Multi-scopic Simulation for Human-robot Interactions Based on Multi-objective Behavior Coordination

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Abstract. Recently, a multi-scopic approach has been applied to various research topics owing to the technological progress in computer science. For example, we can discuss a phenomenon from three different levels of macro-, meso-, and micro- scopic simulation. In the microscopic simulation, we can deal with the dynamics inside objects and internal states. In the mesoscopic simulation, we can deal with approximated dynamics between objects in a surrounding environment. In the macroscopic simulation, we can deal with spatiotemporal relationships between objects without dynamics. In this paper, we propose a multi-scopic simulation to discuss human-robot interactions. First, we discuss how to realize multi-scopic simulation for human-robot interactions. Next, we apply multi-objective behavior coordination to represent human and robot behaviors in mesoscopic simulation. Next, we apply the proposed method to navigation tasks of mobility support robots. Finally, we discuss the effectiveness of the proposed method through several simulation results.

Keywords: Multi-scopic Simulations, Topological Mapping, Multi-objective Behavior Coordination, Mobility Support Robots

1. INTRODUCTION

Recently, the research on cyber-physical systems [1] and digital twin [2] has been done to simulate and analyze the real world in the cyber space. Furthermore, a multi-scopic approach has been applied to various research topics owing to the technological progress in computer science. For example, we can discuss a phenomenon from three different levels of macro-, meso-, and micro-scopic simulation. In the microscopic simulation, we can deal with the dynamics inside objects and internal states. In the mesoscopic simulation, we can deal with approximated dynamics between objects in a surrounding environment. In the macroscopic simulation, we can deal with spatiotemporal relationships between objects without dynamics. In order to simulate a real-world phenomenon, we often have to extract features and structures based on graph theory and topology [3-6]. For example, topological mapping methods are used for 3D modeling available for accurate physics simulation from the microscopic point of view [7,8]. Graph-based methods are used for knowledge representation available for huge-scale rule-based inference from the macroscopic point of view. Furthermore, we can build a topological model and knowledge according to a mesoscopic modeling and simulation approach to connect microscopic models with macroscopic knowledge, called *Topological Twin*. The aim of topological twin is to (1) extract topological structures hidden implicitly in the real world, (2) reproduce them explicitly in the cyber world, and (3) Simulate and analyze the real world in the cyber world. Furthermore, we must deal with social or mental world in addition to cyber-physical systems. Figure 1 shows topological twin in cyber-physical-social systems. In this paper, we propose a multi-scopic simulation to discuss human-robot interactions.

First, we discuss how to realize multi-scopic simulation for human-robot interactions. We discuss human-robot interactions from the spatial points of view, such as intimate, personal, behavioral, and social space. Next, we apply multi-objective behavior coordination [8-11] to represent human and robot behaviors in mesoscopic simulation. Basically, we use collision avoidance, target tracing from the viewpoint of movement, and gestural interactions and behaviors on activities of daily living (ADL). Next, we apply the proposed method to navigation tasks of mobility support robots. Finally, we discuss the effectiveness of the proposed method through several simulation results.

This paper is organized as follows. Section 2 proposes multi-scopic simulations for human-robot interactions. Section 3 explains a method of multi-objective behavior coordination to control human and robotic behaviors. Section 4 shows several numerical simulation results and discuss how to link the mesoscopic and macroscopic simulations. Finally, Section 5 discuss the essence of the proposed method and discusses the future direction of this research.

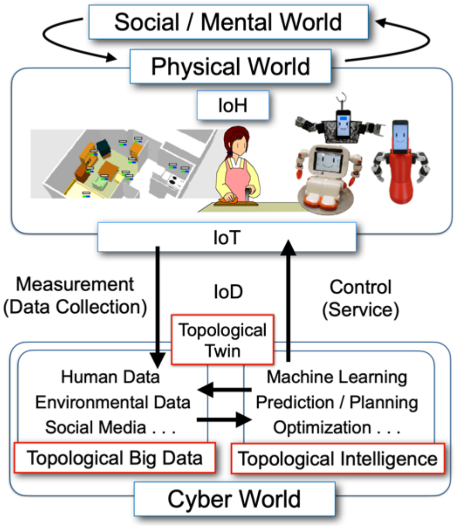
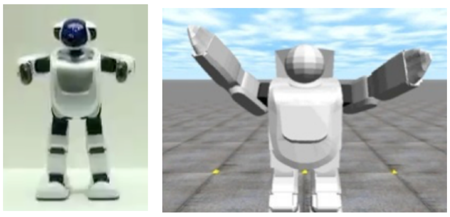


Fig. 1. Topological twin in cyber-physical-social systems.



