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Key Aspects of PSO-Type Swarm Robotic Search: Signals Fusion and Path Planning

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1. Introduction

Extending the particle swarm optimization (PSO) algorithm to be one of systemic modeling and controlling tools, several research groups investigate target search with swarm robots (simulated or physical) respectively (Doctor et al., 2004; Hereford & Siebold, 2008; Jatmiko et al., 2007; Marques et al., 2006; Pugh & Martinoli, 2007; Xue & Zeng, 2008). The common idea they hold is to map such swarm robotic search to PSO and deal it with by employing the existing bio-inspired approaches to the latter case in a similar way (Xue et al., 2009). Of the mapping relations, some aspects including fitness evaluate and path planning have to be especially considered because PSO-type algorithm working depends heavily upon them. Unlike regarding these respects in PSO, however, the actual characteristics of robot and complexity of sensing to environment make it impossible to be simplified even ignored. Bear that in mind, we might as well explore some representative research work. Pugh et al. compare the similarities and differences in properties between real robot and ideal particle, then extend PSO directly to model multiple robots for studying at an abstract level the effects of changing parameters of the swarm system (Pugh & Martinoli, 2007). Xue et al. simplify characteristics of robot by treating each physical robot as a first order inertial element to study mechanism of limited sensing and local interactions in swarm robotic search (Xue & Zeng, 2008). Doctor et al. discuss applying PSO for multiple robot searches, whose focus is on optimizing the parameters of their algorithm (Doctor et al., 2004). Jatmiko et al. exert mobile robots for plume detection and traversal, with utilizing a modified form of PSO to control the robots and consider how the robots respond to search space changes such as turbulence and wind changes (Jatmiko et al., 2007). Hereford et al. consider how well the PSO-based robot search will scale to large numbers of robots by designing specific communication strategies. Based upon this, they have published results of implementing their PSO variants in actual hardware robot swarms (Hereford & Siebold, 2008). Marques et al. analytically compare PSO-based cooperative search and gradient search as well as biased-random walk search to try to find out which performing well in search efficiency. Due to the exchange of information between neighbors in the first search mode, PSO-type olfactory guided search possesses merit in search properties over its two competitors (Marques et al., 2006).
It is clear that all of works mentioned above neither involve target search with PSO-type control algorithm under conditions of realistic sensing to environment, nor handle the problem of obstacle avoidance in the process of target search. On the contrary, each of them assumes a potential target in search space to give off a diffuse residue that can be detected by a single

sensor, which not corresponding with the actual needs and only having theoretical significance (Hereford & Siebold, 2008). In fact, target signals in the real world can not simply be attributed to only one type. Thus, it is need to treat real-time heterogeneous signals fusion rather than measure unisource signals as fitness evaluate. Just take search and rescue in disasters for example. When working miners are confronted with gas outburst accidents in closed roadways, they would be likely to lose touch with outside. Unfortunately, search operations here tend to be difficult because of the extreme risk. Swarm robots may therefore be pitched into carrying out such missions taking the place of human beings. There are multiple kinds of heterogeneous signals, including intermittent sound of call for help and periodic radio frequency (RF) waves as well as continuous gas on disaster spot. We thereupon conduct a case study of target search for propose of PSO-type control. Thus, the rest of this paper proceeds as follows: In Section 2 the system modeling at individual and swarm levels is done to introduce the topics. In Section 3, the properties of target signals are introduced, then a fusion framework is presented. Then, real time path planning strategy for a typical swarm of wheeled mobile robots (WMR) with kinematic constraints in unstructured environment is described in Section 4. To examine the validity of fusion approach and path planning, simulations are conducted in Section 5. Finally, we conclude in Section 6.

2. System Modeling

Consider a swarm of N differentially steered WMRs. The reactive control structure of robot used here makes environment sensing linked with actions directly, without requirement for explicit expression about search space. Meanwhile, the model of our swarm robotic system can be given after mapping PSO to swarm robotic search (Xue & Zeng, 2008). Obviously, the modeling to the system consists of two levels according to abstract degrees, i.e., the microscopic (individual) and the macroscopic (swarm) (Lerman et al., 2005; Martinoli & Easton, 2002; Martinoli et al., 2004).

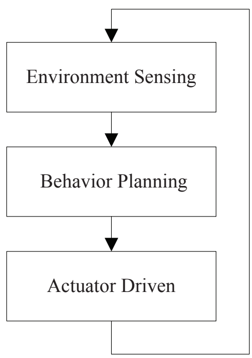


Fig. 1. Control Hiberarchy of Individual Robot

2.1 Modeling for Individual Robot

As the reactive architecture with three functional modules including environment sensing, behavior planning and actuator driven is chosen (Murphy, 2000), see Fig. 1, both proximity sensor system modeling and kinematic modeling should be considered, while the modeling for target signals detection system is dismissed. The reason is that the two former parts are related to path planning and the latter configuration depends on the specific types of target signals rather than physical size of robot and its kinematics.

2.1.1 Proximity Sensor Systemic Model

To integrate collision avoidance mechanism, we assume that proximity sensors (infrared or laser) are equipped on each robot (Jatmiko et al., 2007). Without taking the types and properties of proximity sensors into account, we can only extract the commonness according to the principle of range measurement for modeling. As for the specific configuration of proximity sensors in this work, sixteen proximity sensors are assumed to be equipped on each individual robot, surrounding their body in a discrete circular uniform distributional fashion, see Fig. 2 and Tab. 1 for details, where the black ovals stand for proximity sensors and the arrow points the heading.

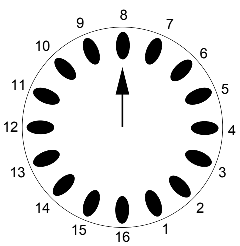


Fig. 2. Proximity Sensor System of Individual Robot

2.1.2 Kinematic Model

The modeling of the kinematics of robots in a two-dimensional plane can be done using either cartesian or polar coordinates. The model in cartesian coordinates is the most widely used and discussion here will be limited to modeling in cartesian coordinates (Maalouf et al., 2006). Typically, the posture of robot at any instant is defined by the position and heading relative to the global frame. The kinematic model is given as follows (Campion et al., 1996):

$$\begin{cases} \dot{x}_i = v_i \cos\theta_i \\ \dot{y}_i = v_i \sin\theta_i \\ \dot{\theta}_i = \omega_i \end{cases} \tag{1}$$

where $p_i = (x_i, y_i)^T$ be position vector or cartesian coordinates of robot R_i under global frame, θ_i its orientation or steering angle, v_i translational or driving or linear velocity and ω_i angular

