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Randomized Robot Trophallaxis

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1. Introduction

Energy is the critical resource of most living mechanisms. Recent research in robotics has been mostly considered in behavioural autonomy rather than in energy autonomy. This chapter presents our study in "randomized robot trophallaxis". The chapter consists of three main parts: modeling, simulation, and implementation.
In the first section, we model energy trophallaxis in multi-robot system through probabilistic modelling. Deterministic modelling of large groups of interacting mobile robots leads to highly complex nonlinear hybrid models, likely to be highly sensitive to pre-conditions, i.e. chaotic. Thus, any imprecision in pre-conditions would turn results from such a model useless even for moderate time horizons. However, chaotic systems often exhibit smooth ergodic properties, i.e. time averages have limit values independent of initial conditions and only smoothly dependent on model parameters, etc. Randomness and ergodic properties may exist naturally in such systems or even be intentionally enforced by introducing inherent uncertainty/randomization into the behaviour of individual robots in order to prevent non productive cyclic behaviour such as deadlock or livelocks. Ergodic properties and randomness calls for probabilistic modelling. We propose a combined probabilistic model covering energy exchange between robots, energy consumption in individual robots, charging at predefined charging stations and finally random mobility, where the latter comes in the shape of highly versatile Markovian mobility model. Stationary results furnish overall system performability analysis, such as the impact of individual behaviour on overall system survivability. The section presents the proposed model and comprises central parts of model development as well as illustrative numerical results.
In the second section, we simulate aspects of energy autonomy inspired by natural phenomena of animal behaviour. Trophallaxis is a natural phenomenon, biologically observed from social insects or vertebrate animals, to exchange food between colony members. This section describes the concept, "Randomized Robot Trophallaxis", based on a group of autonomous mobile robots with capabilities of self-refueling energy and self-sharing energy. We firstly clarify the concept "Randomized Robot Trophallaxis" by given examples of natural animal societies. Secondly, we examine the concept by simulation results in order to point out considerable advantages of trophallactic features when deploying multiple mobile robots. The section is concluded with discussion of "randomization" and its appearances in multi-robot system.

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In the third section, we mainly present hardware implementation of our mobile robots capable of performing not only self-refueling energy but also self-sharing energy. We describe the mechanical and electrical design of a mobile robot, called the CISSbot[1]. The robots are designed towards truly autonomous robots in large populations through energy trophallaxis. Unlike present mobile robots, the CISSbots are energetically autonomous robots because they are able to not only autonomously refuel energy by picking batteries up at a charging station, but also share energy by exchanging batteries to other robots. The CISSbots basically consist of their own processing power, sensors, and actuators. However, to achieve the capability of battery exchange, the CISSbots need a special design of battery exchange mechanism. In this section, we present the realization of the design, both the mechanics and the electronics of the CISSbot. Details on battery exchange technique and power management are clarified. Finally, the section issues an outline of our future work on the CISSbots.

2. A Probabilistic Model of Randomized Robot Trophallaxis

2.1 An Introduction to Probabilistic Modelling

Various mathematical modelling paradigms exist for dynamical systems, which all aim to provide system predictability, i.e. answer questions regarding future state of the system evolving from some initial state or set of initial states. The appropriate model paradigm depends highly on the nature of the questions to be answered, i.e. the scope of required information as well as the form of the answer provided by the model. In the present case, we ask for distribution of energy resources throughout the population of mobile robots as well as the survival state of the population, i.e. how many robots have survived energy starvation over a certain time frame. Of particular interest is the impact, that individual robot behaviour may have on energy distribution and survival.

Any such model should include all aspects of robot behaviour suspected to impact population state. Here we suggest: mobility, energy sharing policy and recharging as well as energy consumption.

Deterministic models appear as differential equations, as discrete state transition systems or combinations of the two former when hybrid modelling is applied. Common to deterministic models is their ability to provide exact answers to exactly formulated questions. That is, when all pre-conditions are exactly stated the future may be exactly predicted. When pre-conditions are only partly known, non-deterministic modelling in the shape of differential inclusions or non-deterministic state transition systems, may be applied. The precision of non-deterministic models follows the precision by which pre-conditions are given.

From a deterministic modelling perspective, large groups of interacting mobile robots correspond to a highly complex nonlinear hybrid model, which is likely to be highly sensitive to pre-conditions, i.e. chaotic. Thus, any imprecision in pre-conditions would turn results from such a model useless even for moderate time horizons. On the other hand chaotic systems like large interacting robot populations are likely to possess so called *mixing* properties. Mixing implies, that from partly known pre-conditions, almost any future development is possible even within moderate time horizons. Thus precision of answers

[1] CISSbot is abbreviated from our center in Danish: Center for Indlejrede Software Systemer (CISS). http:// www.ciss.dk

from non-deterministic models of mixing systems rapidly deteriorates with time. Chaotic systems with mixing properties often exhibit smooth *ergodic* properties, i.e. time averages have limit value independent of initial conditions and only smoothly dependent on model parameters. In other words such systems exhibit predictable statistics. Mixing or ergodic properties may be enforced onto the system by introducing uncertainty/randomization into the behaviour of individual robots. This may prevent the overall system from getting stuck in non productive cyclic behaviour such as deadlock or live locks. As an example randomization is used for wireless access protocols and suggested for the so called *leader election* problem.

Based on the previous arguments we suggest a probabilistic model for trophallaxis among mobile robots including mobility, energy sharing policy and recharging as well as energy consumption. Such a model may serve as the basis for long term stochastic simulation, in which case ergodic properties become critical w.r.t. the meaningfulness of the obtained results. On the other hand, the model may be mathematically tractable, allowing for direct numerical assessment of the coupling between individual behavioural parameters and overall system state. Such a model is presented below.

2.2 Modelling

The developed model aims to combine the effects of all the influential mechanisms associated to trophallaxis in mobile robot populations: mobility, resource sharing, charging and resource consumption. Initially separate models are developed for each of the above effects, which are then assumed additive and conditionally independent given instant system state. System state is defined to be the position $x_i(t)$ of every robot i, its velocity $v_i(t)$ as well as its energy resource $b_i(t)$.

