Synergetic Learning Control Paradigm for Redundant Robot to Enhance Error-Energy Index

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***Abstract*—In order to perform energetically efficient motion as in human control, so-called optimization based approach is commonly used in both robotics and neuroscience. Such an optimization approach can provide optimal solution when the prior dynamics information of the manipulator and the environment is explicitly given. However, the environment where the robot faces with in a real world rarely has such a situation. The dynamics conditions change by the contact situation or the hand load for the manipulation task. Simple computational paradigm to realize both adaptability and learning is essential to bridge the gap between learning and control process in redundancy. We verify a novel synergetic learning control (SyLC) paradigm in reaching task of redundant manipulator. The performance in handling different dynamics conditions is evaluated in dual criteria of error-energy coupling without prior knowledge of the given environmental dynamics and with model-optimization-free approach. This paper aims at investigating the ability of phenomenological optimization with the proposed human-inspired learning control paradigm for environmental dynamics recognition and adaptation, which is different from conventional model optimization approach. Error-Energy index is introduced to evaluate not only the tracking performance, but also the error reduction rate per the energy consumption.**

***Index Terms*—Human Motor Learning, Motor Synergy, Redundancy, Environmental Adaptation, Tacit Learning, Error-Energy Index.**

I. Introduction

The use of bioinspired approaches [14], [32], [21] is rather appealing in controlling articulated robots with redundancy. Even after recent progressive development of humanoid robots, the performance of advanced humanoid is still highly limited especially for the case under new and unknown dynamic environment. When the given dynamics can be written with explicit equations both for the environment and the robot manipulator itself, and if it is especially for predefined tasks, the humanoid motor performance can be higher than the human skills. Such capability is benefitted from the model-based control and the knowledge of detailed dynamics and high-speed actuators differently from fatigable and slow-response muscle actuators embedded in the human system [20]. Whether or not we can have a prior knowledge of the dynamics information brings significant difference in humanoids performance.

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The key to fill the gap between human and humanoid motor control ability is learning and adaptivity, coordination of multiple (redundant) joints, and optimality principles for motor execution toward energy efficiency. In human motor learning control, it has all the above listed capability in seamless and synchronous manner. In contrast, humanoid study tends to use separated component to deal with each feature. For instance, using an explicit dynamics model, some researchers have been dealing with redundancy by applying mathematical optimization. Often, there is no learning feature in such optimization or it is dealt with separated components between the optimization and the motor action. Humans also have a capability to use new tools without the prior-knowledge as if they are part of the human bodies, known as tool-body assimilation through trial and experience [15], [26]. This fact indicates the importance of model-free learning controller for environmental dynamics recognition and adaptation.

In addition, our skeletal system has more degrees of freedom (DOF) than the number of dimensions in our task space. Taking an advantage of dexterity from redundancy, humans can learn new skills and with dynamic adaptivity while keeping certain motion accuracy but also finding easier motor coordination considering our physical biomechanical conditions. Found motor solutions are energetically efficient taking into account our articulated body dynamics [16]. Thus, the human motion is not always so precise. It means when we ask the subject to draw straight line in front of his body in pointing task, that line is often not completely straight since we tend to move in a comfortable way, which is dynamically energy efficient to drive our multi-linked chains. There are also accuracy limitation issues in biological neuromuscular property such as signal-dependent noise and delayed sensory feedback. We need to make the joint stiff to cancel those biological effects, for accurate motor control. Energies need to be added to make more accurate motions. This phenomenon is a proof of multi-criteria on Error and Energy in human motor control. In addition, the human control can change the combination of criteria depending on the way of instruction and their motivation. We have an ability to increase the precision of the straight line if the instructor indicates the task strictly. Basically, making a precise motion is more energy-consuming as we can imagine easily from the example of high-gain proportional-derivative control to remove the error. Human motor control has a good flexibility to handle the dual conflicting criteria. When it seems not necessary to be so precise, we can find a good compromise naturally between the motion accuracy and the energy efficiency. These criteria are often evaluated separately, however we would need

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a new index to evaluate the coupled measure regarding a motor control capability on the trade-off between accuracy and energy. In this paper, we propose a computational "Synergetic Learning Control" as a mean to solve the degrees of freedom problem considering error and energy coupling as well as learn to account for varying dynamics.

II. Modular Model-free Optimization Process

Such general ill-posed problem of DOF was originally formulated by Bernstein [5] as there are infinite solutions in redundant DOFs. Motor synergy is a neural organization of a multi-element system that organizes upper level task among a set of elemental controls. It is still an open problem to answer how motor controllers in the central nervous system (CNS) solve kinematic redundancy for multi-criteria. In this scientific problem, so-called cost function based mathematical optimization is a state-of-art approach to solve such ill-posed problem [8][35] in computational neuroscience.

