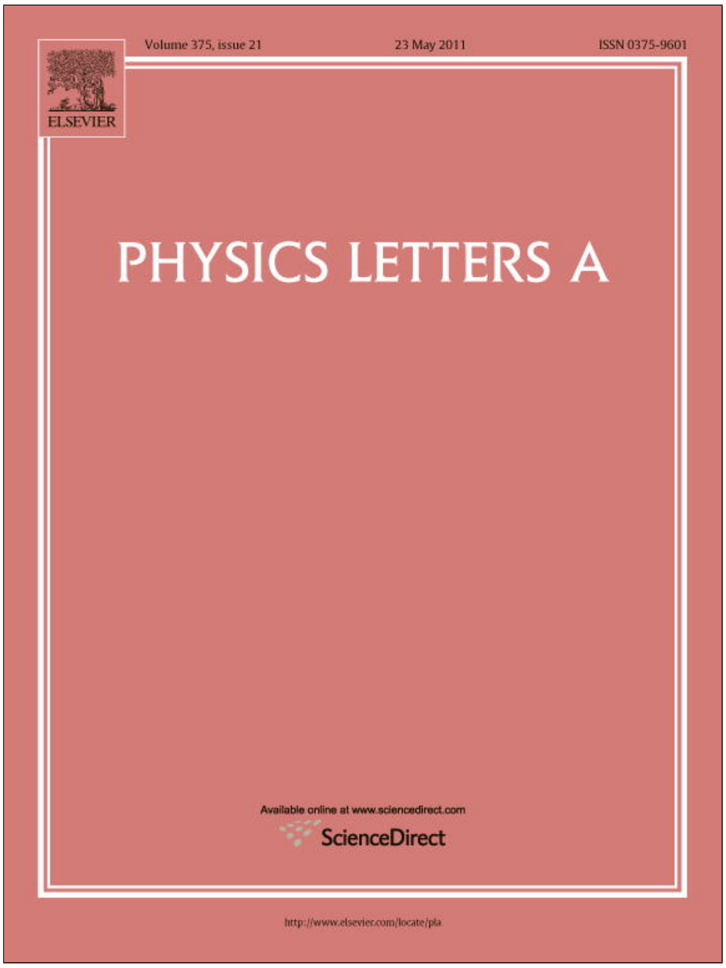
Volume 375, issue 21
23 May 2011
ISSN 0375-9601
ELSEVIER
PHYSICS LETTERS A
Available online at www.sciencedirect.com
ScienceDirect
http://www.elsevier.com/locate/pla

Physics Letters A 375 (2011) 2094–2098

Contents lists available at ScienceDirect

Physics Letters A

www.elsevier.com/locate/pla

Self-organized control in cooperative robots using a pattern formation principle

Jens Starke [a,*], Carmen Ellsaesser [b], Toshio Fukuda [c]

[a] Department of Mathematics, Technical University of Denmark, Matematiktorvet, Building 303 S, DK-2800 Kongens Lyngby, Denmark
[b] Institute of Applied Mathematics & Interdisciplinary Center for Scientific Computing, University of Heidelberg, Im Neuenheimer Feld 294, D-69120 Heidelberg, Germany
[c] Center for Cooperative Research in Advanced Science and Technology, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8603, Japan

ARTICLE INFO

Article history:
Received 3 February 2011
Received in revised form 23 March 2011
Accepted 6 April 2011
Available online 16 April 2011
Communicated by A.R. Bishop

Keywords:
Selection equations
Assignment problems
Distributed robotic systems
Robust behavior

ABSTRACT

Self-organized modular approaches proved in nature to be robust and optimal and are a promising strategy to control future concepts of flexible and modular manufacturing processes. We show how this can be applied to a model of flexible manufacturing based on time-dependent robot-target assignment problems where robot teams have to serve manufacturing targets such that an objective function is optimized. Feasibility of the self-organized solutions can be guaranteed even for unpredictable situations like sudden changes in the demands or breakdowns of robots. As example an uncrewed space mission is visualized in a simulation where robots build a space station.