Since we aim for a probabilistic model, exact values of x_i, v_i and b_i are not tracked. Instead the developed model follows the evolution of the distribution of these random variables and in particular the distribution obtained in stationarity. Non parametric equations are developed for distributions of x_i and v_i, whereas the distribution for b_i is described in terms of 1 st. and 2 nd. moments. To ease exposition, velocities are assumed to take values within a discrete set.

Each separate model for resource sharing, charging and consumption are given as integro-differential equations governing the time evolution of the conditional expectation $b_i(t,x,v) = E(b_i(t)|x_i(t) = x, v_i(t) = v)$ of the resource $b_i(t)$ carried by robot i, given it is located at x at time t, with velocity v. Likewise a second moment model is developed for the time evolution of the conditional variance $V_i(t,x,v) = VAR(b_i(t)|x_i(t) = x, v_i(t) = v)$.

2.2.1 Mobility

Robot populations may be distributed randomly over some domain D, or they may be deployed according to some predefined plan. Additionally robots may be stationary or mobile, e.g. a subset of robots may be assigned highly stationary tasks, whereas a majority of units would be mobile.

A model of robot distribution should account for both deterministic deployment and random distribution. We assign to each robot i the time dependent probability measure L_i of location, i.e. $L_i(A,t)$ expresses the probability that node i is located within the subset A of D, at time t. Adding up for the entire set of nodes yields the additive positive measure L, i.e.

$$L(A,t) = \sum_i L_i(A,t) \tag{1}$$

where $L(A,t)$ expresses the expected number of robots within A at time t. Joint location and velocity measure is assumed to be expressed as

$$L_i(A \times W, t) = \int_A L_i(W|x,t) f_L^i(x,t)dx \tag{2}$$

i.e. position distribution is described by a density f_L^i, whereas velocity has a general conditional distribution $L_i(W|x)$. The notation L_i is consistently used for kinetic state (position and velocity) distribution of robot i. The corresponding argument list indicates the specific perspective in question.

Mobility affects resource distribution in two ways; it changes robot location distribution over time and secondly it changes the conditional resource distribution over time. The former effect is considered in this section whereas the latter is presented in the next section based on the stationary location distribution obtained in this section. Several mobility models exist, including deterministic as well as random movement. Among others we find the *Random waypoint*[Bettstetter et al, 2004], *Random direction* and *Random trip*[Le Boudec et al, 2005] an overview is presented in [Camp et al, 2002]. In this work we consider mobility models both suited for probabilistic modelling of which a special case is Brownian motion [Øksendal et al, 2003]. Brownian motion is characterized by its lack of velocity persistence, i.e. units move without memory of previous direction and speed. A more elaborate model is presented subsequently, which includes velocity persistence.

2.2.2 Less Drunk Model

The Less Drunk Model (LDM) is as Brownian motion a Markovian mobility model, where velocity remains constant between instants $.., t_{-1} t_0, t_1, ..$ of velocity change. Time intervals of constant velocity have random exponentially distributed length, where the intensity parameter λ may depend on position, velocity and time. At an instant t_n of velocity change, a future velocity is selected randomly and independently from a probability distribution L_Q assumed to depend on position.

So equipped we may deduce the following location distribution dynamics

$$\begin{aligned} & \frac{d}{dt}(L_i(W|x,t) \cdot f_L^i(x,t)) \\ = \quad & \lambda(x)(L_Q(W,x) - L_i(W|x,t)) f_L^i(x,t)) \\ - \quad & \int_W < v, D_x[L_i(dv|\cdot,\cdot) f_L^i](x,t) > \end{aligned} \tag{3}$$

where <,> denotes inner product. The second term generalises continuous and discrete parts of L_i, i.e.

$$\begin{aligned} & \int_W < v, D_x[L_i(dv|\cdot,\cdot) f_L^i](x,t) > \\ & = \int_W < v, D_x[f_i(dv|\cdot,\cdot) f_L^i](x,t) > \\ & + \sum_{v_j \in W} < v, D_x[L_i(\{v_j\}|\cdot,\cdot) f_L^i](x,t) > \end{aligned}$$

As an example, L_Q may for all x concentrate probability on a discrete set of velocities $\{v_j\}$. Letting $W = \{v_j\}$ gives

$$\begin{aligned} & \frac{d}{dt}(L_i(\{v_j\}|x,t) \cdot f_L^i(x,t)) \\ = \; & \lambda(x)(L_Q(\{v_j\},x) - L_i(\{v_j\}|x,t))f_L^i(x,t) \\ - \; & < v_j, D_x[L_i(\{v_j\}|\cdot,\cdot)f_L^i](x,t) > \end{aligned} \tag{4}$$

Confinement of motion to a Consider a one-dimensional example, where velocities assume values 1 and -1.

$$\begin{aligned} L_Q(\{1\},x) &= 1/2 \text{ for } -1 \le x \le 1 \\ &= 0 \text{ for } x > 1 \\ &= 1 \text{ for } x < -1 \\ L_Q(\{-1\},x) &= 1/2 \text{ for } -1 \le x \le 1 \\ &= 0 \text{ for } x < -1 \\ &= 1 \text{ for } x > 1 \end{aligned} \tag{5}$$

for a constant value $\lambda(x) = \lambda$ for x outside $[-1,1]$ (4) possesses the following particular stationary solution

$$\begin{aligned} L_i(\{-1\}|x,t)f_L^i(x,t) = L_i(\{-1\}|x,t)f_L^i(x,t) \\ = C_0 \quad \text{for } x \in [-1,1] \\ = C_0 \; exp(\lambda(x-1)) \quad \text{for } x \in (-\infty,-1) \\ = C_0 \; exp(\lambda(1-x)) \quad \text{for } x \in (1,\infty) \end{aligned} \tag{6}$$

where $C_0 = 1/4(1 + 1/\lambda)$ is found from normalization. Stationary solutions for various λ values are shown in figure (1). For large λ, C_0 is approximately $1/4$ and $f_L^i(x,t) = 1/2$ in side D.

