human lives.

2 Evacuation

Natural and man-made emergency events can pose a serious threat to humans. Evacuation is a complex problem because of several aspects mainly due to subjective human behaviors, such as different perception of danger, panic in emergency situations, etc [4]. In literature are available different algorithms and different solutions to optimization [5, 6]. In case of fire, for example, the literature presents some studies concerning the influences of the variables related to human response to evacuations [7]. The results of this studies show that the occupant behavior varies according to three major elements: the occupant, the building and the fire characteristics [8]. The bond between evacuation and human behavior is much studied in literature. However, regardless of the model used, the most crucial aspect of a building's safety in facing fire is the possibility a safe escape. A fundamental role in the evacuation process is played by the wayfinding which is, in most cases, a purposive and motivated activity [9–11]. About the consideration above during the evacuation process the occupiers choice is not always the best one because they are not aware of all the possible alternatives to reach the exit [12]. Therefore it's worth analyzing some optimization algorithms, in particular it will shown how the swarm intelligence could be applied to evacuation process.

3 Swarm Intelligence in evacuation field

Swarm intelligence takes inspiration from the social behaviors of insects and other animals [13].The first studies regarding swarm intelligence date back to early nineties: it's a relatively new approach to problem solving. The most relevant algorithms based on swarm intelligence concept are ACO algorithm (Ant Colony Optimization) and PSO algorithm (Particle Swarm Optimization) [14, 15]. ACO algorithm takes inspiration from the behavior of ant when searching food. More specifically on ants' ability to find always the shortest path between their nest and food sources [16, 17]. PSO is a population-based stochastic approach and it uses swarm intelligence to solve continuous and discrete problems [18]. The PSO is inspired by the natural behavior of fish schools and birds flocks [19]. Their original idea was to simulate the social behavior of a bird flock trying to reach an unknown destination [4, 20]. Due to their flexibility, PSO algorithms were developed as interesting candidates to address complex problems such as the optimization of multi modal functions in various areas of interest. It's fundamental to observe that the modeling of evacuation becomes more complicated when considering some aspects of human behavior, such as the queuing behavior, self-organization, crowd psychology and sub-group phenomena [21]. The understanding of occupants' responses during an evacuation is crucial because our first goal is to determine the optimum evacuation route toward safe areas [19]. The algorithm of standard PSO is described by the following equations:

$$v_i(t+1) = v_i(t) + c_1 r_1(t)(p_i(t) - x_i(t)) + c_2 r_2(t)(p_g(t) - x_i(t)) \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

where $\mathrm{x_i}$ is the $\mathrm{i_{th}}$ particle location in search space, $\mathrm{p_i}$ is the best position achieved so far by the $\mathrm{i_{th}}$ particle, that is the one with the best fitness value, the location $\mathrm{p_g}$ is the best $\mathrm{p_{best}}$ among all the particles, also called $\mathrm{g_{best}}$, $\mathrm{v_i}$ is the velocity for the $\mathrm{i_{th}}$ particle. The basic concept of PSO consists of changing the velocity and the location of each particles towards its $\mathrm{p_{best}}$ (cognition part) and $\mathrm{g_{best}}$ (social part) location. Starting from standard PSO Cheng & al. [22] modified the algorithm introducing an inertia factor ω to prevent particles' premature convergence (the new model is called "Linear Weight Decreasing Particle Swarm Optimization (LWDPSO)"). Inertia weight ω was implemented as:

$$\omega(t) = 0.9 - \frac{t}{MaxNumber} * 0.5 \tag{3}$$

where $\omega\,[0.4, 0.9]$ and MaxNumber is the maximum number of iterations. Once that a particle found the exit, its location is supposed to be $\mathrm{g_{best}}$ for each exit found, this mean that the other particles should compare all the $\mathrm{g_{best}}$ and they should choose the nearest $\mathrm{g_{best}}$ as moving target. So LWDPSO have the equation $p_g(t) = Min(distance(p_i, p_g^j))$ where p_g^j is the j^{th} location of exit.