Sensor Nos.	Degree	Degree	Degree	Degree	Degree	Degree	Degree	Degree
1–8	$-\frac{7}{8}\pi$	$-\frac{3}{4}\pi$	$-\frac{5}{8}\pi$	$-\frac{1}{2}\pi$	$-\frac{3}{8}\pi$	$-\frac{1}{4}\pi$	$-\frac{1}{8}\pi$	0
9–16	$\frac{1}{8}\pi$	$\frac{1}{4}\pi$	$\frac{3}{8}\pi$	$\frac{1}{2}\pi$	$\frac{5}{8}\pi$	$\frac{3}{4}\pi$	$\frac{7}{8}\pi$	π

Table 1. Distribution Degrees of Proximity Sensors

or steering velocity, as is shown in Fig. 3. In the absence of obstacles, the basic motion tasks assigned to a WMR may be reduced to moving between two robot postures and following a given trajectory (Oriolo et al., 2002). Whichever can finally be attributed to the design of control laws, i.e., control command series of inputs $(v, \omega)^T$. Although the actual commands may come in another forms, e.g., the angular velocities ω_R and ω_L of the right and left wheels, respectively, rather than v and ω, we can still make use of analytical module built in robot controller to get the required commands by a one-to-one mapping between these velocities (Oriolo et al., 2002; Siegwart & Nourbakhsh, 2004). For all control schemes, in fact, an additional filtering of original velocity commands is included to account for robot and actuator dynamics.

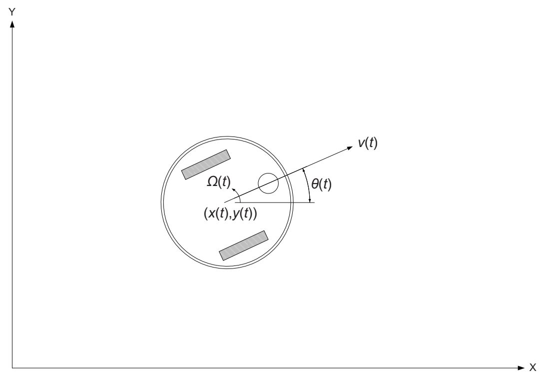


Fig. 3. Kinematic Model of Individual Robot

Due to the abilities of motion mechanism and actuators, there exist limitations on real velocities. Consequently, the actual input commands can be obtained with the following rules:

$$\begin{aligned} v_i &= \begin{cases} v_{max}, & \text{if } v_i(t) > v_{max} \\ 0, & \text{if } v_i(t) < 0 \\ v_i(t), & \text{otherwise} \end{cases} \\ \omega_i &= \begin{cases} \omega_{max}, & \text{if } \omega_i(t) > \omega_{max} \\ -\omega_{max}, & \text{if } \omega_i(t) < -\omega_{max} \\ \omega_i(t), & \text{otherwise} \end{cases} \end{aligned} \tag{2}$$

Note that above rules come from non-holonomic constraints because robot can move along its bearing only, that is, the direction of v_i is always in accordance with the heading of robot, see Fig. 3 and Fig. 4. Then, v_i can be used to decide the orientation of robot R_i. As for the robot at position p_1 with $v_i(t) = (v_{i1}, v_{i2})_t$, we can calculate the orientation:

$$\theta_i(t) = \arctan \frac{v_{i2}(t)}{v_{i1}(t)} \tag{3}$$

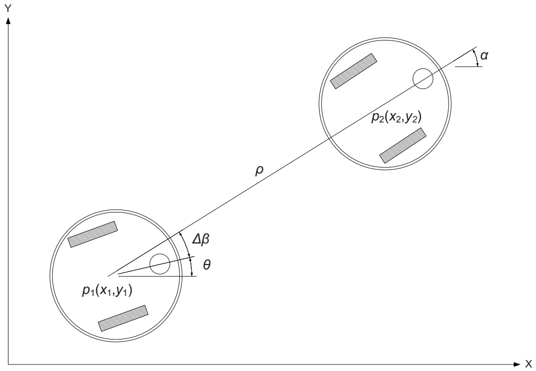


Fig. 4. Motion Control of A WMR

Similarly, the orientation $\theta_i(t+\Delta t) \stackrel{\text{def}}{=} \alpha$ at position p_2 with $v_i(t+\Delta t) = (v_{i1}, v_{i2})_{t+\Delta t}$ can be decided too. Therefore, the required expected turning angle β_i from p_1 to p_2 can be computed and used to further decide ω_i:

$$\Delta\beta_i = \arctan\frac{v_{i2}(t+\Delta t)}{v_{i1}(t+\Delta t)} - \arctan\frac{v_{i2}(t)}{v_{i1}(t)} \tag{4}$$

The posture vectors $(x_i, y_i, \theta_i)^T$ of robot R_i are required as control inputs to individual controller at each time step, depending on the posture estimate with incremental encoder data (odometry). Assume the angular wheel displacements having been measured during the sampling time Δt by the encoders. We can further obtain the linear and angular displacements Δs and $\Delta\theta$. Then, the estimate of posture at time $t+\Delta t$ can be computationally decided (Oriolo et al., 2002; Siegwart & Nourbakhsh, 2004):

$$\begin{pmatrix} \hat{x} \\ \hat{y} \\ \hat{\theta} \end{pmatrix}_{t+\Delta t} = \begin{pmatrix} \hat{x} \\ \hat{y} \\ \hat{\theta} \end{pmatrix}_t + \begin{pmatrix} \Delta s \cos(\hat{\theta} + \frac{\Delta\theta}{2}) \\ \Delta s \sin(\hat{\theta} + \frac{\Delta\theta}{2}) \\ \Delta\theta \end{pmatrix}_t \tag{5}$$

2.2 Modeling for Swarm Robots

Our swarm robotic system is composed of the above-mentioned robots. The meanings of used symbols are as follows: $p_i = (x_{i1}, x_{i2})$ and $v_i = (v_{i1}, v_{i2})$ are position and linear velocity of robot R_i at time t respectively; $p_i^* = (x_{i1}^*, x_{i2}^*)$ and $p_{(i)}^* = (x_{(i)1}^*, x_{(i)2}^*)$ the best historical positions of robot i itself and its communication-based neighborhood (Pugh et al., 2006). Based on this, we can define the best position within its neighborhood (Xue & Zeng, 2008; Xue et al., 2009):

$$p_{(i)}^*(t) = p_k^*(t), \arg_k \max\{I(p_k^*(t)),\ k \in R_i\text{'s neighborhood}\} \tag{6}$$

where $I()$ is the fusion of measurement readings of target signals. Further, we are able to model swarm robotic system with the extended PSO method:

$$\begin{cases} v_{ij}(t+1) = \xi_i v_{ij}(t) + c_1 r_1 (x^*_{ij} - x_{ij}) + c_2 r_2 (x^*_{(i)j} - x_{ij}) \\ v_{ij}(t+\Delta t) = v_{ij}(t) + K_i (v_{ij}(t+1) - v_{ij}(t)) \\ x_{ij}(t+\Delta t) = x_{ij}(t) + v_{ij}(t+\Delta t)\Delta t \end{cases} \tag{7}$$

where $v_{ij}(t)$ and $x_{ij}(t)$ are j-dimensional velocity and position of robot R_i at time t respectively, $v_{ij}(t+1)$ the expected computational velocity, K_i designed parameter of local controller gain which can be chosen by designer. As robot may have to take several time steps $\lambda\Delta t$, in most cases, to reach an expected position from the consecutive previous expected one, adding this factor to obtain a "smoother" displacement. Besides, ξ_i be algorithmic inertia coefficient that can be set constantly or dynamically, c_1 and c_2 cognitive and social acceleration constant respectively, r_1 and r_2 stochastic variables subject to the distribution of $U(0,1)$. We can calculate the linear velocity:

$$v_i(t+\Delta t) = \sqrt{(v_{i1}(t+\Delta t))^2 + (v_{i2}(t+\Delta t))^2} \tag{8}$$