1. Introduction

To be able to achieve a production with high variety, small batch size (i.e. small quantities of specialized products) and short delivery periods new flexible and modular manufacturing processes are required [20]. This modularity increases dramatically the complexity of the processes and therefore their error rate which exceeds the capabilities of traditional control methods [8,24]. Nature shows us in our daily life how robust, flexible and optimal self-organized modular constructions work in complex physical, chemical and biological systems [14,13,23], which successfully adapt to new and unexpected situations. Examples are various pattern formation processes based on self-organization mechanisms such as the Rayleigh–Bénard convection, concentration patterns in the Belousov–Zhabotinsky reaction or the self-repairing growth for hydra. A promising strategy is therefore to use such self-organization and pattern formation principles in engineering [4,19,7]. By extracting selection processes as one of the main principles of pattern formation, we bridge the gap between detailed knowledge of self-organization in complex systems in natural science and its application in engineering. In previous work on adapting pattern formation principles to these problems either no feasibility is guaranteed or only unrealistic toy problems like one-step problems, i.e. no sequences of tasks, are treated [19,22]. These limitations are overcome in the present work where sequential manufacturing tasks in logical order are fully considered with guaranteed feasibility of the assignment solutions.

2. Modelling flexible manufacturing systems

As a model for flexible manufacturing systems with cooperative autonomous robots [11,12,2], time-dependent robot-target assignments are used which abstract a large class of application problems. The basic building blocks are assignment problems [5] from combinatorial optimization: For a given number n of targets and n robots, each target has to be served by one and only one robot and each robot has to serve one and only one target such that the total profits given by the linear objective function $w = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} x_{ij}$ are maximized (or equivalently total costs are minimized). The single profits of a robot i serving target j are denoted with given w_{ij}. The unknown decision variables x_{ij} are equal to 1 if robot i serves target j and 0 otherwise (i.e. $(x_{ij}) \in \{0,1\}^{n \times n}$ is a permutation matrix). First, this can be extended to situations with unequal number of targets and robots so that there are spare targets or robots (cf. Fig. 1). Second, at a given time, targets can be set active or inactive to capture sequential task processing in a logical order. Thus time-dependent robot-target assignment problems are obtained, i.e. in a given time interval each target has to be served by one robot.

To obtain a robust heuristic optimization strategy which solves the introduced time-dependent assignment problems, a selection

* Corresponding author.
E-mail address: j.starke@mat.dtu.dk (J. Starke).

0375-9601/$ – see front matter
doi:10.1016/j.physleta.2011.04.009

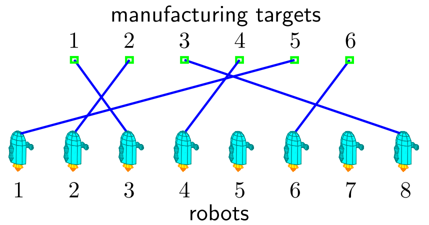

Fig. 1. Robot-target assignments: Example of an assignment with 8 robots and 6 manufacturing targets. The values of the decision variables of assigned robots which are most suitable to the accordant targets are $x_{15} = 1$, $x_{22} = 1$, $x_{31} = 1$, $x_{44} = 1$, $x_{66} = 1$, $x_{83} = 1$, while all others are zero.

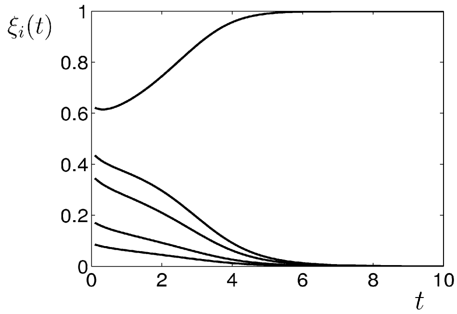

Fig. 2. Selection equation: Numerical solutions $\xi_i(t)$, $i = 1, \ldots, 5$, over time t of Eq. (1) with $\beta = 2$. The largest initial value wins the competition while all others decay to zero.

process choosing the largest single profits for each robot-target assignment is used in the following.