Several types of optimality model have been proposed. Such model is often defined as 'minimum X', where X can be jerk, torque changes [37], motor command [12] and energy consumption [1]. In redundant manipulators, such a cost function based optimal control was successfully applied in [36][11]. In robotics, several methods were studied to deal with the redundancy [23], [2]. The robotics approach basically assume the use of a physical inverse dynamic model [24] or approximation-based model [28]. The model-based approach is commonly employed for inducing optimized solution rather than using learning process.

As for a model-free approach, adaptive feedback control is known in control society. However, adaptive control can not be applied to redundant systems without using a-priori optimization. Feedback-error-learning (FEL) is well studied to provide computational adaptation paradigms [18]. FEL is proven as a special form of adaptive feedback control [25]. Then it does not provide a mechanism that can systematically improve performance toward optimal solutions under redundancy.

Final solution likely to be performed by humans can be obtained with optimization approach. However, mathematical optimization basically requires the dynamic model of the system and involves complex computation. In addition, such computational operation requires a global image of the system and to know the overall variables at different levels in the system, which is a quite complex process to be embedded in the CNS as a modular configuration [9][34]. Modular computational principle which can handle total system optimization is preferred to be considered as an embedded algorithm in the CNS. However, the current mathematical optimization is not a module-oriented computational operation. If we could find an alternative modular algorithm which can manage to induce the total system phenomenological optimization, it could be a candidate as a computational principle to be likely embedded in the CNS.

Recently, a novel learning scheme named *Tacit Learning* was developed [33] as an unsupervised learning paradigm. The experimental results demonstrated that the walking gait composed of primitive motions was well adapted to the environment in terms of walking efficiency [33]. Based on the tacit learning concept, we reformulated the paradigm as a supervised learning structure, especially to be used for intentional motion generation. It is applied to cyclic reaching tasks using the feedback motor command error as a supervising signal. Synergetic motor control paradigm for optimizing energy efficiency of multijoint reaching is proposed to systematically induce the motor synergy emergence in reaching task [13], [6]. It demonstrated to produce energy efficiency while finding a way to compensate the interaction torques in multijoint reaching, which was only verified in the computer simulation. Here, we aim at investigating the feasibility of Synergetic learning control (SyLC) paradigm to be first applied for redundant articulated robot with physical electromechanics in this paper.

Seamless learning and control for environmental dynamics recognition and adaptation is an important aspect, which is difficult to be managed with conventional model-based optimization in robotics. It is not realistic to apply mathematical optimization every time the dynamic environment is changed as it can happen at any time in general environmental interaction. Furthermore, the issue of how such exact model description is obtained for time-variant physical environment would also limit the application of model-based optimization in a real world.

III. Method -Redundant Robot Configuration

The human skeletal system has complex series of linkages that produce coupled dynamics. For instance, when we quickly move our forearm by flexing the elbow joint, the flexion torques on the elbow joint accelerate our forearm. However, due to the forearm's inertia, this acceleration produces torques also on the shoulder. These interaction torques induce the undesired effect of accelerating the upper arm segment. The dynamics of multijoint limbs often causes such complex torques especially during vertical reaching task due to gravity. In human control, the able-bodied subject can easily handle such interaction torques with motor learning and its predictive control [31][4]. In this work, we aim to verify the performance of redundant manipulator driven by Synergetic learning control under vertical reaching as the configuration used in [4].

In a sagittal plane, 3 Degrees-of-Freedom (DOF) composed of shoulder, elbow, wrist joint was arranged as illustrated in Fig.1. The upper arm, forearm and hand segments were connected through each joint. Each joint is actuated using a DC motor with an encoder and a harmonic drive gearing for backdrivability as depicted in Fig.1(a). 10W motors are used for Joint 1 (Shoulder) and 2 (Elbow), and 4.5W motor is used for Joint 3 (Wrist). The ratio of the gears is all 1/100. The motor located below Joint 3 is used to grasp the object by the hand. Each motor is current-controlled with servo-amplifier drives. Thus, each joint has a local torque control to generate the specified joint torque by the Synergetic learning controller for the robot. The control algorithms are executed with the sampling frequency of 500Hz on a master PC with the interface of AD and DA converters from the encoders and

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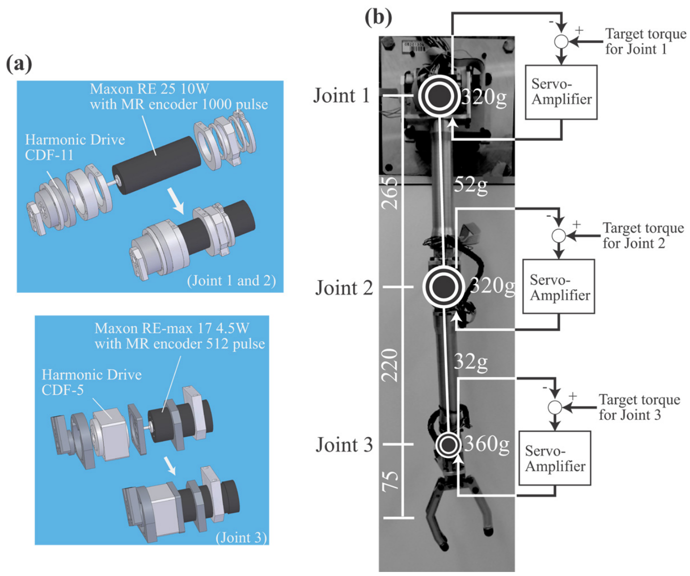