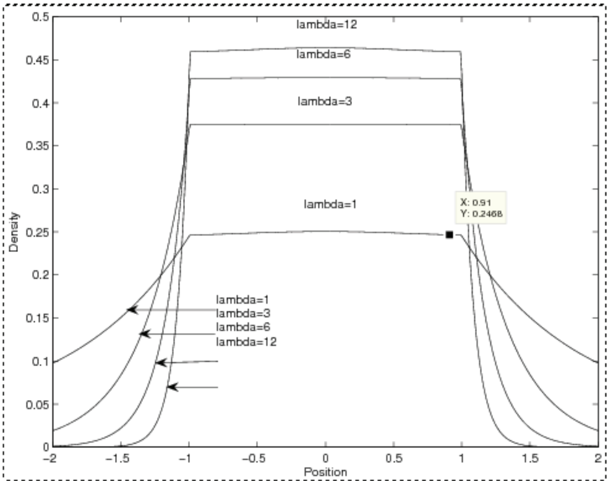

Figure 1. Stationary location densities for various λ-values

2.2.3 Mobility Impact on Energy Distribution

Consider a small sub domain A at times t and $t+\delta$. Not considering exchange nor consumption, the amount of energy resources carried by robot i in A at time $t+\delta$ is identical to the amount of resources moving (along with robot i) into $A \times \{v_j\}$ during $[t, t+\delta]$. The expected energy resource $E_{A\times\{v_j\}}(t+\delta)$ in $A \times \{v_j\}$ at time $t+\delta$, is expressed through the conditional resource given position and velocity $b_i(t,x,v)$, i.e.

$$E_{A\times\{v_j\}}(t+\delta) = \int_A b_i(t+\delta, x, v_j) L_i(\{v_j\}|x) f_L^i(x) dx (2.3.1) \tag{7}$$

whereas the amount carried into $A \times W$ by i is found by conditioning on position and velocity x' and v' at time t and marginalizing, i.e.

$$\begin{aligned} &E_{A\times\{v_j\}}(t+\delta) \\ &+(1-\lambda\delta)\int_A b_i(t, x-v_j\delta, v_j) f_L^i(x-v_j\delta)\ L_i(\{v_j\}|x-v_j\delta)\ dx \\ &+\lambda\delta\int_A L_Q(\{v_j\},x)\sum_k\ b_i(t, x-v_k\delta, v_k) f_L^i(x-v_k\delta)\ L_i(v_k|x-v_k\delta)\ dx \end{aligned} \tag{8}$$

Equating expressions (7) and (8) for every subset A and differentiating w.r.t. δ, we may show that $b_i(t,x,v)$ fulfils

$$\begin{aligned} &f_L^i(x) L_i(\{v_j\}|x)\ \frac{d}{dt} b_i(t,x,v_j) \\ &= -< v_j, D_x[b_i\ f_L^i\ L_i](t,x,v_j) > \\ &\quad + \lambda\ (L_Q(\{v_j\},x)\ b_i(t,x) -\ L_i(\{v_j\}|x)\ b_i(t,x,v_j)) f_L^i(x) \end{aligned} \tag{9}$$

where

$$b_i(t,x) = \sum_k b_i(t,x,v_k) L_i(\{v_k\}|x) \tag{10}$$

Equivalent results can be found for then conditional second moment $b2_i$

$$\begin{aligned} &f_L^i(x) L_i(\{v_j\}|x)\ \frac{d}{dt} b2_i(t,x,v_j) \\ &= -< v_j, D_x[b2_i\ f_L^i\ L_i](t,x,v_j) > \\ &\quad + \lambda\ (L_Q(v_j,x)\ b2_i(t,x) - L_i(\{v_j\}|x)\ b2_i(t,x,v_j)) f_L^i(x) \end{aligned} \tag{11}$$

2.2.4 Numerical Example

We continue the numerical example from above and extend it with expressions and results for energy distribution. We assume the stationary solution (6) for $f_L^i\ L_i$ for each robot i. Likewise we assume λ to be high outside D and thereby neglecting movement outside D. Thus we have $f_L^i\ L_i = 1/4$ inside D and zero outside. Likewise

$$\begin{aligned} &< v_j, D_x[b_i\ f_L^i\ L_i](t,x,v_j) > = 1/4 < v_j, D_x[b_i](t,x,v_j) > \\ &< v_j, D_x[b2_i\ f_L^i\ L_i](t,x,v_j) > = 1/4 < v_j, D_x[b2_i](t,x,v_j) > \end{aligned} \tag{12}$$

altogether we have from (9) and (11)

$$\frac{d}{dt}b_i(t,x,v_j) = - < v_j, D_x[b_i](t,x,v_j) > +\lambda\ (b_i(t,x) - b_i(t,x,v_j))$$
$$\frac{d}{dt}b2_i(t,x,v_j) = - < v_j, D_x[b2_i](t,x,v_j) > +\lambda\ (b2_i(t,x) - b2_i(t,x,v_j)) \quad (13)$$

Inserting discrete velocities $\{1\}$ and $\{-1\}$ gives

$$\begin{aligned}\frac{d}{dt}b_i(t,x,-1) &= b_i'(t,x,-1) + \lambda/2(b_i(t,x,1) - b_i(t,x,-1))\\ \frac{d}{dt}b_i(t,x,1) &= -b_i'(t,x,1) + \lambda/2(b_i(t,x,-1) - b_i(t,x,1))\\ \frac{d}{dt}b2_i(t,x,-1) &= b2_i'(t,x,-1) + \lambda/2(b2_i(t,x,1) - b2_i(t,x,-1))\\ \frac{d}{dt}b2_i(t,x,1) &= -b2_i'(t,x,1) + \lambda/2(b2_i(t,x,-1) - b2_i(t,x,1))\end{aligned} \quad (14)$$

revealing that, when mobility is studied in isolation, stationary solutions for expected battery resources as well as second moments are constant over D, which coheres well with intuition.