3. Selection processes

One of the basic principles of self-organization and pattern formation in complex systems of nature is, that complicated patterns are composed from simple ones, so-called modes. These emerge in the course of time by a selection process (see e.g. [14,13,3,6]). Examples are convection patterns in fluid dynamics, waves with certain wavelength in a laser and concentration patterns in chemistry or biology. In many cases, this process can be described by a simple version of the Ginzburg–Landau equation [6], a selection equation of the type

$$\frac{d}{dt}\xi_i = \xi_i\left(1 - \xi_i^2 - \beta\sum_{i'\neq i}\xi_{i'}^2\right) \tag{1}$$

where $\xi_i \in \mathbb{R}$ describes the contribution of the mode i. One can show [15] that for nonnegative initial values and coupling strength $\beta > 1$ in the course of time the largest initial value $\xi_i(0)$ wins the competition and tends to 1 while all others decay to 0 (cf. Fig. 2). This behavior is due to the appropriate couplings of the species i with all other species $i' \neq i$ which avoids the coexistence of several species and is also known from Darwin's "survival of the fittest".

This selection behavior explains how the heuristic principle of solving assignment problems with selection equations works: due to its linearity, the objective function of the total profits w is maximized by selecting the largest single profits $w_{ij} \in \mathbb{R}$ from the matrix (w_{ij}) such that in each row and in each column at most one element is selected. To assign the robots to the manufacturing targets a dynamical system is constructed such that the above described constraints are fulfilled. Therefore, Eq. (1) is extended with specific coupling terms, time-dependent parameters $\alpha_{ij}(t)$ and $\lambda_{ij}(t)$ and initial conditions $\xi_{ij}(0) = w_{ij}$ ($\geqslant 0$ without loss of generality) to coupled selection equations

$$\frac{d}{dt}\xi_{ij} = \kappa\xi_{ij}\left(\alpha_{ij}\left(\lambda_{ij} - \xi_{ij}^2\right) - \beta\sum_{i'\neq i}\xi_{i'j}^2 - \beta\sum_{j'\neq j}\xi_{ij'}^2\right) \tag{2}$$

which define the time evolution of preferences $\xi_{ij}(t)$ for robot i to manufacturing target j. The selection process of (2) chooses in the course of time the largest single manufacturing profits so that the total profits are maximized, i.e. the solution $\xi_{ij}(t)$ tends to the unknown decision variables x_{ij} which is for equal numbers of robots and targets a permutation matrix. For unequal numbers of targets and robots (cf. Fig. 1), the column or row elements of spare targets or robots tend to zero. To avoid stagnation at stationary but unstable points, some noise is added to (2). The time scaling factor κ adjusts the speed of the selection or decision making process compared to the velocities of the robots. The weight parameter $\alpha_{ij}(t) > 0$ captures updates of manufacturing profits and environmental changes which can be respected with deviations from the default value $\alpha_{ij}(t) = 1$ for all i, j, t. This leads to an individual speed of the selection for the assignment preferences ξ_{ij} and can favour or penalize them. Furthermore, the activation parameter $\lambda_{ij}(t)$ takes sequential manufacturing steps and changes in demands of time-dependent assignment problems into account. Changing the sign of $\lambda_{ij}(t)$ switches over active and inactive targets: positive $\lambda_{ij}(t)$ stabilize the selection for active targets and negative $\lambda_{ij}(t)$ destabilize it for inactive targets. To obtain asymptotically stable points with elements being either equal to one or zero, $\lambda_{ij}(t)$ has to be either +1 or negative. A remarkable feature of this specifically constructed dynamical system is that feasibility of solutions can be guaranteed for large enough coupling strength ($\beta > \frac{1}{2}\max_{i,j,t}\alpha_{ij}(t)$), i.e. the system tends only to solutions of the assignment problem without having spurious states. This behavior is equivalent to the statement that there is a one-to-one correspondence between the set of feasible points to the set of asymptotically stable points of (2) and that the ω-limit set contains only stationary points and no other objects like limit cycles. This can be proven by following [25] or respectively [27] and rewriting Eq. (2) as gradient flow $\frac{d}{dt}\xi_{ij} = -\frac{\partial}{\partial\xi_{ij}}\Phi$ and examination of the Hessian of the corresponding potential Φ at stationary points. The local minima of Φ correspond then to the asymptotically stable points of (2). The proof can be done under the assumption that $\alpha_{ij}(t)$ and $\lambda_{ij}(t)$ tend to constants in the course of time until a target is served. These assumptions are clearly reasonable because otherwise one could outsmart the system by e.g. fast oscillating demands such that the targets cannot be reached or the tasks cannot be finished. Furthermore, it has to be remarked, that in contrast to [16,28,9] and [10], the inhomogeneity of the growth rates α_{ij} affects in (2) not only the linear term but also the cubic one. As result of the fact that the ratio of the coefficients of these two terms is one, the stable points are located at $\xi_{ij} = 0$ or $\xi_{ij} = 1$ (suppose the coupling strength is strong enough) and not at intermediate values. This is not only mathematically more elegant but simplifies also engineering applications of this dynamical systems approach.