With kinematics model given in Eq. (1), the input of linear velocity (Peng & Akella, 2005) and angular velocity (Siegwart & Nourbakhsh, 2004) can be decided:

$$\begin{cases} v_i(t+\Delta t) & = & \min(v_{max}, v_i(t+\Delta t)) \\ \omega_i(t+\Delta t) & = & \begin{cases} \omega_{\max}, & \text{if } \frac{\beta_i}{\Delta t} \geq \omega_{\max} \\ \frac{\beta_i}{\Delta t}, & \text{otherwise} \end{cases} \end{cases} \tag{9}$$

where β_i is the computational expected turning angle from the current position to the next expected one, also see Fig. 4 for details.

3. Signals Fusion

The key to PSO-type search algorithm is to take detection and fusion of target signals as fitness evaluate so as to decide the best-found position, since each individual robot is guided by the best experience of itself own and its neighborhood. Obviously, the temporal and spatial features of different types of signals should be explored in advance.

3.1 Signal Properties

With mathematical models of signals propagation, we can generate a set of theoretically computed signal strength data akin to the empirical data set to design fusion algorithm rather than collect the data on spot.

3.1.1 Sound

The identical model may be used for both propagation and measurement as to the same space. Compared with the size of environment, the mouth of victim can be considered as a point sound source. Let N robots equipped with acoustic sensors construct a mobile sensor field, where an immovable target emits omnidirectional acoustic signals. The signal energy measured on the i^{th} sensor over time interval t, denoted by (Li & Hu, 2003):

$$y_i(t) = g_i \frac{s(t-t_i)}{|r(t-t_i) - r_i|^{\alpha}} + \varepsilon_i(t) \tag{10}$$

where t_i is time delay for sound propagates from target to the i^{th} robot, $s(t)$ is a scalar denoting energy emitted during sampling time t; $r(t)$ coordinates of target during t; r_i coordinates of the i^{th} stationary sensor; g_i gain factor of the i^{th} acoustic sensor; $\alpha(\approx 2)$ energy decay factor, and $\varepsilon_i(t)$ cumulative effects of modeling error of g_i, r_i, α and the additive observation noise of $y_i(t)$, see Fig. 5.

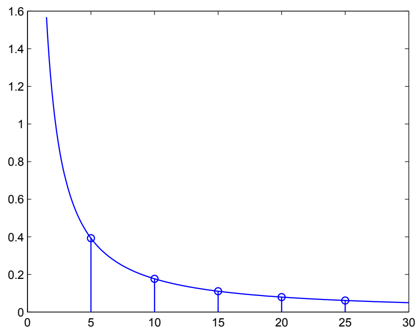


Fig. 5. Acoustic Energy Loss Fitting

3.1.2 RF Waves

Typically, underground mine personnel tracking systems rely more and more upon radio frequency identification (RFID) technologies today. Such a system has basic components including readers and tags. The latter is categorized as either passive or active (Ni et al., 2004). As for coal mine application, a tag is often mounted on a miner's helmet with his lamp. For a radio channel, the transmitted signal reaches receiver via multiple paths (Bahl & Padmanabhan, 2000):

$$P(d) = P(d_0) - 10\alpha \lg \frac{d}{d_0} - \eta \tag{11}$$

where α indicates loss rate, $P(d_0)$ is signal power at reference distance d_0 and d transmitter-receiver distance. The value of $P(d_0)$ can be derived empirically or obtained from the wireless network hardware specifications. In general, η value is derived empirically, see Fig. 6.

3.1.3 Gas

The gas in coal mines will diffuse quickly in closed roadways after gas outburst. The pervasion process can be described as affecting by some odor point sources. For convenience, they can be viewed as only one by linear combination. Let the projection of leak point on the ground be origin, average direction of downwind x-axis, a right hand three-dimensional coordinate system can be set. Then, we can calculate gas concentration in any point on the ground $(z = 0)$ following the law (Marques et al., 2006):

$$C(x, y, t) = \frac{Q}{2\pi\sigma_y(x,t)\sigma_z(x)} \exp\{\frac{(y(t) - y_0(x,t))^2}{-2\sigma_y^2(x,t)}\} \tag{12}$$

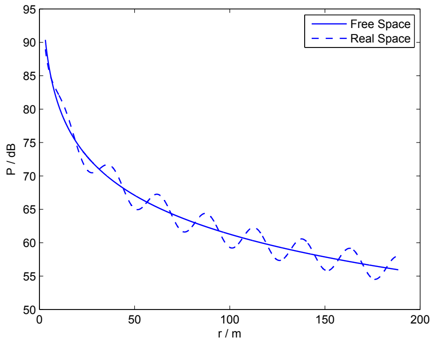


Fig. 6. Log-Normal Signal Loss Distribution

where Q represents release rate, plume center y_0, width w and height h as a function of time t and downwind distance x. $\sigma_y(x,t) = \frac{w(x,t)}{\sqrt{2\pi}}$, $\sigma_z(x) = \frac{h(x)}{\sqrt{2\pi}}$. Fig. 7 shows an example of a time averaged Gaussian plume (Marques et al., 2006). Further, the heterogeneous signals distribution in search environment can be shown in Fig. 8.

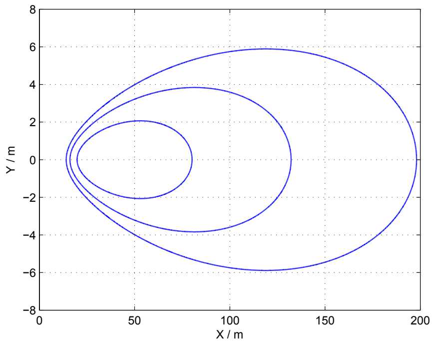


Fig. 7. Gas Concentration Contours on the Ground after Emitted Sufficient Long Time

3.1.4 Signals Propagation Space

The space is divided into six sub-areas (numbered Area 1–6) according to the distribution of signals. The lines in Fig. 8 represent the minimum detectable signal contours corresponding to thresholds 0.0016 kg/m^3, -90 dBm and to maximum detectable ranges 200 m, 45 m respectively Li & Hu (2003); Ni et al. (2004). It is need to point out that the sound threshold is not given definitely because it is closely related to the sensor sensitivity. Hence, given a specific power (milliwatt magnitude) of call-for-help in a loud voice, our attention lines in finding how far the emitted sound signals can reach. In simulation, we will make an experiential but reasonable assumption on this value.