(a) PALRO (Fujisoft, Japan)

(b) Human support robot (HSR, Toyota, Japan)

(c) An example of smart senior car

(d) Mobility support robot

Fig. 2. Robot partners.

2. Multi-scopic Simulation for Human-Robot Interactions

2.1. Robot Partners

Recently, various types of robot partners have been developed to realize human-robot interaction [15-17]. For example, communication robots are used to realize information support service for elderly care, child nursing and others. Mobile robots are used for delivery service and mobility supports. The mobility support is very important for elderly people to enhance the motivation for going out and to prevent them from locomotive syndrome and dementia.

We have developed and used various types of robot partners such as MOBiMac, Palro, Palmi, HSR, iPhonoid, iPadrone, Animaloid for the support to elderly people, rehabilitation support, and robot edutainment [11-17]. Palro has been applied to edutainment [18,19] and exercise support [20]. Figure 2 (a) shows a humanoid robot Palmi developed by Fujisoft Inc. and DMM.com. Palmi has 20 degree-of-freedom and Palmi is equipped with various sensors such as gyro, accelerometer, infrared LED, camera, microphone and speaker. HSR is a home-care robot with five degree-of-freedom of an arm consisting of four revolving joints and a prismatic shoulder joint, with a payload of 1.2kg [21]. Moreover, the robot can move omnidirectionally up to 20cm/s with a differential wheel and central yaw joint placed in the base. An RGBD head camera, a pair of wide-angle RGB cameras in a stereo setup, and a hand RGB camera are equipped as the integrated perception system. For the navigation system, HSR used the IMU and laser range finder in the base that can be used for 2D map construction and localization Furthermore, we have developed smart senior cars for elderly people shown in Fig.2 (c), but we will use electric wheelchairs (Fig.2 (d)) in this research to enhance the human mobility in a room.

2.2. Multi-scopic Simulation

Figure 3 shows a concept of multi-scopic simulation. As we explained in the introduction, we deal with three different scopes of micro-, meso-, and macro- scopic simulations.

We deal with the dynamics inside objects and internal states in the microscopic simulation. In order to realize the human-robot physical interactions, we will use a method of estimating human muscle state by using inverse dynamics based on neuro-musculoskeletal simulations. Furthermore, we consider the concept of affordance and effectivity discussed in ecological psychology. In general, affordance is defined an opportunity for action offered by the environment and the effectivity is defined as the possibility of realizing action restricted by the current posture. If the posture is changed, its corresponding possible action is also changed. Therefore, a suitable posture is required to specify its corresponding affordance. The goal-specific information is specified as affordance in an intentional behavior, while the goal-relevant control is specified as effectivity. In this paper, an action is defined as a motion sequence observed by an internal description, while the behavior is defined as a motion sequence followed by an external description. Therefore, while action control is done in the microscopic level of intimate space, behavior control is done in the mesoscopic level of personal or behavioral space.

In the mesoscopic simulation, we deal with approximated rigid body dynamics between objects in a surrounding environment of humans and robots. An intentional behavior is done based on the coupling of