The comparison between LWDPSO model and other models - e.g. "social force"model and CA (Cellular Automata) model - shows that LWDPSO provides better results. Results show that behaviors like avoid impact, queuing and congestion are well performed. LWDPSO model has good efficiency and practicability. Fang & al. [19] suggested, paying attention to jamming and clogging phenomena, a new formula to evaluate the velocity adopted to move to a subsequent location.

$$v_i(t+1) = \omega_i^t \otimes v_i(t) + c_g^t \otimes (x_g^t - x_i^t) + c_p^t \otimes (x_i^p - x_i^t) \tag{4}$$

where ω_i^t is the motion inertia factor, c_g^t and c_p^t are gain factor whose elements are confined within limits [0,1] and they are sampled from some probability distributions. x_g^t is the best performing particle and is determined by a problem dependent fitness function such that $g = argmin_i f(x_{i=1,..N}^t)$ for a minimization problem. x_i^p is the best performing instances of individual particles and is given by $p = argmin_\tau f(x_i^{\tau=1,...t})$. Therefore the future location of a particle or its behavior is influenced by its motion inertia, the interaction among swarm and its own past experience. Using the PSO algorithm can be obtained deep observations about evacuation phenomena e.g. embedding the leader following behavior in a crowd of occupants, efficient evacuation results with a linear relationship between the number of individuals and the time for all occupants to leave the room. In 2009 Iziquierdo & al. [23] studied PSO to achieve an optimization by the introduction of a fitness function defined as "the sum of the distances between each occupant and the set of exits". The minimization of such a function is achieved by minimizing each distance of individuals to the set of exit. They proposed some conditions, such as considering continuos movement, taking into account both individual behavior and social interaction, and so on. The evolution of the particles is defined in the following way:

$$newX_i = currentX_i + newV_i \tag{5}$$

$$newV_i = \omega * currentV_i + c_1 * rand() * (P_i - currentX_i) + c_2 * rand() * (P_a - currentX_i) \tag{6}$$

where: $\omega * currentV_i$ represent particle current trajectory and the formula for inertia is:

$$\omega = 0.5 + \frac{1}{2 * (logk + 1)} \begin{cases} k \text{ is the iteration number} \\ \omega \text{ decrease asymptotically from 1 (k=1) to 0.5(k=}\infty\text{);} \end{cases}$$

$rand()$ is a function generating uniform pseudo-random numbers between 0 and 1; c_1 and c_2 are the acceleration constants (respectively 3 and 2) and they represent the weight of stochastic acceleration terms that pull each particle simultaneously toward its best-ever reached or desired position and the best global position; P_i associated with the perceived best position for individual i, is calculated taking into account some aspects as "familiarity of the individuals with venue" and "queuing behavior"; P_g directly points to the closest exit for i_{th} individual. It's important to note that: $newV_i$ has an upper bound (maximum velocity) used to prevent excessive roaming and to adapt people movement to reasonable value and if $newX_i$ is occupied by another particle, the direction velocity is changed by a small angle and a new updating attempt is made. If the situation still persists the particle is bounded to a limited movement or even stays at its current position during current iteration. The optimization is obtained through the following, non linear, function (fitness function which measures the distance between a particle to the exit):

$$F(X) = d(X, E) = min(d(X, e), e \in E) \tag{7}$$

Iziquierdo & al. [23] studied also the influence of the door size and door allocation on the evacuation process and, in order to reduce the evacuation time, they studied how to optimize the allocation of people and areas to the different available exits. The PSO-based model presented allows the assessment of behavioral patterns followed by individuals during a rapid evacuation process and the forecast of the time required for evacuation under different conditions. Yusoff & al. [18] implemented two discrete algorithm DPSO (different from canonical PSO at initialization stage as it introduces a new fitness value: pickup best) and improved-DPSO (introduces instead an additional loop required for velocity clamping and updating particle position) aimed to optimize the number of vehicles to be sent to the flooded area. This problem, identified as Vehicle Assignment Problem (VAP), is formulated, subject to some constraints, as follows:

$$maxZ = \sum_{v \in V} \sum_{e,p \in P} Y_{pev} \tag{8}$$

DSPO and improved-DPSO are proposed and experimented to examine their performances. The coefficients used in DPSO are $c_1 = 2.5$ and $c_2 = 1.5$. The study indicates a decreasing trend of g_{best} value for both static weight ($\omega = 0.9$) and dynamic weight (starting from 1.4 to 1) and demonstrates that improved-DPSO gives generally better performance compared to DPSO, but also that both DPSO and improved-DPSO provide solutions near to the optimal. Zheng

& al. in 2012 [20] presented a new pedestrian evacuation model, applying a new PSO-based heterogeneous evacuation model. The concepts of local density and of compressibility were introduced. Both the maximal velocity and the area occupied by a particle are supposed to depend on local density that varies with time and space. Based on eq. (6) calculated velocity should not exceed certain value: $V_i \leq V_{max}$ and in crowd situations it reduces according to local density. In order to take into account the fact that during a real evacuation process each person has its own area and that the others are forbidden to enter, the authors introduced also a relationship between local density and diameter of the particles (defined as "Compressibility of particles"). The new velocity, calculated according eq. (6) will be adjusted to avoid conflicts in case the new position of a particles is occupied by another one. In a real emergency situation, movement may cause damages or injuries to the occupants. This is taken into account by introducing in the model two thresholds I_a and I_b which represent respectively the threshold of damage impulse and the threshold of injury impulse. So the maximum speed depend on I_a and I_b. In particular when the impulse is greater than I_b, the particle probably is injured and cannot move after, whereas, when the impulse is greater than I_a but less than I_b, the particle is damaged and its mobility is reduced. If the maximal velocity, for a damaged particle, decreases to zero the particle is regarded as an injured equally. Looking at simulation results we can affirm that the implemented model is more flexible in describing the velocities of individuals since it is not limited to discrete values and directions according to the new updating rule. This gives higher precision and flexibility to the model. Zheng & al. [24] introduced a multi-objective particle swarm optimization (MOPSO) to achieve an effective method for population classification in fire. The main purpose of population classification is to identify the situation of evacuees and the possible interactions among the evacuees themselves and also between the evacuees and the responders. Two objective functions are used to evaluate the quality of classification rules, their goal, "precision"and "recall". Where precision can be thought as a measure of exactness whereas recall is a measure of completeness. The MOPSO wanted to maximize both functions, although their trends showed an inverse relationship between them. The multi-objective method (MOPSO) is able to optimize the two measures simultaneously. Zheng & al. [24] introduce two new strategies to the MOPSO: the first concerns updating p_{best} and the second describes the updating of particles' velocity. The starting equations are:

$$v_j^{(t+1)} = \chi(v_j^{(t)} + c_1 r_1(pbest_j^{(t)} - x_j^{(t)}) + c_2 r_2(gbest_j^{(t)} - x_j^{(t)}) \tag{9}$$

$$x_j^{(t+1)} = x_j^{(t)} + v_j^{(t+1)} \tag{10}$$

where χ is a constriction factor derived from acceleration constants for controlling the velocity:

$$\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|} \qquad \varphi = c_1 + c_2$$

c_1 and c_2 are two acceleration constants reflecting the weight of cognitive and social learning, respectively, and r_1 and r_2 are two distinct random numbers in $[0, 1]$. So eq. (9) has a different expression:

$$v_j^{(t+1)} = \chi(v_j^{(t)} + cr(cbest_j^{(t)} - x_j^{(t)})) \tag{11}$$

where every particle χ can learn from a different exemplar at each dimension j, increasing the information shared by the particles. Comparative experiments have shown that the proposed algorithm performs better than some state-of-the-art methods and it has high ductility and can be extended to many multi-objective rule mining problems. Li & al. [25] present a simulation model based on PSO by setting the following criteria: people may choose different escape strategies in emergencies and two behaviors are simulated by familiar-coefficient and following-coefficient. The effect of both, smoke and heat and their influences on human behavior, are considered. Each particle is represented in a two-dimensional space through a set of vectors. A hazard model is used to simulate the influences of fire and its secondary factors. It is used a Fractional Effective Dose (FED) model to consider the physiological effect of fire hazards on moving speed of the occupants.

$$FED_{FIRE} = FED_{HEAT} + FED_{GAS} + FED_{SMOKE}$$

$$V_x^t = (1 - FED_{FIRE})(v_o + r * \Delta v_0) * C_x^t; V_y^t = (1 - FED_{FIRE})(v_o + r * \Delta v_0) * C_y^t$$

The model is based on the hypothesis that during an emergency only three escape strategies are possible: shortest-path, backtracking and following-up. The model assumes that half of pedestrians are familiar with the site and the other half follows the crowd in the process of evacuation, i.e. $familiar - coefficient = following - coefficient = 0.5$. The study of results of the extended particle swarm optimization (E-PSO) model reveals that the general pattern of evacuation consists of two phases: an efficient evacuation (graphically a steep part) and an inefficient evacuation (graphically a flat part). Sharper is the slope with the higher density of occupants, better the evacuation efficiency is. The results indicate also that adding a new exit is better than widening its size in order to minimize evacuation time. Zong & al. [21] presented an evacuation model for mixed traffic flow based on temporal-spatial conflict and congestion. To solve this mixed evacuation problem they proposed a novel discrete particle swarm optimization with learning factor (DPSONLF). In this problem more than one objective need to be optimized simultaneously, such as minimal total evacuation time, minimal pedestrian-vehicle temporal-spatial conflict degree and minimal temporal-spatial congestion degree. The conflict-congestion model for pedestrian-vehicle mixed evacuation is described below:

$$minF_1 = \sum_{k=1}^{M} \sum_{(i,j) \in P_k} t_{ij}^k$$

$$minF_2 = \sum_{i \in N} \sum_{t=0}^{T} Conflict_i(t) \cdot \Delta t; minF_3 = \sum_{i \in N} \sum_{t=0}^{T} Congestion_i(t) \cdot \Delta t$$

To improve the effectiveness of the DPSO algorithm it has been introduced a neighborhood learning factor. The velocity update function is modified as:

$$v(t+1) = \omega \cdot v(t) + c_1 r_1 (P_{pbest} - X(t)) + c_2 r_2 (P_{nbest} - X(t)) + c_3 r_3 (P_{gbest} - X(t))$$

The results of this paper indicate that DPSONLF has better performance in the control of conflict and congestion both in time and in space during the evacuation process for mixed pedestrian and vehicles.

4 Conclusions

In this paper has been compared several algorithms and the study pointed out interesting results. PSO algorithms best performs the optimization in case of evacuation, the reason is inside the following statement "the information exchange take place locally in a dynamic way". It means that in PSO-based algorithms the evaluation process is based on real time information exchanged continuously in response to changing environmental conditions. The literature shows different approaches to the PSO algorithms: discrete or continuos, with or without inertia factor, different value assigned to the inertia factor, the use of two learning factor c_1 and c_2 or adding c_3. Starting from this assessment, the future development will be the comparison of PSO-based models and the implementation of a new PSO-based model taking into account additional factors, not yet considered. This study will identify the appropriate design solutions that enable interaction between "environment"and "population"in order to "drive"evacuees' behavior. In this sense, computers and extensively the Internet of Things can certainly be an important aid in the implementation of considered design solutions.

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