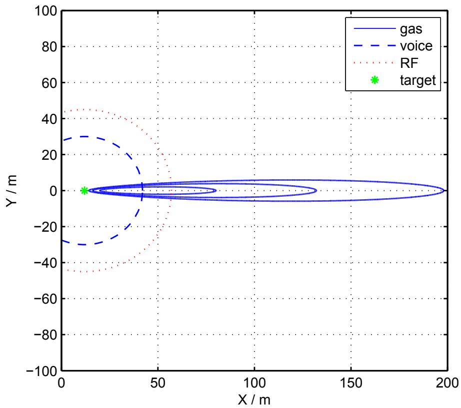


Fig. 8. Signals Distribution in Search Space

3.2 Fusion

Different types of signals are presented in different forms. For instance, gas diffusion distance may be up to several hundreds of meters (Marques et al., 2006); the detectable range of RF waves with frequency $f = 7.5\,\mathrm{s}$ emitted by active tags approach to 150 ft ($\approx 45\,\mathrm{m}$) (Ni et al., 2004) and the localization accuracy with RF RSSI-based method can be 2 m; the detectable range of sound usually reaches not more than 30 m (Li & Hu, 2003), and the estimation error with sound RSSI method may be up to 50%. Therefore, detectable range, statistical properties, localization types and accuracy have to be considered simultaneously in signals fusion.

3.2.1 Sensing Event

Introduce a 2-value logic into describing perceptual process so that we can define perception event in advance. Let A_i $(i = \mathrm{GAS}, \mathrm{RF}, \mathrm{CALL})$ be perceptual event in event space $\Omega = \{0, 1\}$. Then $A_i = 1$ represents detect-success (beyond threshold) and $A_i = 0$ detect-failure. At the same time, we normalize those measurement readings beyond threshold to $\mathrm{Nm}_i \in (0, 1)$. Clearly, events A_i and A_j $(i \neq j)$ are mutually independent and the probability of each event can be calculated with its statistical properties. Further, let $(A_{i\mathrm{GAS}}(t), A_{i\mathrm{RF}}(t), A_{i\mathrm{CALL}}(t))$ be the joint sensing event of robot R_i at time t, then there may be $2^3 = 8$ joint events according to the time characteristic of signals distribution. Again, consider the spatial distribution of signals. Those robots in signal blind area (Area 1) attempt to capture signal clues independently in a spiral move manner to further search for target locally (Hayes, 2002; Marques et al., 2006), without directed by swarm intelligence principle locally, while the robots in Area 2–6 do so (Marques et al., 2006). Thus, it is easy to know that there are six joint events everywhere except source. The possible joint events occurred in each sub-area are listed in Tab. 2. These joint events can be encoded with 3-bit binary numbers. Since the source is characteristic of such encode, we can also express it with 3×1 "characteristic" vector $\vec{C}$. Finally, take the above Nm_is of measurement readings to replace the corresponding elements "1" in vector $\vec{V}$.

3.2.2 Virtual Communication

View signals measurement as continuous communication between robots and target. In this case, each robot possesses its own channel, with source (target) and destination (robot). The individual robot discretizes three types of measurement readings to 1-bit binary digit respectively with corresponding threshold. As for the same signal emitted from source, robots in different sub-areas may obtain different results due to the effect of distance. Consequently, while there are $2^3 = 8$ encodes of full permutation in source, the "received" encodes by robots in different sub-areas may vary. We suppose the duration of emission by target can guarantee the detection success in sampling period (400 ms here). But the transmission time from source to destination is small enough so as to be ignored. Thus, the detection process can transfer continuous information to time- and amplitude-discrete random signal series. Since we suppose Δt be sufficient small interval, the above perception event occurs once at most in every sampling process.

3.2.3 Information Entropy

We can calculate the information entropy from the received information encodes through virtual communication process.

- **Gases.** Robots start to locally search for target as soon as gas can be sensed in global search stage (Marques et al., 2006). As to the continuous gas diffusion, event $A_{\text{GAS}} = 1$ will occur at any time t in Area 2–4 (Hayes, 2002; Marques et al., 2006). Then $P\{A_{\text{GAS}}(t)\} = 1$, i.e., this information is decisive, say, $H(X_{\text{GAS}}) = 0$.
- **RFID Waves.** The perception process of RF signals $\{X_{\text{RF}}(t), t \geq 0\}$ can be viewed as Poisson process with intensity λ_{RF}. As the process has stationary independent increment, those equal intervals may lead to equal probability of $A_{\text{RF}} = 1$. Suppose the sampling period Δt is sufficient small time interval and satisfies the sampling theory. The event $A_{\text{RF}} = 1$ occurs once at most in every sampling. Since events $A_{\text{RF}} = 1$ and $A_{\text{RF}} = 0$ are contrary ones, then we can draw a conclusion $P\{A_{\text{RF}}(t) = 0\} = 1 - P\{A_{\text{RF}}(t) = 1\}$. And the relationship can further be captured by computing probabilities:

$$\begin{cases} P\{A_{\text{RF}}(t) = 1\} = e^{-\lambda_{\text{RF}}\Delta t}\lambda_{\text{RF}}\Delta t \\ P\{A_{\text{RF}}(t) = 0\} = e^{-\lambda_{\text{RF}}\Delta t} \\ e^{\lambda_{\text{RF}}\Delta t} = \lambda_{\text{RF}}\Delta t + 1 \end{cases} \tag{13}$$

"Emitted"	Sub-Area	Possible Event	"Received"
111	1	$(0,0,0)$	000
111	2	$(1,0,0)$	100
111	3	$(1,0,0)$, $(1,1,0)$	100, 101
111	4	$(1,0,0)$, $(1,1,0)$, $(1,0,1)$, $(1,1,1)$	100, 110, 101, 111
111	5	$(0,0,0)$, $(0,1,0)$	000, 010
111	6	$(0,0,0)$, $(0,0,1)$, $(0,1,0)$, $(0,1,1)$	000, 001, 010, 011

Table 2. Joint Event Encodes $(A_{\text{GAS}}, A_{\text{RF}}, A_{\text{CALL}})$ in Search Space

Signal	Entropy	Detectable Range(m)	Localization Type	Accuracy (m)
GAS	0	200	indirect	200
RF	0.0156	45	direct	2
CALL	0.2055	30	direct	15