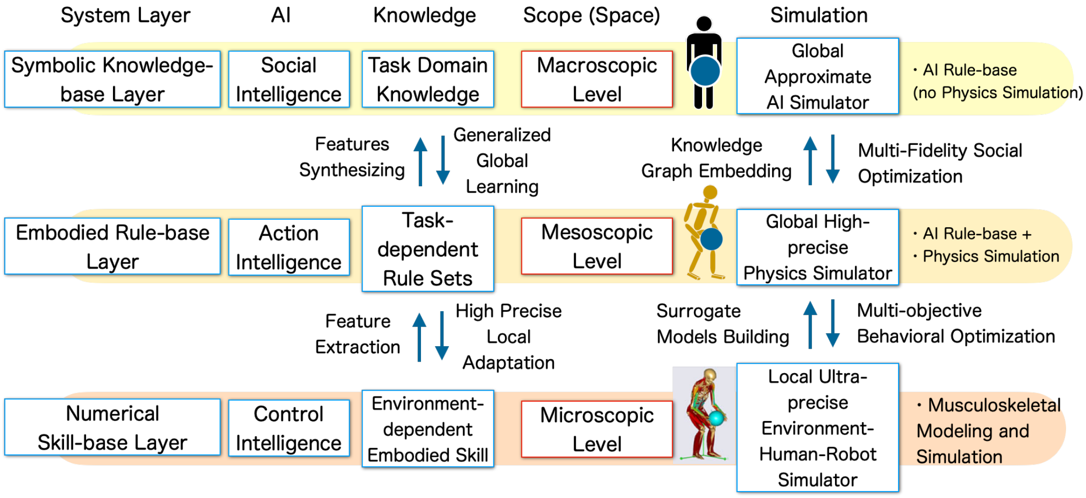


Fig.3. Towards cyber-physical system using mobility support robots.

perceptual system and action system under the constraint based on social knowledge and rules from the macroscopic level. A behavior is described by task-dependent rule sets.

In the macroscopic simulation, we deal with spatiotemporal relationships between objects without using dynamics. A task is described as a sequence of behaviors and a path is described as a sequence of nodes in a topological map. Task domain knowledge is represented by graph neural networks and knowledge graphs.

3. Multi-objective Behavior Coordination

3.1. Mesoscopic Simulations

In this paper, we focus on the mesoscopic simulation of mobility support robots linked to macroscopic simulation. We assume P people and R robots in the simulation. We use two types of mobility support robots; electric wheelchairs and robot assist walkers where a robot is controlled by independent two independent wheel drives (Fig.4). Each person and robot can take multi-objective behaviors of collision avoidance and target tracing by using fuzzy control [18,19]. The position data of humans and robots measured in the mesoscopic simulation are transferred to the macroscopic simulation through the simple TCP/IP communication.

3.2. Fuzzy Control

A behavior of a person or robot is represented using fuzzy rules based on simplified fuzzy inference. It is easy for human operators to understand and to design the logical structure written by fuzzy rules. In general, a fuzzy IF-THEN rule using simplified fuzzy inference is described as follows,

IF x_1 is $A_{i,1}$ and ... and x_m is $A_{i,m}$
THEN y_1 is $w_{i,1}$ and ... and y_n is $w_{i,n}$

where $A_{i,j}$ and $w_{i,k}$ are a Gaussian membership function for the j-th input and a singleton for the k-th output of the i-th rule; m and n are the numbers of inputs and outputs, respectively. The simplified fuzzy inference is described by,

$$\mu_{A_{i,j}}(x_j) = \exp\left(-\frac{(x_j-\alpha_{i,j})^2}{\beta_{i,j}^2}\right) \quad (1)$$

$$\mu_i = \prod_{j=1}^{m} \mu_{A_{i,j}}(x_j) \quad (2)$$

$$y_k = \frac{\sum_{i=1}^{r} \mu_i w_{i,k}}{\sum_{i=1}^{r} \mu_i} \quad (3)$$

where $\alpha_{i,j}$ and $\beta_{i,j}$ are the central value and the width of the membership function $A_{i,j}$; r is the number of rules. The outputs of the robot are motor output levels. Fuzzy controller is used for collision avoidance and target tracing behaviors. The inputs to the fuzzy controller for collision avoidance and target tracing are the distance to the obstacle measured by laser range finder (LRF), and the relative direction to a target point, respectively. Basically, a target point is given by a human operator.

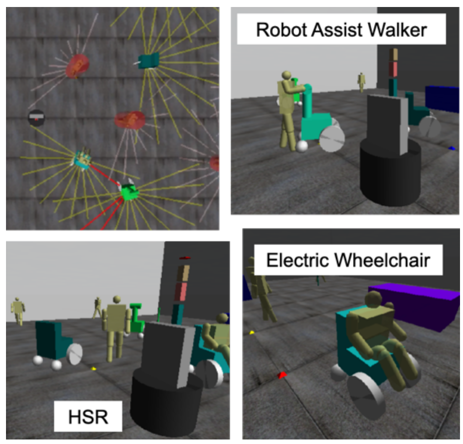


Fig.4. Mesoscopic simulation of humans and mobility support robots.