2.2.5 Energy Transfer

Energy exchange is in this work considered to be an unplanned epidemic process, i.e. transfer of energy between robots take place during accidental rendezvous. Epidemic propagation is previously studied in other contexts, such as disease spread [Medlock et al, 2003] and information spread [Schiøler et al, 2005],[Moreno et al, 2004]. All mobile units are assumed to move randomly in patterns generated by a Less Drunk mobility process as described above. When two robots come within a suitable (not too large) distance to each other, conditions promote energy exchange as illustrated in figure (2).

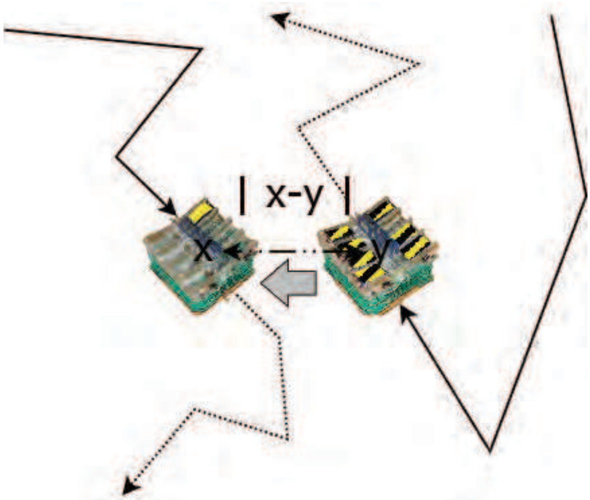

Figure 2. Two robots in accidental rendezvouz, candidating for energy exchange

More precisely two robots i and j positioned at positions $x = x_i$ and $y = x_j$ respectively are assumed to engage in a battery exchange within the time interval $[t, t + dt]$ with a probability $\alpha\ dt\ K(x_i, x_j)$, where α is a rate parameter and $K$is a *neighbourhood kernel* modelling the dependence of relative/absolute positions on exchange probability. The decision to engage in battery exchange is taken randomly and represented by the random Boolean selector Ce_{ij}, where $P(Ce_{ij}) = \alpha\ dt\ K(x_i, x_j)$. At time t robots i and j mutually communicate remaining battery resources $b_i(t)$ and $b_j(t)$ respectively. The final choice of battery exchange is taken randomly and represented by the random Boolean selector Cf, where

$$P(Cf_{ij}) = C|b_i(t) - b_j(t)| \tag{15}$$

where C is chosen, so that $P(C_f) \leq 1$ always. If exchange is decided, a fixed size quantity Q is exchanged, where $Q = |Q|\ sign(b_j(t) - b_i(t))$. Altogether the exchange dynamics for two robots can be written as

$$b_i(t + dt) = b_i(t) + Ce_{ij}\ Cf_{ij}\ |Q|\ sign(b_j(t) - b_i(t)) \tag{16}$$

Potentially i may exchange batteries with every other robot j in the entire population, so the overall exchange dynamics can be written like

$$b_i(t + dt) = b_i(t) + \sum_{j \neq i} Ce_{ij}\ Cf_{ij}\ |Q|\ sign(b_j(t) - b_i(t)) \tag{17}$$

When robot positions are unknown, a location measure L_i is associated to each robot i. Likewise we define $b_i(t, x, v)$ to be the conditional expectation of $b_i(t)$ given i is positioned at x with velocity v at time t. Thus from (16)

$$\begin{aligned} b_i(t + dt, x, v) &= b_i(t, x, v) + |Q| \sum_{j \neq i} E[Ce_{ij} Cf_{ij}\ sign(b_j(t) - b_i(t))] \\ &= b_i(t, x, v) + |Q| C\alpha dt \sum_{j \neq i} E[K(x, x_j)|b_j(t) - b_i(t)| sign(b_j(t) - b_i(t))] \\ &= b_i(t, x, v) + |Q| C\alpha dt \sum_j \int_D K(x, y^{x_j}) b_j(t, y) - b_i(t, x, v)) L_j(dy) \end{aligned} \tag{18}$$

Where velocity is marginalized away in b_j, i.e.

$$b_j(t, y) = \int b_j(t, y, v) L_j(dv|x) \tag{19}$$

Adding location measures ($L = \sum_j L_j$), leads from (18) to

$$\begin{aligned} \frac{d}{dt} b_i(t, x, v) = &|Q| C\alpha \sum_j \int_D K(x, y) b_j(t, y) L_j(dy) \\ &- |Q| C\alpha\ b_i(t, x, v) \int_D K(x, y) L(dy) \end{aligned} \tag{20}$$

and for the conditional second moment $b2_i(t,x,v)$ of $b_i(t)$ given position x and velocity v at time t.

$$\begin{aligned}&\frac{d}{dt}b2_i(t,x,v) = \\ &2|Q|C\lambda\ (b_i(t,x,v)\sum_j\int_\Omega K(x,y)b_j(t,y)L_j(dy) - b2_i(t,x,v)\int_\Omega K(x,y)L(dy)) \\ &+|Q|C\lambda\ \sum_j\int_\Omega K(x,y)|b_j(t,y)-b_i(t,x,v)|L_j(dy)\end{aligned} \tag{21}$$

2.2.6 Charging Station

Charging stations may be considered as only robot units serving special objectives. Formally we define a robot i to be a charging station, when $i \in CS$, where CS is the index subset for charging stations.

Specific to charging stations is the fact, that batteries should never be received by these, and additionally that they may move according to a specific mobility patterns. With respect to the former exception we exclude from the model the resource level of charging stations and simply assume resource levels always to assume an upper bound, i.e. $b_i(t,x)=\bar{b}\ \ \forall\ t,x$. This excludes the possibility of battery units to be handed over to charging stations. Likewise it may be desirable to have separate control of the exchange rate from the charger. Thus we set the exchange rate parameter for the charger by $\alpha_C = r_C\alpha$, where r_C is a positive real typically > 1.