Table 3. Characteristics of Signals Propagated in Search Space

Accordingly, the entropy of RF signals in information source at t can be calculated with the above conclusion:

$$H(X_{\mathrm{RF}}) = \lambda_{\mathrm{RF}}\Delta t + (e^{-\lambda_{\mathrm{RF}}\Delta t} - 1)\log(\lambda_{\mathrm{RF}}\Delta t) \tag{14}$$

- **Sound of Call-for-Help.** The detected sound of call for help $\{X_{\mathrm{C}}(t), t \geq 0\}$ be Poisson process with intensity λ_{C}. Similarly, we can determine the probability detect-success and detect-failure of call for help to further obtain the entropy of such sound at any time t:

$$H(X_{\mathrm{C}}) = \lambda_{\mathrm{C}}\Delta t + (e^{-\lambda_{\mathrm{C}}\Delta t} - 1)\log(\lambda_{\mathrm{C}}\Delta t) \tag{15}$$

3.2.4 Weight

A criterion to signals fusion can be used by robot. Among all factors, apart from information entropy, the localization type and accuracy with RSSI-based method should also be considered. For instance, gas source is not same as the target location, i.e., we localize target indirectly by localizing gas source based on the fact that one should move quickly upwind in risk avoiding poison gas leakage. Consequently, such estimate may get the worst accuracy (200 m assumed). While the RSSI-based estimate with RF or sound intensity can localize target directly. But the two types of signals differ in accuracy of location estimate, see Tab. 3 for details (Li & Hu, 2003; Marques et al., 2006; Ni et al., 2004). As shown in Eq. (16), the entropy, localization type and accuracy are all required to be integrated by weighted sums.

$$w_i = \frac{aH(X_i)}{\sum\limits_i H(X_i)} + b\kappa + \frac{c}{\tau_i \sum\limits_i \frac{1}{\tau_i}},\ i = \mathrm{GAS}, \mathrm{RF}, \mathrm{CALL} \tag{16}$$

where logic variable κ represents localization type, "indirect" is assigned 0 and "direct" 1. τ is localization accuracy and $a, b, c \in (0, 1]$ are all positive coefficients that need to be determined empirically. Then, we can take three weight values as elements to construct a 1×3 vector $\vec{W}$.

3.2.5 Signals Fusion

An fusion mechanism for making decision on the best positions is discussed here, being suitable for deciding on cognitive of individual and social of swarm. The mechanism can be expressed with weighted sums operation using vectors $\vec{V}$ and $\vec{W}$, i.e., obtaining the fusion by calculating the inner product of two vectors $fusion = \vec{V}_{(1\times3)} \cdot \vec{W}_{(3\times1)}$.

3.2.6 Description of Fusion Algorithm

A full-distributed fusion algorithm run on each individual robot can be presented. First, we assume each robot has an unique ID, carrying a set of sensors and a on-board fusion module so as to measure signals and fuse them independently. Besides, all sensors are assumed to react to signals in sufficient short time. Finally, we design a character structure denoting as "ID"+"Position"+"*fusion*", which can be viewed as the communication protocol. As for the local communication hardware, it can be achieved by wireless transmission systems, like RF or infrared.

Algorithm 1 Real-Time Heterogeneous Signals Fusion

Input: sensor readings
Output: the best-found position and fusion of signals
confirm ID and current position *iPos*;
initialize
    set counter $t \leftarrow 0$;
    set $(A_{i\mathrm{GAS}}, A_{i\mathrm{RF}}, A_{i\mathrm{CALL}})_{t=0} = 000$;
    set $fusion = 0$;
    construct "ID"+"Position"+"*fusion*";{communication protocol}
    set best position of itself *ibPos* ← *iPos* ;
    set best position of neighborhood *sbPos* ← *iPos*;
repeat
    make measurement;
    discretize to 0 or 1 by comparing threshold value;
    format data with characteristic structure;
    if $(A_{i\mathrm{GAS}}, A_{i\mathrm{RF}}, A_{i\mathrm{CALL}})_t = 000$ **then**
        keep silence;{do nothing}
    else
        elect *ibPos* and update;
        broadcast data within its neighborhood;
    end if
    listen for others;
    if receive data containing $(A_{j\mathrm{GAS}}, A_{j\mathrm{RF}}, A_{j\mathrm{CALL}}) \neq 000$ **then**
        elect *sbPos* and update;
    end if
    $t \leftarrow t + 1$;
until termination condition is met

4. Path Planning

In PSO-type swarm robotic search algorithm, each individual robot makes decision on its expected destination at every time step as its current target to move towards in a full distributed fashion by combining its own inertia and cognitive experience as well as experience of swarm. The experience of robot itself and its neighbors depends on fitness evaluate, i.e., target signals measurement and fusion, which is discussed in the above section. In other words, the trajectory of each robot "searching" for target is formed by linking a series of expected positions orderly.

Similar to single autonomous robot, path planning of individual robots in swarm robotic system also involves how to move towards their own goals with static/dynamic obstacle avoidance (Warren, 1990). Performed in an iterative manner, artificial potential field (APF) method is usually employed for such task in controlling autonomous robot (Khatib, 1986). Theoretically, robot moves in the direction of the resultant of the attraction force pulling the robot towards the goal, and the repulsive force pushing the robot away from the obstacles. As expected, the robot stops moving after reaching the goal position. Unfortunately, it always suffers from local minima where if trapped (Zou & Zhu, 2003). Looking for a local-minimum-free solution has become a central concern in this approach. Aiming at the problem solving, some modified APF methods are proposed to overcome local minimum. The key ideas may be fallen into two categories: one establishes new potential functions with a few or even no local minima (Ge & Cui, 2000; Warren, 1990); the other uses some techniques to escape from local minima, including random walk (Janabi-Sharifi & Vinke, 1993), wall following (Borenstein & Koren, 1989), and other heuristic methods (Singh et al., 1996). Except for these efforts, Jugh et al. apply the PSO algorithm to path optimization of multiple robots (Pugh & Martinoli, 2006). However, above methods are incompatible with the case of swarm robotic search. New difficulties arise when we apply APF method to swarm robots path planning. One major challenge is to bridge the high-level task planning and the low-level path planning and integrate them into one framework (Ren, 2005). Thus we combine APF method and PSO to plan path towards target with collision avoidance because of low computational cost and better real-time performance.