The information of the row and column elements of (ξ_{ij}) in the coupling terms has to be exchanged as feedback about the current preferences $\xi_{ij}(t)$ from time to time between the cooperative robots to achieve a distributed instead of a centralized control. This leads to additional robustness, this time with respect to possible failures of the hardware used for the control [26].

The optimization results of the coupled selection equations compare very well with other optimization algorithms also with respect to the scaling of the problem size [27,16,28]. Furthermore, these equations, introduced as heuristics, can be justified theoretically by a formulation as gradient descent solution of a specific penalty method. Details of this will be published in a forthcoming article. This extends also the results in [10] about optimality of solutions with the selected winnings w_{ij} being large compared to the not selected. An additional advantage is that due to the continuous decision process which works locally in time of the manufacturing sequence, sudden changes in the demands can still be considered in the selection process without the need of restarting the whole process. If a new active target is more profitable even already assigned robots are considered to change their present goal. These are the key points for the robustness and fault tolerance which outperforms other approaches.

4. Navigation of the robots

To demonstrate the proposed approach in combination with autonomous robots, as one option for the navigation part, a specifically constructed behavioral force model [1] is used. The equation of motion

$$\frac{d}{dt}\mathbf{r}_i = v_i^0 \mathbf{e}_i^0(\mathbf{r}_i, \xi) + \mathbf{f}_i(\mathbf{r}_i) \tag{3}$$

controls the positions $\mathbf{r}_i \in \mathbb{R}^3$ of the robots i with velocity constant v_i^0. This simplifies earlier approaches which use an equation of motion for the velocities instead [17,22]. The temporal changes of the positions essentially depend on the destination vector $\mathbf{e}_i^0(\mathbf{r}_i, \xi)$ which direction tends correspondingly to the current preference matrix $\xi = (\xi_{ij}(t))$ towards the selected target but also on a collision avoidance term $\mathbf{f}_i(\mathbf{r}_i)$.

The destination vector

$$\mathbf{e}_i^0(\mathbf{r}_i, \xi) = \mathbf{N}_{\gamma\delta}\left(\sum_j \xi_{ij}(t)\mathbf{N}_{\gamma'\delta'}\big(\mathbf{g}_j - \mathbf{r}_i(t)\big)\right) \tag{4}$$

is defined as normed linear combination of the normed difference vectors of the position $\mathbf{r}_i(t)$ to all target positions $\mathbf{g}_j$ weighted with $\xi_{ij}(t)$ to obtain the property that its direction tends in the course of time towards the selected target. The operator $\mathbf{N}_{\gamma\delta}(\mathbf{y}) = \frac{1}{\|\mathbf{y}\|+1/(\gamma\|\mathbf{y}\|+\delta)} \cdot \mathbf{y}$ with $\gamma, \delta > 0$, where $\|\cdot\|$ is the Euclidean norm, mainly normalizes the vector $\mathbf{y}$ and avoids singularities for the numerical integration at $\mathbf{y} = \mathbf{0}$.