Regarding mobility of charging stations, they may as a first suggestion be stationary at known locations. Location measure L_i for a charging station is in, this case, concentrated at a particular point x_C, i.e. $L_i(\{x_C\})=1$. Even for stationary charging stations, locations may be unknown, in which case locations are specified according to some a priori measure L_i. For non stationary charging stations some mobility model may be assumed and L_i may be time dependent converging to a stationary measure as for robot units.

2.2.7 Example

Continuing the above example we have for mobile units $L_j(A)=|A|/|D|$. Furthermore we assume $b_i(t,x,v)=b(t,x,v)$ for all mobile units i, whereas $L_i(A)=I_A(x_c)$ and $b_i(t,x,v)=\bar{b}$ for a single charging station located at a fixed position x_C. Assuming N robots equations (20) and (21) yield

$$\begin{aligned}&\frac{d}{dt}b(t,x,v) \\ &= |Q|C\alpha N/|D| \\ &\cdot\int_D K(x,y)\ (\frac{b(t,y,\{-1\})+b(t,y,\{1\})}{2} - b(t,x,v))\ dy \\ &+|Q|C\alpha\ r_C\ K(x,x_C)(\bar{b}-b(t,x,v))\end{aligned} \tag{22}$$

and for the conditional second moment $b2(t,x,v)$

$$
\begin{aligned}
&\frac{d}{dt}b2(t,x,v) = \\
&-2|Q|C\alpha\ b2(t,x,v)(N/|D|\int_D K(x,y)dy + r_C\ K(x,x_C)) \\
&+2|Q|C\alpha\ 2b(t,x,v) \\
&\cdot(N/|D|\int_D K(x,y)\frac{b(t,y,\{-1\})+b(t,y,\{1\})}{2}\ dy + r_C\bar{b}K(x,x_C)) \\
&+|Q|C\alpha \\
&\cdot(N/|D|\int_D K(x,y)|b_j(t,y)-b_i(t,x,v)|dy \\
&+r_C\ K(x,x_C)|\bar{b}-b_i(t,x,v)|)
\end{aligned}
\tag{23}
$$

2.2.8 Energy Consumption

Various models for energy consumption in mobile robotics are suggested in literature [Mei et al, 2006a, 2006b]. In this case choosing a suitable model involves a trade-off between precision and mathematical tractability. The rate of energy consumption may depend on various parts of the system state, i.e. on aspects of the state of the entire population as well as the state of the individual robot. Since robots may be equipped with energy preserving activity policies, their individual activity may depend on their remaining energy resources. Taking such behaviour into account may be achieved by letting consumption rate depend on remaining resources. In this case we suggest a Poisson modulated model, i.e.

$$
b_i(t) = b_i(0)\cdot exp^{-n}(-r/\gamma)\quad \text{for}\quad t\in[t_n,t_{n+1}]
\tag{24}
$$

where $\{t_n\}$ is an increasing Poisson generated sequence of time instants, where remaining battery resources are discounted through multiplication by $exp(-r/\gamma) < 1$ so that (2.8.1) exhibits an expected exponential consumption profile, i.e.

$$
\begin{aligned}
&E(b_i(t)|x_i(t)=x, v_i(t)=v) = b_i(t,x,v) \\
&= b_i(0,x,v)\cdot exp(-\gamma t(1-exp(-r/\gamma))
\end{aligned}
\tag{25}
$$

which, for large values of γ can be approximated by

$$
b_i(t,x,v) = b_i(0,x,v)\cdot exp(-rt)
\tag{26}
$$

For our Poisson modulated consumption model (23), we may deduce

$$
\begin{aligned}
&\frac{d}{dt}b_i(t,x,v) = \gamma\ (exp(-r/\gamma)-1)\ b_i(t,x,v) \\
&\frac{d}{dt}b2_i(t,x,v) = \gamma\ (exp(-2r/\gamma)-1)\ b2_i(t,x,v)
\end{aligned}
\tag{27}
$$

which for large values of γ can be approximated by

$$
\begin{aligned}
&\frac{d}{dt}b_i(t,x,v) = -r\ b_i(t,x,v) \\
&\frac{d}{dt}b2_i(t,x,v) = -2r\ b2_i(t,x,v)
\end{aligned}
\tag{28}
$$

2.2.9 Complete Model

A complete model is presented which combines the effects of mobility, energy exchange and energy consumption. The developed model assumes the shape of integro-differential equations governing the time evolution of the conditional expectation $b_i(t, x, v)$ of the battery resource $b_i(t)$ of robot i given this robot is located at position x at time t, with velocity v. Likewise integro-differential equations for the conditional variance $b2_i(t, x, v) = E(b_i^2(t))$ are given. The model is developed for stationary location distributions.

All individual model parts (mobility, exchange, consumption) are developed from elementary dynamics giving $b_i(t+\delta)$ from $b_i(t)$ for an infinitesimal time step δ, i.e. $b_i(t+\delta) = b_i(t) + D_M(\delta)$, $b_i(t+\delta) = b_i(t) + D_E(\delta)$, $b_i(t+\delta) = b_i(t) + D_C(\delta)$, where D_M, D_E and D_C are random variables modelling randomized mobility, energy exchange and energy consumption respectively. Thus the complete integro-differential equation for conditional expectation is found as

$$\frac{d}{dt}(b_i(t, x, v)) = \frac{d}{d\delta}E[D_M(\delta)] + \frac{d}{d\delta}E[D_E(\delta)] + \frac{d}{d\delta}E[D_C(\delta)] \tag{29}$$

D_M, D_E and D_C are assumed independent, being continuous at $\delta = 0$ and having 1st. and 2nd. moments with finite non-zero 1st. derivatives at $\delta = 0$. This allows aggregation of separate model components for conditional 2nd. moments by addition i.e.

$$\frac{d}{dt}b2_i(t, x, v) = \frac{d}{d\delta}E[D_M^2(\delta)] + \frac{d}{d\delta}E[D_E^2(\delta)] + \frac{d}{d\delta}E[D_C^2(\delta)] \tag{30}$$

2.2.10 Example

The complete model is illustrated by examples combining the previous examples in this chapter. It is not possible to provide an overview of results for the entire parameter space, so therefore only a few illustrative examples are shown. Parameter settings for the provided examples are selected below to mimic a realistic situation. It is basically assumed that all robots inhabit a one-dimensional domain of operation $D = [-1, 1]$ and move with two possible speeds $\{-1, 1\}$. Thus crossing the entire domain without speed changes lasts 2 time units.