4.1 Traditional APF

The nature of APF method lines in defining the motion space for robot as a virtual potential filed $U(x)$ including virtual gravitational field $U_G(x)$ and repulsion field $U_R(x)$, in which robot is attracted by target and repelled by obstacles. Then, the resultant force field can be defined with (Khatib, 1986):

$$U(x) = U_G(x) + U_R(x) \tag{17}$$

Meanwhile, we can further define attractive force $F_G(x)$ and repulsive force $F_R(x)$ as the negative gradient of the virtual gravitational field and repulsion field respectively. Therefore, the virtual force $F(x)$ acted by the virtual potential field can be derived using space dynamics equation and Lagrange equation:

$$\begin{cases} F(x) = F_G(x) + F_R(x) \\ F_G(x) = -\nabla(U_G(x)) \\ F_R(x) = -\nabla(U_R(x)) \end{cases} \tag{18}$$

Clearly, the direction of robot motion depends upon the direction of $F(x)$ (Khatib, 1986). Although the traditional APF method has the virtue of being the easiest to implement, it has some limitations above yet. At first, the traditional APF method is applied to the case of global environment information being known rather than the case of environment being partly known or even unknown because the virtual potential field is computationally obtained and what robot sensing environment with its own equipped sensors is not supported. Second, the inherent disadvantage of traditional APF method comes through in being easily trapped to local minima and in target being not able to reach. It is important that the traditional method has to be modified in accordance with robot sensing environment with its sensors. The robot navigates in search space without obstacle collision depends completely upon equipped sensors through collecting measurement readings to judge states including obstacles distribution and possible target position.

4.2 Sensor-Based APF

Generally, when searching for target in unknown environment, the environment map is partly known or even unknown. In this case, the robot behaviors for obstacle avoidance have to rely on continuous local path planning by means of locally sensing surroundings with equipped sensors. As robot moves within search space, the obstacles surrounding robot are inevitably in different conditions. Learning from the traditional APF method to improve real-time property, we can integrate it with the multi-sensor structure of robot to construct virtual potential force with change of sensor readings. Hence, it is need to make some modifications to Eq. (18) based on above structural sensor model, see Fig. 2.

$$\begin{cases} F_i'(x) = F_{iG}'(x) + F_{iO}'(x) \\ F_{iG}'(x) = x_i' - x_i \\ F_{iO}'(x) = \sum_{j=1}^{16} \overrightarrow{\Delta S_{ij}} \\ \Delta S_{ij} = S_R - S_{ij} \end{cases} \tag{19}$$

where $F_i'(x)$ be the resultant force imposed on robot R_i in constructed virtual potential field, $F_{iG}'(x)$ the force attracted by the expected target position, and $F_{iO}'(x)$ the force repelled by surrounding obstacles. Furthermore, S_R be the maximum detection range of all sensors and S_{ij} the current distance reading of sensor j, $\overrightarrow{\Delta S_{ij}}$ represents the increment of the j^{th} sensor reading. Note that $\overrightarrow{\Delta S_{ij}}$ be a vector because of the directionality of sensors.

4.3 Control System Architecture

To decide input commands $(v_i, \omega_i)^T$ of individual robots every time step, the control architecture including swarm and individual levels should be deterministic. From swarm aspect, the architecture is distributed and the PSO-type algorithm runs on each robot. In individual's eyes, robot has a two-level virtual control architecture, which may refer to (Oriolo et al., 2002) for details. Our designed algorithm is at high-level layer, running with a sampling time of $\Delta t = 100\,\text{ms}$. While the low-level layer is charge of analyzing and executing the velocity commands from upper level. The outputs of algorithm are the command series $(v_i, \omega_i)^T$ in every time step. As is shown in Eq. (9), $v_i(t + \Delta t)$ and $\omega_i(t + \Delta t)$ are the required control inputs of linear and angular velocity at the next time step respectively. While $v_i(t)$ and $\omega_i(t)$ are the obtained current variables by sampling.

4.4 Description of Control Algorithm

It is shown that the PSO-type algorithm is capable of controlling individual robots to move about in space for target search with obstacle avoidance according to the modified sensor-based APF method. Under the conditions of limited sense and local interaction in unknown environment, a valid navigation algorithm can be designed for target search with collision avoidance. Such idea can be implemented in accordance with the three phases below:

- **Compute the Expected Positions.** In terms of the model of swarm robotic system, i.e., Eq. (7), the respected velocities and positions of each robot at time step t can be computational decided by means of interactions within its own neighborhood.

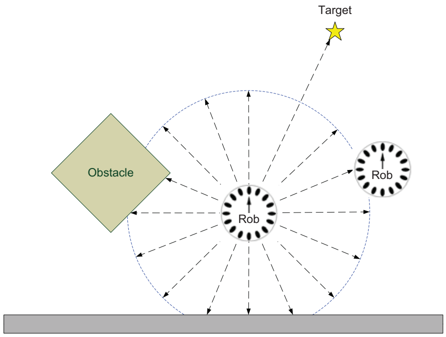


Fig. 9. Schematic of Virtual Force Acted on Robot with Proximity Sensor Readings

- **Decide Virtual Force.** With the modified sensor-based APF model, we can construct a potential field and get the virtual force in this field. The specific way is to take the expected position of robot at time step as the current temporary target which will attract the robot, while the robot will be repelled by the detected static or dynamic obstacles.
- **Compute the Real Positions.** As the velocity of robot at time $t+1$ is gotten, the position of robot at time $t+1$ can be computationally obtained according to the kinematics of robot.

A full distributed PSO-type algorithm for target search is developed, which can be implemented on each robot in parallel. Without loss of generality, we can describe the algorithm run on robot R_i as Algorithm 2.

5. Simulation and Discussions

To elaborate how to fuse the specific heterogeneous signals and how to decide the best positions, the simulations are designed and conducted for the purpose. First, virtual signal generators are arranged where same as target situates, emitting signals following their own time characteristic. Then, a series of detection points are set in signal Area 1–6. Our task is to investigate what happened in each information sink (robot) when different combination of signals is emitted from source by virtually measuring and fusing. We observe for sufficient long time until all eight encodes transmitted from source. Then we try to find the relationship between distance and fusion result.

5.1 Signals Generating

Consider the properties of a given Poisson process with intensity λ. The successive coming time of events obey exponential distribution with mean $\frac{1}{\lambda}$. We can empirically set the value in some interval, for example, the upper bound and lower bound can set to 0.01 and 0.001 respectively, i.e., $\lambda_C \in (0.001, 0.01)$, while the intensity of RF signals can be $\lambda_{RF} = 0.1333$ according to its primitive definition, which reflect the temporal characteristics of target signals.