The term $\mathbf{f}_i(\mathbf{r}_i)$ avoids collisions with obstacles or other robots. It has finite range in order to avoid that far away from the obstacles, small residuals of the collision avoidance terms add up to unwanted spurious states, i.e. unfeasible stable points [22], which could trap the robots, and cause the system to fail. The collision avoidance term

$$\mathbf{f}_i(\mathbf{r}_i) = \sum_{i' \neq i} \mathbf{f}_{ii'}^{\mathrm{r}}\big(\mathbf{d}_{ii'}^{\mathrm{r}}\big) + \sum_k \mathbf{f}_{ik}^{\mathrm{o}}\big(\mathbf{d}_{ik}^{\mathrm{o}}\big) \tag{5}$$

consists of a part for collision avoidance between robot i and other robots $i' \neq i$ and one between robot i and obstacles k. The terms $\mathbf{f}_{ii'}^{\mathrm{r,o}}(\mathbf{d}_{ii'}^{\mathrm{r,o}}) \in \mathbb{R}^3$ depend on distance vectors $\mathbf{d}_{ii'}^{\mathrm{r,o}}$ between the surfaces of the objects obtained by the robots' sensors. They tend to infinity for small distances and are identical zero for distances over a given threshold $\sigma^{\mathrm{r,o}}$ and can be defined as (cf. Fig. 3):

$$\mathbf{f}_{ii'}^{\mathrm{r,o}}(\mathbf{d}) = \begin{cases} s^{\mathrm{r,o}}(\tan\psi(\|\mathbf{d}\|) - \psi(\|\mathbf{d}\|))\frac{\mathbf{d}}{\|\mathbf{d}\|}, & \|\mathbf{d}\| \leqslant \sigma^{\mathrm{r,o}}, \\ 0, & \|\mathbf{d}\| > \sigma^{\mathrm{r,o}}, \end{cases} \tag{6}$$

where $s^{\mathrm{r,o}} \in \mathbb{R}$ is the strength of the collision avoidance term, $\psi(\|\mathbf{d}\|) = \frac{\pi}{2}\big(\frac{\|\mathbf{d}\|}{\sigma^{\mathrm{r,o}}} - 1\big)$ and $\|\cdot\|$ is the Euclidean norm. For convex obstacles which are far enough away from each other this type of behavioral force model does not produce local traps. Otherwise, for non-convex obstacles, additional strategies could be used to avoid the trapping. It should be emphasized that alternatively other path-planning methods (see e.g. [18,21,26]) can be combined with the coupled selection equations to take advantage of the self-organized assignment process.

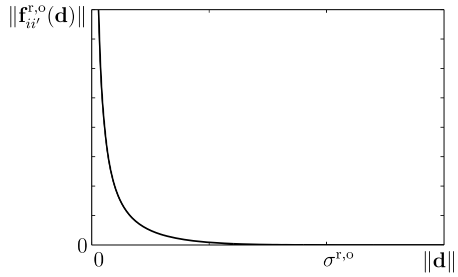

Fig. 3. The Euclidean norm of the forces used in the collision avoidance term (5) between a robot and other robots or obstacles as defined in Eq. (6).

5. Application

The capabilities of the proposed method are demonstrated for a challenging example of flexible manufacturing, the assembling of a space station with autonomous robots (cf. Fig. 4). The robots were assigned to collect different components from a space shuttle and deliver them to certain positions at the space station. We assume each of the 8 robots is able to transport and install all types of components (assembling bars and solar panels), they have distance sensors in order to avoid collisions and can detect the relative direction towards the manufacturing targets to maneuver using Eq. (3). For reasons of visualization, as initial values $\xi_{ij}(0)$ large profits w_{ij} were used for small Euclidean distances between robots and manufacturing targets. The same holds for the weight parameter $\alpha_{ij}(t)$ which specific choice respects time delays from maneuvering around obstacles for the selection process.