For the mobility parameter λ we assume robots to change velocity 10 times for each such 2 time units, i.e. $\lambda = 5$.

In order for an energy propagation mechanism to be worthwhile, a significant power loss should be associated with travelling from the peripheral of the domain of operation to the charger. Thus we assume, that a direct travel half way across D discounts the energy resources by 2/3, i.e. $exp(-r) = 0.3$ or $r \approx 1$.

Regarding energy exchange, we normalize the charger resource by $\bar{b} = 1$ defining an upper bound for b_i. In accordance we set $C = 1$ and $Q = 1/10$, that is, the energy quantum exchanged is far lower than the upper bound for remaining resource. The neighbourhood kernel K is assumed to allow energy exchange within a fixed distance $d = 0.1$, i.e. $K(x, y) = I_{|x-y|<0.1}$. The charging process is assumed to be faster than the energy consumption process. Thus we set $\gamma < \alpha_C = 40$. The mutual robot exchange rate α is varied to illustrate its effect on energy distribution. A charger placed at a fixed location $x_C = 0$ serves $N = 50$ robots.

2.11 Survivability

Energy resources at each robot needs to be above a certain critical lower level L to maintain robot functionality. Below this level robots are no longer capable of moving, communicating or exchanging energy. Thus energy levels below L implies irreversible entrance to a *death* state. The suggested consumption model above prescribes consumption to take place at discrete moments $\{t_n\}$ in time, where energy resources are discounted by a factor $exp(-r/\gamma)$. Every robot holding an energy level less than $Lexp(r/\gamma)$ is therefore a candidate for entering the death state at the next discrete consumption instant t_n. Since $\{t_n\}$ is assumed to be a homogeneous Poisson process with intensity γ the death rate associated to such a robot is γ. Likewise we may find the overall expected death rate ρ_D of the population by

$$\rho_D = P(b(t) \leq L\ exp(r/\gamma))\ N\ \gamma \tag{31}$$

Approximating the conditional stationary distribution of $b_i(t)$ by a normal distribution we get

$$\rho_D = \int_D erf(L\ exp(r/\gamma) \cdot \sigma_i(x,v) - b_i(x,v)) L_i(dv|x) f_i(x) dx\ N\ \gamma \tag{32}$$

where $\sigma_i = \sqrt{b2_i - b_i^2}$ is the conditional standard deviation and $erf()$ is the error function. Figures (3) and (4) show stationary energy distributions for values of α 0.5 and 10. Corresponding death rate values are $\rho_D = 268$ and $\rho_D < 2E-16$, where the latter indicates a result below machine precision. Thus the effect of the mutual exchange rate is rather dramatic.

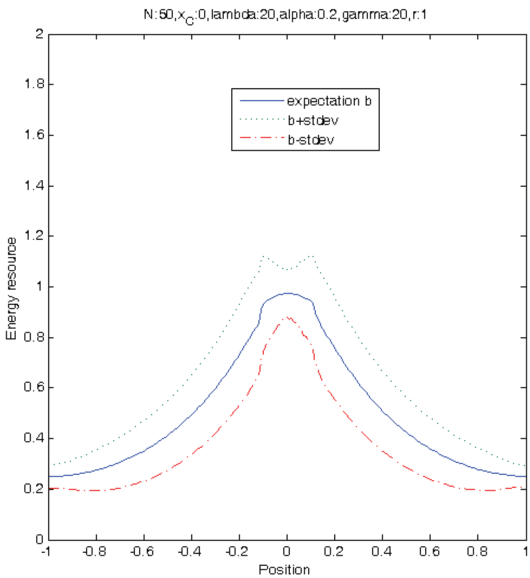

Figure 3. Energy distributions for low level of $\alpha = 0.2$

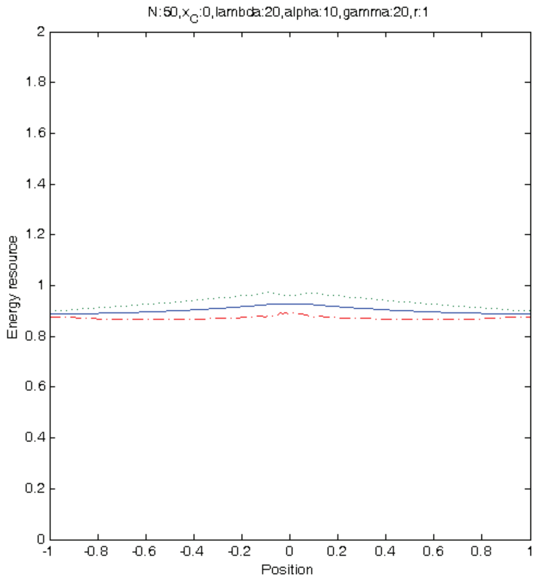

Figure 4. Energy distributions for high level of $\alpha = 10$

An increased mutual exchange rate increases the flow of energy away from the neighbourhood of the charger, which in turn allows more flow from the charger to its neighbourhood. Additionally, mutual exchange transports energy resources to the peripheral of D increasing survival far away from the charger. As seen from figures (3) and (4) mutual exchange levels energy resources among robots and in turn reduces variance and improves survival.