Algorithm 2 Path Planning for Swarm Robots in A Full-Distributed Way

initialize
    set counter $k \leftarrow 0$;
    initialize constants;
    initialize v_k^i, x_k^i;
    initialize position of target;
    initialize robot's own cognition
        make measurement I_k^i;
        $I_{\max}^i \leftarrow I_k^i$;
        $p_k^i \leftarrow x_k^i$;
    initialize shared information
        $I_{\max}^g \leftarrow I_k^i$;
        $p_k^g \leftarrow x_k^i$;
    confirm index of best individual;
repeat
    $k \leftarrow k+1$;
    communicate among neighborhood
        confirm neighborhood;
        for $j = 1$ to $number\_of\_neighbors$ **do**
            compute I_k^j;
            $I_{\max}^g \leftarrow \max(I_k^i, I_k^j)$;
            $p_k^g \leftarrow x_k^m, \arg_m \max\{I(x_k^m),\ m \in (i,j)\}$;
        endfor
    compute expected velocity and position
        $\overline{v_{k+1}^i} \leftarrow w_k v_k^i + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^i)$;
        $\overline{v_{k+\Delta k}^i} \leftarrow v_k^i + K_i(\overline{v_{k+1}^i} - v_k^i)$;
        $x_{k+\Delta k}^i \leftarrow x_k^i + \overline{v_{k+\Delta k}^i}\Delta k$;
        $\xi_k \leftarrow c_3 \xi_k$;$\{0 < c_3 < 1\}$
    compute velocity with kinematics
        $v_{k+\Delta k}^i \leftarrow \min(v_{\max}, \overline{v_{k+\Delta k}^i})$;
        compute $\omega_{k+\Delta k}^i$;
            if shared information updated by neighbor **then**
                compute next expected position;
            endif
until succeed in search

5.2 Deployment of Measuring Points

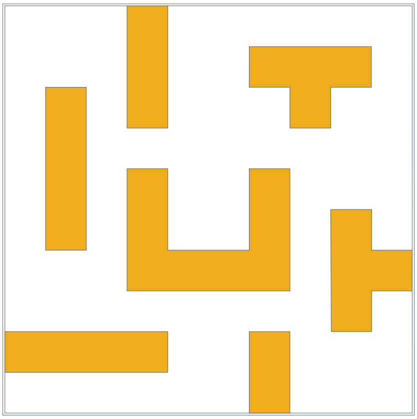
We set a series of measuring points, assigning one with each sub-area. Different points are different far away from the source. Note that a pair of points in different areas having the same distance value are arranged to study the relation between fusions at the same time.

5.3 Main Parameter Settings

We simulate signals fusion using parameter configuration $a = 1$, $b = 0.001$, $c = 1$, $\lambda_C = 0.2055$, $\lambda_{RF} = 0.0156$. For convenience, target is fixed to $(0, 0)$ all time and the coordinates of six measuring points are $(100, 40)$, $(150, 0)$, $(40, 0)$, $(20, 0)$, $(0, 35)$, $(0, 20)$ orderly. Meanwhile, we focus on if the coverage of all joint events occur in sufficient long time rather than the moments.

5.4 Map Processing

In study on path planning of autonomous robotics, how to represent the working space, i.e., how to model the space is one of the important problems. Based on the difference of sensing to environment, modeling approaches to known or unknown map fall into two ones. Here we model working space for swarm robots with digit image processing technology. The obstacle information relative to each point in search space is expressed with a two-dimensional arrays. Of representative symbols, 0 represents passable point and 1 passless. The Fig. 10 is the example of mapping processing.



(a) Original Map

0	0	0	1	0	0	0	0	0	0
0	0	0	1	0	0	1	1	1	0
0	1	0	1	0	0	0	1	0	0
0	1	0	0	0	0	0	0	0	0
0	1	0	1	0	0	1	0	0	0
0	1	0	1	0	0	1	0	1	0
0	0	0	1	1	1	1	0	1	1
0	0	0	0	0	0	0	0	1	0
1	1	1	1	0	0	1	0	0	0
0	0	0	0	0	0	1	0	0	0

(b) Digitizing

Fig. 10. Working Space for Swarm Robotic Search

5.5 Obstacle Avoidance Planning

Based on the fusion method, we run the swarm robotic search algorithm having a specific function of path planning. The unequal sized swarms ($N = 3,\ 5,\ 8,\ 10$) are used, repeated the algorithm running for ten times respectively. Then, the statistics about total distance and time elapsed in different cases are collected to support our presented method.

5.6 Results and Discussions

Conducting the above simulations repeatedly, we can get the following results. And then we may hold discussions and draw some conclusions.

- The fused values in simulation are shown in Fig. 11, from which robots can "find" out the best positions by simple election operation. It's perceptible that the bigger the fusion value, the nearer the measuring point from target. At the same time, it is observed that as for No. 4 and No. 6 points, the fusion results are the same in cases of $Source = 001, 010, 011$, and different in cases of $Source = 101, 110, 111$ although they are equal to distance of target. We may explain it in this manner: robots searching for target depend on measurements because they do not know the position of target. While the two points are located in different sub-areas, the situation of signals cover is different.

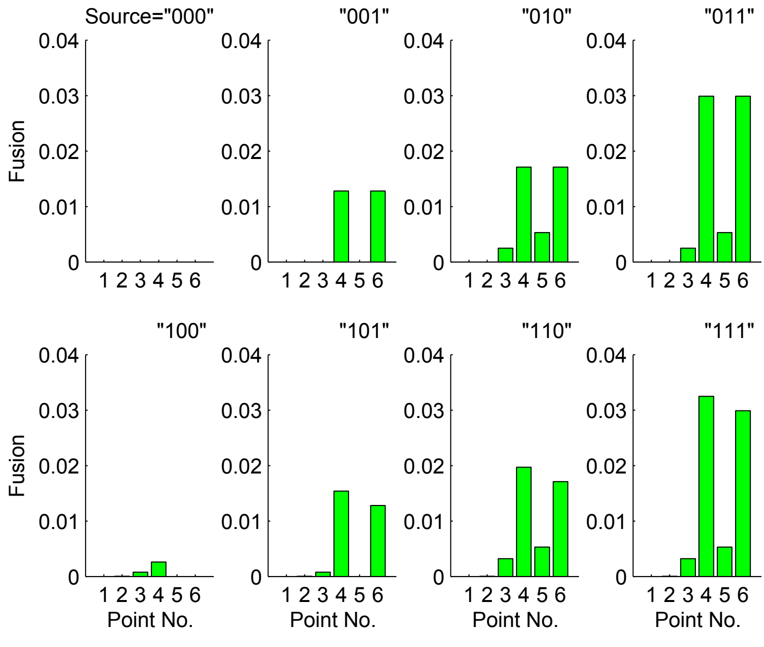
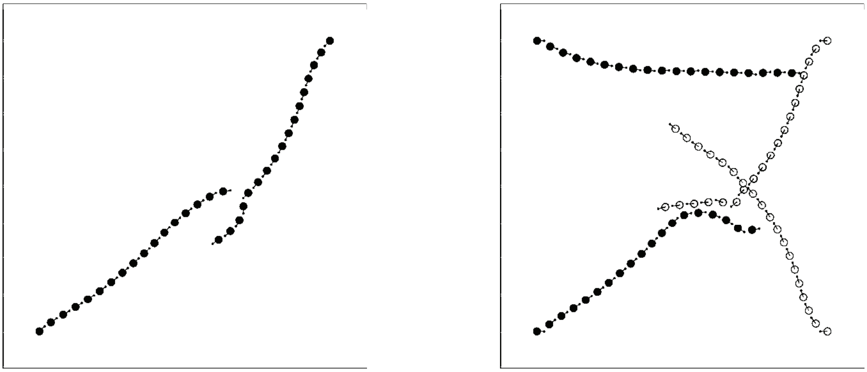


Fig. 11. Fusion results at the assigned six measuring points under different encodes of information source. Note that the title Source="000" of the left corner sub-figure represents no GAS, no RF, and no CALL signals are emitted when sampling. One can understand the other cases in a similar manner. Besides, the fusion is a scalar value without any physical meaning.