To obtain large values for small Euclidean distances $d_{ij}(t) = \|\mathbf{g}_j - \mathbf{r}_i(t)\|$ between robots i and manufacturing targets j and small ones for large distances, a linear transformation $W_{ij}^{a,b}(t) = a - b\frac{d_{ij}(t) - \min_{i',j'} d_{i'j'}(t)}{\max_{i',j'} d_{i'j'}(t) - \min_{i',j'} d_{i'j'}(t)}$ with $a, b > 0$ and $a \geqslant b$ such that $W_{ij}^{a,b}(t) \in [a-b, a]$ is used for the initial values $\xi_{ij}(0) = w_{ij} = W_{ij}^{a,b}(0)$ and weight parameters $\alpha_{ij}(t) = W_{ij}^{a',b'}(t)$ where the parameter pairs (a, b) and (a', b') can be chosen differently.

At each time t the activation parameter $\lambda_{ij}(t)$ is chosen $+1$ for active and -10 for inactive manufacturing targets. The absolute value $|\lambda_{ij}(t)|$ determines how fast the stabilization and destabilization occurs, i.e. the destabilization is chosen 10 times faster than the stabilization to achieve faster new availability. Each of the 44 manufacturing targets, either at the space station or at the material depot of the space shuttle, becomes active for a certain period in the logical order of the sequential processing. This example intends to illuminate possible future concepts in various fields with complex requirements. Breakdowns of robots can be respected either by setting the corresponding ξ_{ij} identical to zero for all future times or switching the activation parameters λ_{ij} negative. The latter was chosen in the presented example. Both results in the growth of an alternatively available robot and a subsequent replacement by it which works like the usual selection process of the equations.

Fig. 4 shows the simulation results for this task: between part (a) and (b) the assignment has been developed in the preference matrix for the first time. Our results in Fig. 4(d) and (e) show how the total mission will be completed by an automatic and self-organized replacement of a failed robot after a triggered breakdown which demonstrates the robustness. In addition, the algorithm is also stable against other failures like multiple breakdowns of robots or communication failures. Fig. 4(e) shows how collisions