3. Biologically Inspired Robot Trophallaxis Simulation

3.1 An introduction to Biologically Inspired Robot Trophallaxis

The term "trophallaxis" is simply defined as mutual exchange of food between adults and larvae of certain social insects or between parents and offspring of vertebrate animals [Camazine, 1998]. In other words, trophallaxis is the regurgitation of food by one animal for the other in a colony. This phenomenon is mostly observed from social insects e.g., ants, fireants, bees, or wasps. For instance, *food* is exchanged among adults and larvae in the ants' trophallaxis process. The ant workers carry baits back to the colony's nursery. Because adult ants cannot actually digest *solid foods*, the bait is fed to the larvae which digest the material and regurgitate the baits in a *liquid form* back to adult ants. In turn, these ants feed other members of the ant colony. In this manner, ant baits are spread throughout the targeted ant colony. Without trophallaxis the ant bait would not penetrate the *gigantic organism* constituted by the ant colony. The phenomenon is also seen from vertebrate animals e.g., birds or wild dog. For example, bird parents looks for food to store it in their crops when *far away* from the nest. To feed their offspring, they fly back to the nest and *regurgitate* foods to transfer to their young. Trophallaxis is also performed by members of the dog family. In the wild, a hunting dog will regurgitate food *gorged* when far from its lair in order to feed its puppies. To *trigger* trophallaxis, these puppies *lick* the face of their parents. For domestic dogs, they are tame because of arrested development, and will treat with certain humans, in particular their *owner,* as their "parents". Therefore, a dog may manifest a vestigial feeding instinct when it licks human face.

Besides trophallaxis, *pheromones* [Sumpter et al, 2003],[Payton et al, 2005], act as agents to keep all members within the group. For example, the ant queen produces a special pheromone without which the workers will begin raising a new queen.

In short, "trophallaxis" obtains the meanings of *food reproduction* and *food exchange* while "pheromones" is implicitly recognized as means of communication, *global agents* and *local agents*. In details, 1) ant larvae digesting solid food into liquid form and bee pupa digesting nectar into honey are good examples of the *foods reproduction* phenomenon, 2) bird parents feeding their offspring, hunting dogs regurgitating foods for their puppies, ant larvae returning liquid baits to ants, and ants feeding the others typically manifest the phenomenon of *foods exchange*, 3) ants or bees also lay down their pheromones along their trails as *global agent*s to group all colony members together, 4) puppies lick their parents to trigger the trophallaxis of regurgitated foods or nestlings rub their beak to their parents' one as *local agents* for the trophallaxis.

Inspired from the natural phenomena, we have created a system of multiple autonomous mobile robots that is capable of performing energy trophallaxis to sustain robots' life without human intervention. This immediately rises a central question: what are the minimal requirements to achieve energy trophallaxis in multiple mobile robots? Some answers can be found the following section where the meaning of "Randomized Robot Trophallaxis" is clarified.

3.2 The "Randomized Robot Trophallaxis" Concept

The term "autonomous robot" is widely used to define robotic systems to function without human intervention. In fact, people have attempted to build systems, which could operate without human control. However, the term "autonomy" [Ieropoulos et al, 2004] is difficult to assess due to policy of inventors, which are leading to ambiguous meaning in use. In our opinion, a truly autonomous robot is a robot that must obtain two policies: *behavioral autonomy* and *energetic autonomy* in which behavior and energy are closely related. Until now, the term "autonomy" in robotics has mostly been addressed in the sense of "behavioral autonomy" only, not including "energetic autonomy".

In the further perspective, we have paid interest especially to large populations of mobile robots in which each robot is a truly autonomous agent. But, like animal societies, a potential method to achieve entire autonomy is that robots must demonstrate the capabilities of *energy trophallaxis* obtaining two functionalities: the self-refueling energy and the self-sharing energy. However, due to the randomized robot behaviors in large populations, obviously based on assigned tasks, the energy trophallaxis could be *randomized*. That is, the desired robots have to independently perform not only individual behaviors but also cooperative behaviors to achieve energy trophallaxis randomly.

Next we attempt an answer to the question of minimal requirements appearing in the previous section:

Foods reproduction:

Most electronic vehicles are nowadays equipped with rechargeable batteries to power their executions. In particular, for mobile robots, rechargeable batteries seem presently to be the best solution. Thereby, rechargeable batteries are considered as “foods” and “foods reproduction” is the process of refueling battery stored energy. A few previous systems e.g., Roomba vacuuming[2] robots, mentioned “foods reproduction” as a docking station where a robot can move back to dock with the station for battery recharging. Unlike the recharging process of Roomba robots, animal trophallaxis includes the exchange of “foods” from one to another other. Inspired from the foods reproduction of animals e.g., *solid foods* digested into *liquid foods*, we create a charging station where hundreds of rechargeable batteries are automatically recharged and available to mobile robots.

Foods exchange:

Like the phenomenon where bird parents feed their offspring, hunting dogs regurgitate foods for their puppies, or ant larvae returns liquid baits to ants, and ants shares baits to the others, “foods exchange” through direct “mouth-to-mouth” contact is the key to achieve *energetic autonomy*. It requires a robot to have a battery exchange mechanism that allows batteries to be exchanged to other robots. Comparing with the method of battery charging, this approach holds the potential for saving much time of electrical energy transfer. However, ants, bees or dogs can exchange/feed its foods to the other if and only if they can find heir colony/family members. Similarly, the self-sharing energy process of mobile robots is completely successful if and only if a robot is capable of searching the other and establishing a “mouth-to-mouth” contact with the other. A battery exchange mechanism is purely required to perform the energy trophallaxis through “mouth-to-mouth contacts”. Indeed, the former is global agents in a colony while the latter is local agents between two colony members. Features of the agents will be explained in details next sections

Global agents:

Natural stigmergy is a concept to describe a method of *indirect communication* [Payton et al, 2005] in a self-organizing emergent system where its individual parts communicate with one another by *modifying their local environment*. In particular, ants communicate to one another by laying down pheromones along their trails, i.e. where ants go within and around their ant colony is a stigmergic system. However, stigmergy is not restricted to eusocial creatures in growth. For examples, in passive way, birds rely on the earth magnetic field to emigrate in the winter. In active way, a pole-cat marks its own areas by spreading out its feces while another pole-cat enlarges their own area by moving the poops. Inspired from the natural behaviors, we define “global agents” as “agents” that are able to keep communication of all colony members together or to manage their own behaviors in relation with other members in the colony. In our experimental setup, a pre-built grid map on which mobile robots can follow lines is the “classical stigmergy” inspired solution. For the “evolved stigmergy”, using external sensors e.g., compass to estimate related orientation among robots, infrared array to detect lines are methods to enable robots being aware of their locations. However, to overcome the limit of “stigmergy”, global radio frequency communication may be a good choice to complement *indirect communication.*