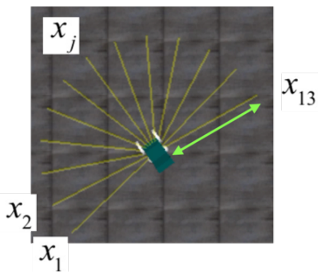
3.3. Multi-objective Behavior Coordination

In general, a mobile robot has a set of behaviors for achieving various objectives and must integrate these behaviors according to the facing environmental conditions. Therefore, we proposed the method for multi-objective behavior coordination (Fig.5). This method is composed of a sensory network, behavior coordinator, and behavior weight updater.

The sensory network extracts the perceptual inputs from LRF. Figure 5 (a) shows an example of measurement by LRF where the number of inputs is 13 (m = 13). In case of the collision avoidance behavior, the robot can update the attention range according to the facing environmental condition. For example, if there are many obstacles in the environment, the robot should move slowly towards the target point with avoiding collision. On the contrary, if there are few obstacles, the robot can move fast towards the target point without slowdown. The robot should dynamically update the sensing range according to the facing environment. The sensory network can control the scalable attention range, which adjust the shape of membership functions. In this paper, we use two membership functions corresponding to the linguistic labels of 'Dangerous' and 'Safe' for collision avoidance (Fig.5). When we assume the scalability of control rules, the sensory network changes the output of fuzzy controller according to the time-series of sensory inputs. The attention range to $\alpha_{i,j}$ $(\alpha_{\min} \le \alpha_{i,j} \le \alpha_{\max})$ is updated simply as follows,

$$\alpha_{i,j} \leftarrow \begin{cases} \alpha_{i,j} - \gamma & \text{if } \forall x_j < \alpha_{i,j} \\ \alpha_{i,j} + \gamma & \text{otherwise} \end{cases} \tag{4}$$

where $\gamma\ (\gamma > 0)$ is an update length; $l_{\min}$ and $l_{\max}$ are minimal and maxaimal attention ranges, respectively (Fig.5(b), (c)).



(a) Membership function at $\alpha_{\max}$

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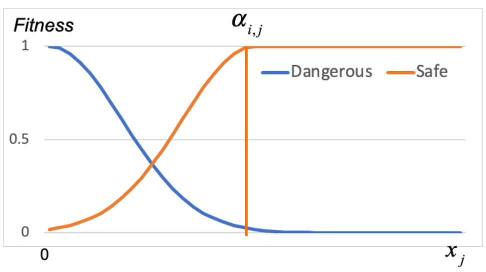


(b) Membership function at $\alpha_{\min}$

Fig.5. Attention range for collision avoidance.

Table 1 shows an example of fuzzy rules for collision avoidance where the number of fuzzy rules is 11 (r = 11) The number of outputs is 2 (n = 2) corresponding to the output levels of actuators of two independent wheel drives. For example, the Rule 1 means [if the right side is dangerous then fast left-turn]. The robot can turn left because y_1 (output of left actuator) is smaller than y_2 (output of right actuator).

A behavior weight is assigned to each behavior. Based on (3), the final motor output is calculated by

$$y_k = \frac{\sum_{h=1}^{b} wgt_h(t) \cdot y_{h,k}}{\sum_{h=1}^{b} wgt_h(t)} \tag{5}$$

where $y_{h,k}$ is updated as the output of the h-th behavior from y_k in (3); b is the number of behaviors; $wgt_h(t)$ is a behavior weight of the h-th behavior over the discrete time step t. By updating the behavior weights, the robot can take a multi-objective behavior according to the time series of perceptual information. The update amount of each behavior is calculated as follows,

$$\begin{pmatrix} \Delta wgt_1 \\ \vdots \\ \Delta wgt_b \end{pmatrix} = \begin{pmatrix} dw_{1,1} & \cdots & dw_{1,s} \\ \vdots & \ddots & \vdots \\ dw_{b,1} & \cdots & dw_{b,s} \end{pmatrix} \begin{pmatrix} u_1 \\ \vdots \\ u_s \end{pmatrix} \tag{6}$$

where Δwgt_h is the update amount of $wgt_h(t)$; u_i is the parameter on the i-th perceptual information; s is the number of perceptual inputs; $dw_{h,i}$ is the parameter which represents the effect of u_i to update behavior weights. This method can be considered as a mixture of experts if the behavior coordinator is considered as a gating network.