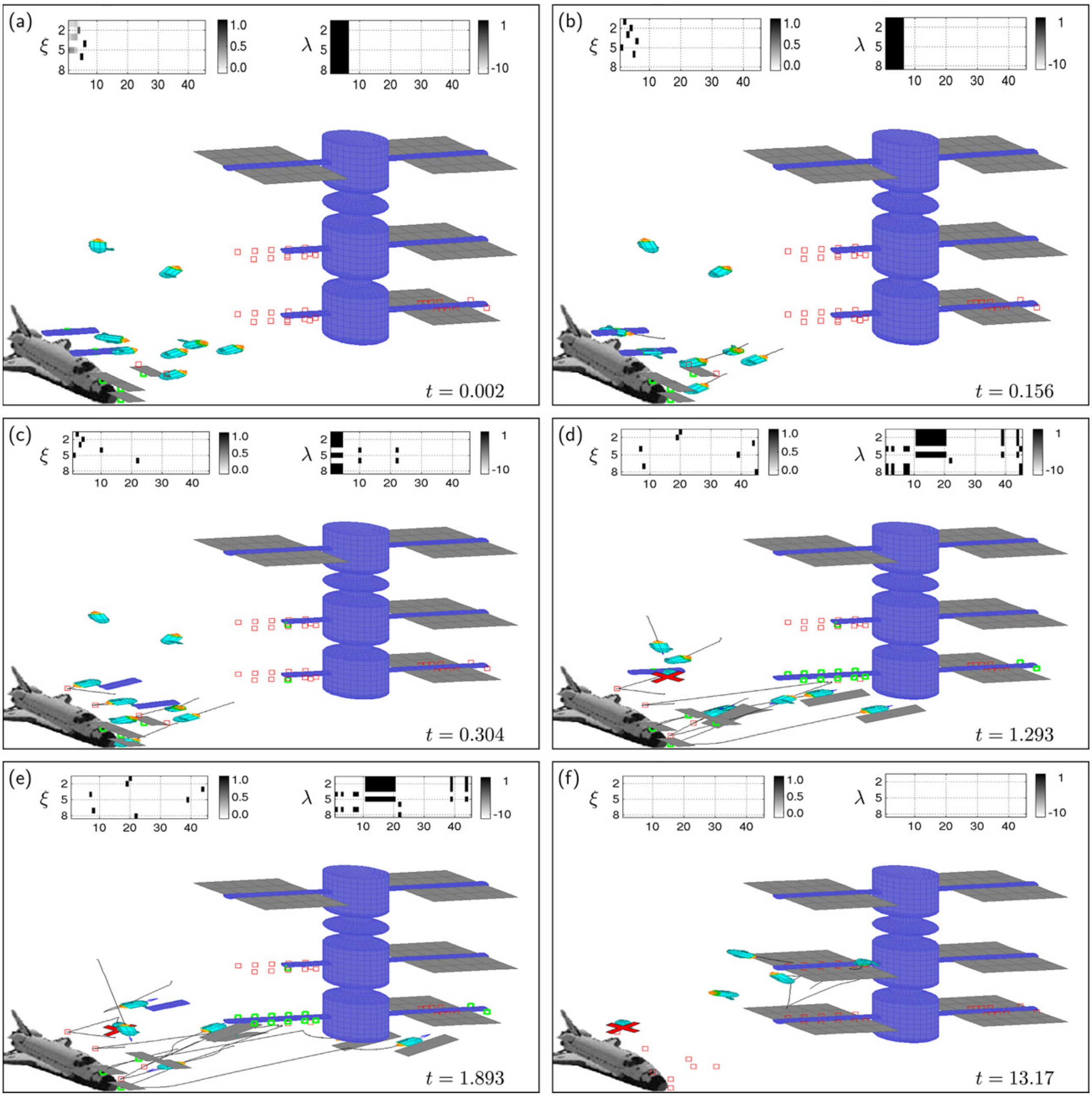

Fig. 4. Simulation results: Assembling of solar panels of a space station as example for a complex time-dependent manufacturing process. The preference matrix ξ and the activation matrix λ are given in the upper left respectively right corner of each snapshot. Active targets are green, inactive targets red boxes. Short histories of the robots' trajectories are plotted in black. Between (a) and (b) the assignment has been developed in the preference matrix ξ. As demonstration of considering required logical orders in the manufacturing, the assembling of the bar between (c) and (d) is necessary before the solar panels can be assembled at this wing. Collision avoidance with obstacles can be observed in (e) where 2 robots maneuver around the space station. Fault resistance is shown by a triggered break down of a robot in (d) and the following workaround by taking over the task by other robots while the whole process continues. (f) shows the complete assembled space station. The numerical solutions of Eqs. (2)–(6) were calculated with the parameters $\kappa = 15$, $\beta = 4$, $a = 0.9$, $b = 0.8$, $a' = 1.5$, $b' = 1$ for the coupled selection equations as well as their initial values and $v_i^0 = 0.3$, $\sigma^r = 0.1$, $\sigma^o = 0.02$, $s^{r,o} = 1$, $\gamma = 10$, $\delta = 1$, $\gamma' = 10^6$, $\delta' = 10^6$ for the behavioral force model. (For interpretation of colors in this figure, the reader is referred to the web version of this Letter.)

with obstacles are avoided, i.e. two robots maneuver around the space station. The last figure (f) shows the completely assembled space station.

6. Conclusions

The suggested approach is not only promising for various types of complex manufacturing but shows in addition a way how to utilize self-organization principles, in particular selection processes for engineering problems. This includes especially situations with required flexible, modular and decentralized structures where the total process has to continue even if the risk of partial failures is high like in uncrewed space missions or in industrial manufacturing like production with high variety, small batch size and short delivery periods. The presented results provide a basis for a wide range of applications and further detailed investigations of simulations or real experiments as well as analytical studies.

Acknowledgements

The authors would like to thank P. Molnár and M. Schanz for fruitful discussions.

Appendix A. Supplementary material

Supplementary material related to this Letter can be found online at doi:10.1016/j.physleta.2011.04.009.