- Fig. 12 shows the scenario of two robots decide their respective motion behaviors with modified APF method to plan paths for obstacle avoidance.



(a) 2-Rob (b) 4-Rob

Fig. 12. Obstacle Avoidance between Unequal Sized Robots with Sensor-Based APF Method

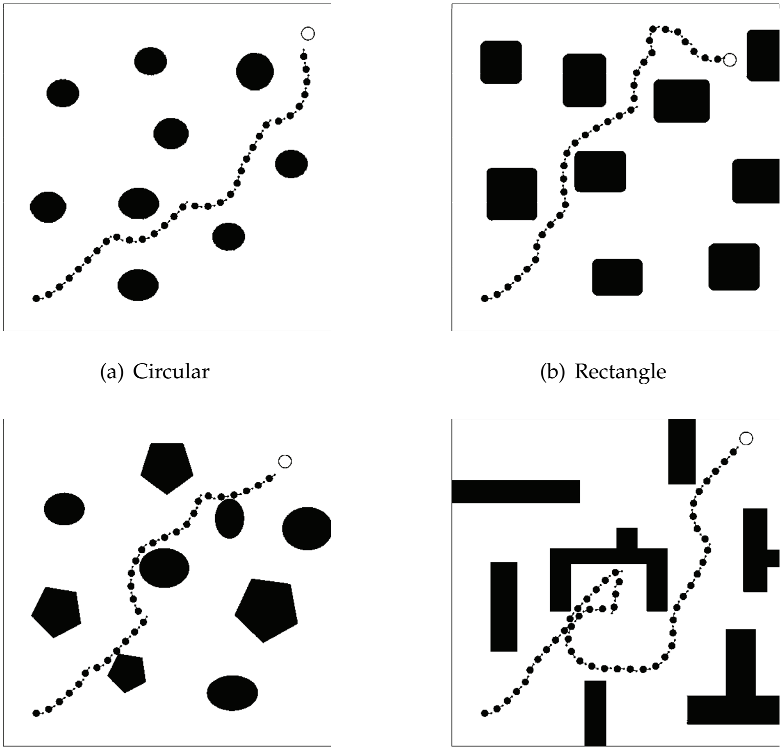
Swarm Size	Average Time	Average Total Distance
3	278	1930
5	232	2410
8	197	3136
10	184	4380

Table 4. Statistics from Search for Target Simulations

- Fig. 13 shows the scenario of one single robot planning its path using multiple sensor-based APF method without obstacle collision to search for target successfully under different conditions of obstacle types.
- Consider the total displacements and time (iterative generations) when the search succeeds. The statistical results shown in Tab. 4 and the relations between average distance/generations and swarm size are charted as Fig. 14.

6. Conclusions

As for PSO-type control of swarm robots, the experience both of individual robots and of population is required. In order to decide the best positions, we take the characteristic information of target, such as intensity or concentration of different signals emitted by target, as the “fitness”. Therefore, the problem of multi-source signals fusion is proposed. To this end, we model the process of signals measurement with robot sensors as virtual communication. Then, the detected target signals can be viewed as transmitted encodes with respect to information source. We thereupon present some concepts of binary logic and perceptual event to describe the “communication“ between target and robots. Besides, we also put forward information entropy-based fusion criteria and priority to fuse signals and election mechanism



(a) Circular (b) Rectangle

(c) Allotype (d) Complicated

Fig. 13. Single Robot Move to the Potential Target with Path Planning

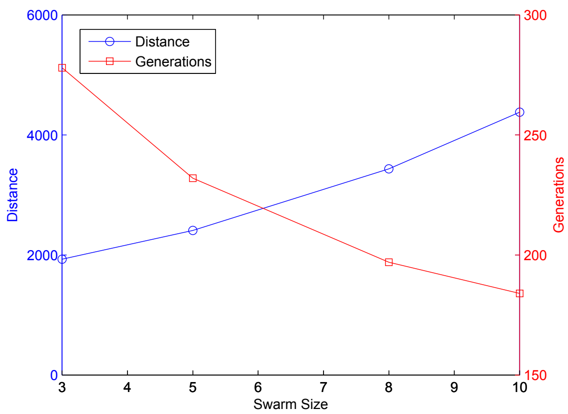


Fig. 14. Relations between Average Distance/Generations and Swarm Size

to decide the best positions on the basis of space-time distribution properties of target and robots. Simulation conducted in closed signal propagation environment indicates the approximate relation between fusion and distance, i.e., the nearer the robot is far away from target, the higher the fusion of signals. Also, a modified artificial potential field method is proposed based on the multiple sensor structure for the space resource conflict resolution. The simulation results show the validity of our sensor-based APF method in the process of search for potential target.

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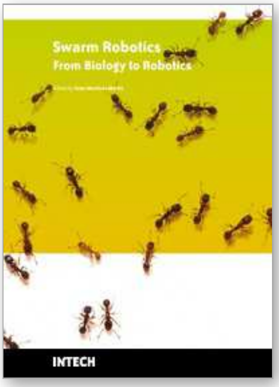

Swarm Robotics from Biology to Robotics
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In nature, it is possible to observe a cooperative behaviour in all animals, since, according to Charles Darwin's theory, every being, from ants to human beings, form groups in which most individuals work for the common good. However, although study of dozens of social species has been done for a century, details of how and why cooperation evolved remain to be worked out. Actually, cooperative behaviour has been studied from different points of view. Swarm robotics is a new approach that emerged on the field of artificial swarm intelligence, as well as the biological studies of insects (i.e. ants and other fields in nature) which coordinate their actions to accomplish tasks that are beyond the capabilities of a single individual. In particular, swarm robotics is focused on the coordination of decentralised, self-organised multi-robot systems in order to describe such a collective behaviour as a consequence of local interactions with one another and with their environment. This book has only provided a partial picture of the field of swarm robotics by focusing on practical applications. The global assessment of the contributions contained in this book is reasonably positive since they highlighted that it is necessary to adapt and remodel biological strategies to cope with the added complexity and problems that arise when robot individuals are considered.