Table 1. An example of fuzzy rules for collision avoidance behavior.
(0: Dangerous, 1: safe in the input x_i)

	x1	x2	x11	x12	x13	y1(L)	y2(R)
Rule 1	1	1	1	0	0	0.9	1.0
Rule 2	1	1	0	0	1	0.7	1.0
Rule 11	0	0	1	1	1	1.0	0.9

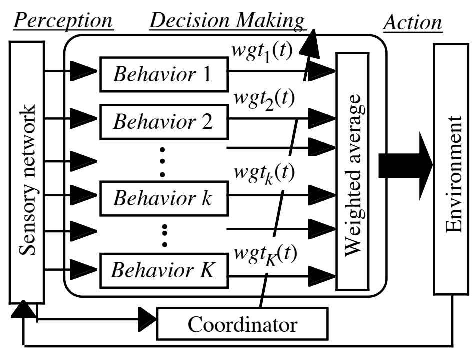
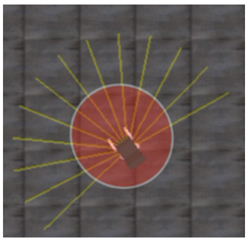
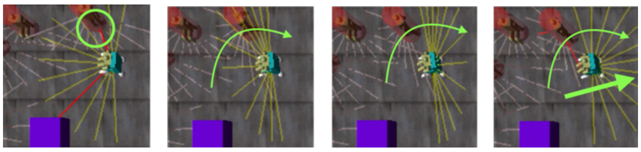


Fig.5. A method of multi-objective behavior coordination [].

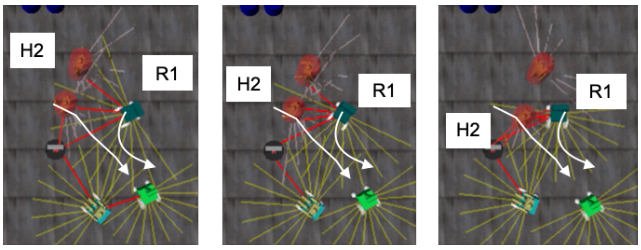
We use an emergency avoidance behavior in addition to collision avoidance and target tracing. Figure 6 (a) shows the asymmetric personal space for emergency avoidance behavior. If the other human or robot enters in the personal space, the robot stops and goes back after changing its sensing range of LRF. Fig.6 (b) shows an example of the emergency avoidance behavior when a human enters in the right side.



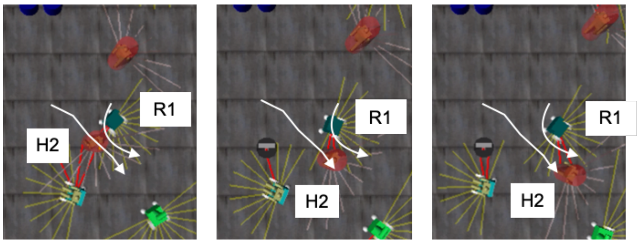
(a) Personal space for emergency avoidance behavior



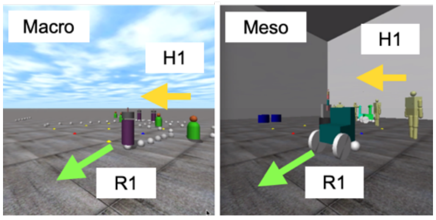
(b) An example of emergency avoidance behavior
Fig.6. Emergency avoidance behavior based on personal space.



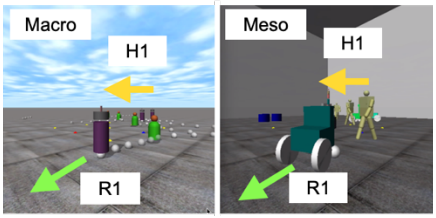
(a) (b) (c)



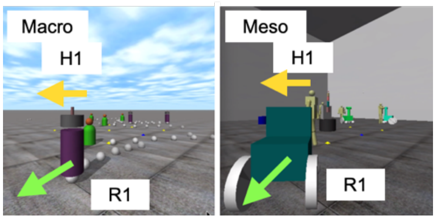
(d) (e) (f)
Fig.7. Collision avoidance behavior of humans and robots.