Local agents:

Trophallaxis between two colony members is successfully completed if and only if they are able to communicate or activate the trophallatic state in each other simultaneously. For examples, puppies will lick their parents to start the foods regurgitation when they are hungry. Thereby, licking or rubbing are local agents between two individuals engaged in trophallaxis. Similar to the dialogue of animals, a line of sight infrared local communication

[2] See www.irobot.com

complemented by contact detection systems within each robot is typically required for trophallaxis process to be successful.
In particular, we have developed a new prototype of robots, named CISSbot capable of performing energy trophallaxis in three forms: robots with mother-ship, robots with robots, and robots with their child. In other words, the robots are capable of carrying out not only energetic autonomy but also behavioural autonomy. The realization of the robots is on the one hand expected to redefine the definition of "autonomy" in robotics. On the other hand, the unique design can suggest a new method to generate truly autonomous robots in large populations.

3.1 Simulation of Randomized Robot Trophallaxis

In this section we address simulated results of energy trophallaxis in terms of self-refuelling energy and self-sharing energy. Like animal life, we assume that a group of mobile robots share a nest, that is, a charging station where they can come back to refuel energy. A simulation setup can be seen in figure 5. The simulation state is shown in four windows (from left to right): Motion, Energy Distribution, States of Energy, and Tasks.
We firstly establish an energy model for single robots. Obviously, battery measure is the best way to estimate the remaining energy of a robot at an instant. However, because the energy consumption model is not uncertain to every robot due to its own mechanism, control, assigned tasks, etc., it is hard to model battery measure for a robot. Therefore, we temporally choose Peurket's discharging function $C = I^{K}t$ where k is supported by the battery manufacturer since the function is close to the linear equation of experimental power consumption of a mobile robot

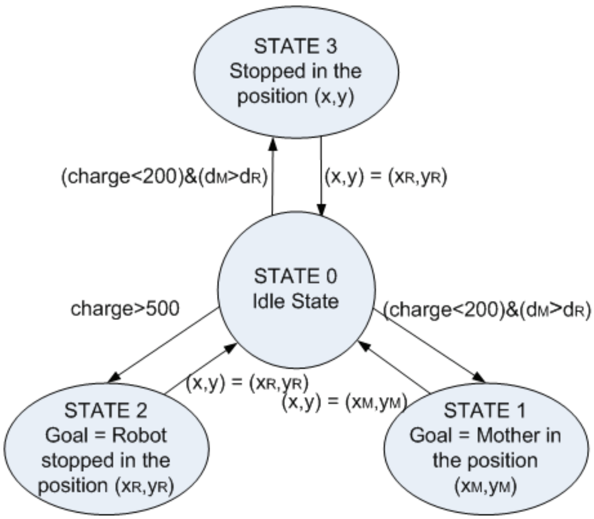

Figure 5. Model of single robot

Basically a robot is initialized with 800 energy units (**eu**) corresponding to the 8 battery holder of every robot. The robot consumes a specific amount of energy, using Peukert's equation, for each step. We propose 4 energy states of robot corresponding to behaviours and energy states:

- State 1 is an interaction between a robot and the mother charging station in the organization. Arobot has to go to the mother charging station to refill energy if its energy is less than 200 **eu**, and by default, it has a higher priority to go to the mother charging station.
- State 2 is an interaction between two robots on demand in a organization. A robot is able to exchange 100 **eu** with anoother robot demand if its energy amount is more than 500 **eu.**
- State 3 is also an interaction between two robots in organization and their interaction with the environment (for example, due to an assigned task), but it is different from the State 2. A robotic agent will stop to wait for another robot coming to share 100 **eu** if its energy is less than 100 **eu** and it is impossible to go to the mother charging station due to its estimation of the relative distance and remaining energy.
- State 0 is an interaction between a robot and its environment (for example, obstacle avoidance among robots, and between robots and lateral walls). A robotic agent is autonomously free to explore in order to consume energy.

To approach a solution for battery exchange quickly, we suppose a coordination algorithm for the multi-robot system based on two phases: path planning and battery exchange. The algorithm is proposed to emphasize the interaction of agents irrespective of their surrounding environment which should be taken into account in practice.

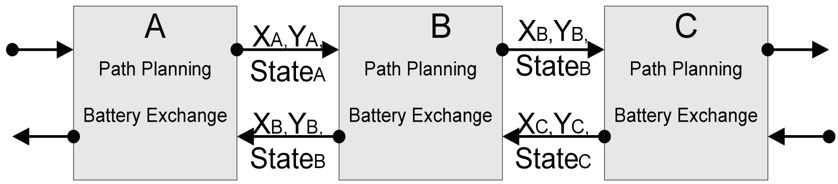

Figure 6. Model of multi-robot system coordination

Briefly, each robot has its own battery exchange supervisor. The supervisor collects input data from the robots, e.g., the current coordinate (X,Y) and the current energy state STATE; deals with this updated data; and issues output commands, e.g., NEXT STATE of energy, goal coordinate (Xgoal, Ygoal). A more detailed algorithm of the battery exchange executes infinite loops of comparisons of energy states and current positions among the robots as well as the robot with the mother, in order to give commands about what the robot should do next (the goal of the robot). Meanwhile, the path planner guides the robot to reach the directed goal and update the next position, which is used as feedback for the battery exchange algorithm to compute the next states (fig.6) Detailed information of the simulation setup can be found in [Ngo et al, 2007].

Firstly, inspired from the instinct of self-preservation in ant colonies where worker ants return to the nest to eat a liquid foods produced by the larvae, a simulation of self-refuelling energy is performed to demonstrate the capability of self-refuelling energy. Secondly, like feeding of bird or dog parents to their offspring, we establish a simulation to demonstrate the capability of self-sharing energy among robots. Thirdly, we examine a combination of self-refueling energy and self-sharing energy to point out an efficient solution for energetic