References

[1] R. Arkin, Behavior-Based Robotics, The MIT Press, Cambridge, London, 1998.
[2] H. Asama, T. Arai, T. Fukuda, T. Hasegawa (Eds.), Distributed Autonomous Robotic System (DARS 5), Springer-Verlag, Heidelberg, Berlin, New York, 2002.
[3] M. Bestehorn, H. Haken, Zeitschrift für Physik B 82 (1991) 305.
[4] R. Brooks, Science 253 (1991) 1227.
[5] R. Burkard, Annals of Discrete Mathematics 4 (1979) 193.
[6] M. Cross, P. Hohenberg, Reviews of Modern Physics 65 (3) (1993) 851.
[7] G. Di Marzo Serugendo, A. Karageorgos, O.F. Rana, F. Zambonelli (Eds.), Engineering Self-Organising Systems – Nature-Inspired Approaches to Software Engineering, Springer-Verlag, Heidelberg, Berlin, New York, 2004.
[8] Tay Feh, Journal of Manufacturing Systems 18 (5) (1999) 345.
[9] T.D. Frank, Physics Letters A 373 (45) (2009) 4127.
[10] T.D. Frank, Physics Letters A 375 (12) (2011) 1465.
[11] T. Fukuda, S. Nakagawa, Journal of Intelligent and Robotic Systems 1 (1) (1988) 55.
[12] T. Fukuda, T. Ueyama, Cellular Robotics and Micro Robotic Systems, World Scientific Series in Robotics and Automated Systems, vol. 10, World Scientific, Singapore, New Jersey, Hong Kong, 1994.
[13] H. Haken, Advanced Synergetics, Springer Series in Synergetics, Springer-Verlag, Heidelberg, Berlin, New York, 1983.
[14] H. Haken, Synergetics, An Introduction, Springer Series in Synergetics, Springer-Verlag, Heidelberg, Berlin, New York, 1983.
[15] H. Haken, Synergetic Computers and Cognition – A Top–Down Approach to Neural Nets, Springer Series in Synergetics, Springer-Verlag, Heidelberg, Berlin, New York, 1991.
[16] H. Haken, M. Schanz, J. Starke, Physica D 134 (1999) 227.
[17] D. Helbing, J. Keltsch, P. Molnár, Nature 388 (July 1997) 47.
[18] L.E. Kavraki, J.-C. Latombe, Probabilistic roadmaps for robot path planning, in: K. Gupta, A.P. del Pobil (Eds.), Practical Motion Planning in Robotics: Current Approaches and Future Directions, Wiley, 1998, pp. 33–53.
[19] M.J.B. Krieger, J.-B. Billeter, L. Keller, Nature 406 (2000) 992.
[20] A. Kusiak, International Journal of Production Research 23 (6) (1985) 1057.
[21] J.-C. Latombe, Robot Motion Planning, 3 edition, Kluwer Academic Publishers, Dordrecht, Boston, London, 1993.
[22] P. Molnár, J. Starke, IEEE Transaction on Systems, Man and Cybernetics: Part B 31 (3) (2001) 433.
[23] G. Nicolis, I. Prigogine, Self-Organization in Non-Equilibrium Systems, Wiley, New York, 1977.
[24] Z. Simeu-Abazi, C. Sassine, International Journal of Flexible Manufacturing Systems 13 (3) (2001) 267.
[25] J. Starke, Kombinatorische Optimierung auf der Basis gekoppelter Selektionsgleichungen, PhD thesis, Universität Stuttgart, Verlag Shaker, Aachen, 1997.
[26] J. Starke, T. Kaga, M. Schanz, T. Fukuda, The International Journal of Robotics Research 24 (2005) 465.
[27] J. Starke, M. Schanz, Dynamical system approaches to combinatorial optimization, in: D.-Z. Du, P. Pardalos (Eds.), Handbook of Combinatorial Optimization, vol. 2, Kluwer Academic Publishers, Dordrecht, Boston, London, 1998, pp. 471–524.
[28] J. Starke, M. Schanz, H. Haken, Physica D 134 (1999) 242.