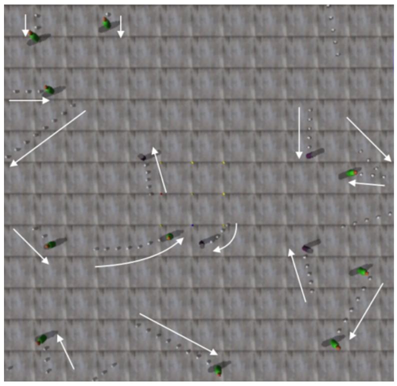
(a)



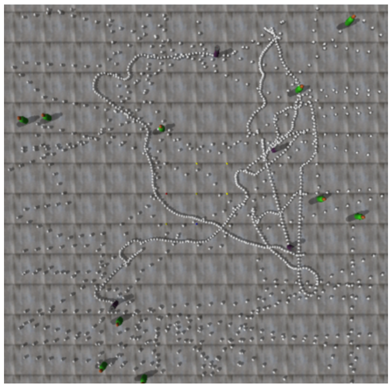
(b)



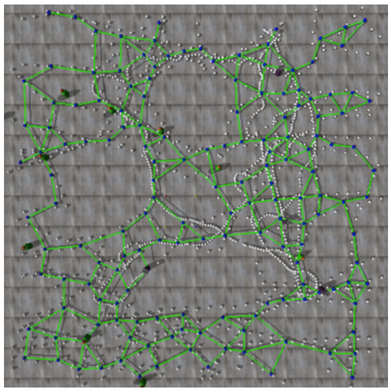
(c)
Fig.8. An example of meso- and macro- scopic simulations.



(a) Temporal trajectories of all humans and robots



(b) Trajectories of all humans and robots



(c) Topological mapping from trajectories of all humans and robots
Fig.9. Tracking and movement feature extraction of humans and robots in macroscopic simulations.

4. Simulation Results

This section shows simulation results of the proposed method. The numbers of humans and mobility support robots are 10 (P = 10) and 4 (R = 4), respectively; $\gamma = 0.2$; in this simulation. We also use fuzzy control for collision avoidance of humans. The position of humans and robots is transferred to the macroscopic simulation.

Figure 7 shows an example of collision avoidance behavior of humans and robots. There are two robots encountering two humans, but they are avoiding collisions each other. Figure 8 shows an example of meso- and macro-scopic simulations. The position of a human and robot in the mesoscopic simulation is reflected to that in the macroscopic simulation. Figure 9 shows (a) Temporal trajectories of all humans and robots, (b) Trajectories of all humans and robots, and (c) Topological mapping from trajectories of all humans and robots for movement feature extraction. We used multi-scale batch-learning growing neural gas [22] to extract topological features from the trajectory data of humans and robots. The topological mapping will be used for the path planning or robots and human navigation.

5. Conclusion

In this paper, we proposed a multi-scopic simulation to discuss human-robot interactions. First, we discussed how to deal with three different scopes of micro-, meso-, and macro- scopic simulations. We deal with the dynamics inside objects and internal states in the microscopic simulation. While action control is done in the microscopic level of intimate space, the behavior control is done in the mesoscopic level of personal or behavioral space. In the mesoscopic simulation, we deal with approximated rigid body dynamics between objects in a surrounding environment of humans and robots. Next, we applied multi-objective behavior coordination to represent human and robot behaviors in mesoscopic simulation. Next, we applied the proposed method to navigation tasks of mobility support robots in the behavioral and personal space. The sensory network can update the attention range in the behavior space. Furthermore, the proposed method realizes that the robot can take an emergency avoidance behavior when other humans or robots enter to the personal space. The simulation results show that the multi-objective behavior coordination can conduct collision avoidance and target tracing. The trajectory data are transferred to the macroscopic simulation and are used to extract the topological feature of the movement of humans and robots. In this way, the simulation results show the importance of coupling of mesoscopic simulation and microscopic simulations.

As a future work, we intend to develop a path planning method and human navigation in the macroscopic simulation and discuss how to use the planned path for mobility supports robots in the mesoscopic simulation. Furthermore, we will develop a human-robot interaction method based on neuro-musculoskeletal models in intimate space as the microscopic level.

Acknowledgements

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References:

[1] C.Greer, M.Burns, D.Wollman, E.Griffor, Cyber-Physical Systems and Internet of Things, NIST Special Publication 1900-202, 2019.

[2] T.Banyai, A.Petrilloand, F. De Felice, Industry 4.0: Impact on Intelligent Logistics and Manufacturing, IntechOpen, 2020.

[3] B. Fritzke: A growing neural gas network learns topologies; Advances in Neural Information Processing Systems, Vol. 7, 1995, pp. 625-632.

[4] T. Kohonen: Self-Organizing Maps; Springer, 2000.

[5] R.B. Bapat, Graphs and Matrices, Hindustan Book Agency, 2014

[6] Albert-László Barabási, Márton Pósfai, Network Science, Cambridge University Press, 2016

[7] Y.Toda, W.Chin, N.Kubota, Unsupervised neural network based topological learning from point clouds for map building, 2017 International Symposium on Micro-NanoMechatronics and Human Science (MHS), 2017.

[8] Y.Toda, N.Kubota, Topological Structure Learning Based Enclosing Formation Behavior for Monitoring System, 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2018, pp.831-836.

[9] T.Fukuda, N.Kubota, An Intelligent Robotic System Based on A Fuzzy Approach, Proceedings of The IEEE, Vol.87, No.9, 1999, pp.1448-1470.

[10] N.Kubota, N.Aizawa, Intelligent Control of Multi-Agent System based on Multi-Objective Behavior Coordination, Proc. of the 2008 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2008), pp.1458-1463, Hong Kong, China, June 1-6, 2008

[11] J.Woo, Y.Ohyama, N.Kubota, Robot partner development platform for human-robot interaction based on a user-centered design approach, Applied Sciences, 10 (22) , 2020, pp.1-20.

[12] A.Yorita, T.Hashimoto, H.Kobayashi, N.Kubota, Remote Education based on Robot Edutainment, Proc. (CD-ROM) of The 5th International Symposium on Automomous Minirobots for Research and Educatinment (AMiRE 2009), pp, 204-213, Incheon, Korea, August 16 - August 18, 2009.

[13] T. Obo, C. K. Loo and N. Kubota, "Imitation Learning for Daily Exercise Support with Robot Partner," 2015 24th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), pp. 752–757, 2015.

[14] J. Woo, J. Botzheim and N. Kubota, "System integration for cognitive model of a robot partner," Intelligent Automation & Soft Computing (AUTOSOFT), 24(4), pp. 829–842, 2018.

[15] K. Umetsu, J. Woo and N. Kubota, "Effects of the Audience Robot on Robot Interactive Theater Considering the State of Audiences," 2019 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1430–1434, 2019.

[16] S.Yamamoto, J.Woo, W.H.Chin, K.Matsumura, N.Kubota, Interactive information support by robot partners based on informationally structured space, Journal of Robotics and Mechatronics, 32 (1) , 2020, pp. 236-243.

[17] C.-S.Lee, M.-H.Wang, Y.-L.Tsai, W.-S.Chang, M.Reformat, G.Acampora, N.Kubota, FML-Based Reinforcement Learning Agent with Fuzzy Ontology for Human-Robot Cooperative Edutainment, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 28 (6), 2020, pp.1023-1060.

[18] Hiroyuki Masuta, Tetsuya Kawamoto, Kei Sawai, Tatsuo Motoyoshi, Takumi Tamamoto, Ken'ichi Koyanagi, and Toru Oshima, Presentation Robot System with Interaction for Class, IEEE Symposium Series on Computational Intelligence SSCI 2018, pp, 1801-1806, 2018.

[19] Hiroyuki Masuta, Hiroki Kanamori, Kei Sawai, Tatsuo Motoyoshi, Takumi Tamamoto, Ken'ichi Koyanagi, and Toru Oshima, Development of Presentation Robot System for Classroom Based on State of Participants, 2019 IEEE Symposium Series on Computational Intelligence (SSCI), pp, 2222-2227, 2019.

[20] T.Obo, Human-Robot Communication Based on Self-Serving Bias for Daily Exercise Support, International Journal of Artificial Life Research, Vol. 7, Issue 1, pp. 24-37, 2017.

[21] T. Yamamoto, K. Terada, A. Ochiai, F. Saito, Y. Asahara, and K. Murase, "Development of the Research Platform of a Domestic Mobile Manipulator Utilized for International Competition and Field Test," *IEEE Int. Conf. Intell. Robot. Syst.*, pp. 7675–7682, 2018.

[22] M.Iwasa, N.Kubota, and Y.Toda, Multi-scale Batch-Learning Growing Neural Gas for Topological Feature Extraction in Navigation of Mobility Support Robots, The 7th International Workshop on Advanced Computational Intelligence and Intelligent Informatics (IWACIII 2021), 2021 (submitted).