Fig. 1. 3DOF Manipulator for Experiments: **(a)** structures of motor component: Each joint consists of a DC motor with an encoder and a Harmonic Drive gearing. **(b)** Overview of the 3DOF manipulator with some parameters. Each joint has the local servo-amplifier to create the targeted joint torque.

to the motors, respectively. This manipulator is redundant as the motor axes are in parallel. Some manipulator parameters are described in Fig.1(b).

We perform the control of this robot only with the proposed learning controller without using the explicit dynamics equations of the robot. Thus, we have an access only to the control of each joint torque and no access to the manipulator dynamics model in the learning process. It should be noted that this configuration is in so-called Bernstein's DOF problem where we have actuation redundancy since the task is performed in 2D with 3DOF manipulator.

IV. Synergetic Learning Control

Synergetic learning control (SyLC) scheme for reaching motion of redundant robotic manipulator is represented as in Fig.2. The control architecture is formulated as a supervised learning paradigm using the feedback motor command error as illustrated in the block diagram. Conceptually, it has an approach in common with FEL in how to use feedback errors as supervising signals [18]. However, in FEL, prior optimization is still necessary to achieve optimality for redundant system [29]. Thus, we aim to provide a primitive mechanism for learning without using a cost function. As in the mechanism of the cerebellum with regard to long-term associative potentiation/depression, simple tacit learning with torque signal accumulation is employed to realize systematic adaptation from feedback-error learning structure and energy minimization from the torque accumulation seamlessly. We assume only forward kinematics (FK) information is available. The multijoint dynamics information is not given to the learning controller, thus this paradigm is to find a way to manage interaction torques through the repetitive interactions with the environment.

The proposed Synergetic learning control paradigm shown in Fig. 2 consists of these separated elements in loop:

1) The intention to follow the target is expressed by a force vector in the task space, which represents the direction to the target, and the distance as its intensity, using the proportional (P) feedback error between the target and current endpoint.
2) The feedback force error is mapped through the Jacobian of the arm into the joint torque space. It can be regarded as motor-command error that works as a supervising signal, as in FEL.
3) Local proportional derivative (PD) control mainly corresponds to a local reflex loop as a function of the muscle spindles. This part basically contributes to changing the joint angles smoothly.
4) Torque command accumulation part shown as gray box corresponds to tacit learning. This Integral (I) part serves as a unique learning process. This motor pattern accumulation part starts to learn how to compensate the interaction torques, and turns into a predictive torque patterns for a given repetitive task.

Specifically, the controllers for PD feedback and SyLC control can be expressed as follows.
PD feedback:

$$\boldsymbol{\tau}_1(t) = -\boldsymbol{J}^T(\boldsymbol{\theta})k\Delta\boldsymbol{p} - \boldsymbol{A}\boldsymbol{\theta} - \boldsymbol{B}\dot{\boldsymbol{\theta}}. \quad (1)$$

SyLC control:

$$\boldsymbol{\tau}_2(t) = -\boldsymbol{J}^T(\boldsymbol{\theta})k\Delta\boldsymbol{p} - \boldsymbol{A}\boldsymbol{\theta} - \boldsymbol{B}\dot{\boldsymbol{\theta}} + \boldsymbol{C}\int \boldsymbol{\tau}_1 dt. \quad (2)$$

$$\boldsymbol{\tau}_1, \boldsymbol{\tau}_2, \boldsymbol{\theta}, \dot{\boldsymbol{\theta}} \in R^m, \Delta\boldsymbol{p} \in R^n, \boldsymbol{J}^T(\boldsymbol{\theta}) \in R^{m\times n}, \boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C} \in R^{m\times m}$$

where m is the number of the joints, n is the task space dimension, $\boldsymbol{\tau}$ denotes the control torque inputs of the joints, $\boldsymbol{\theta}$ denotes the angles of the joints, $\dot{\boldsymbol{\theta}}$ denotes the angular velocities of joints. $\boldsymbol{J}^T(\boldsymbol{\theta})$ is the transpose of the Jacobian of the arm, k is the gain of the task space proportional feedback, $\Delta\boldsymbol{p}$ is the endpoint error vector. The Jacobian transpose term corresponds to the neural substrate of force mapping functionality presumably due to corticospinal control [7]. The Jacobian transpose mapping has been populary used in robotics [2] and it is recently proposed as a Passive motion paradigm [22]. However, the Jacobian has a kinematic information only. This method itself can not provide a way to alter the multi-joint manipulation considering different dynamics conditions.

$\boldsymbol{A}$ and $\boldsymbol{B}$ are diagonal matrices which consist of the proportional and derivative gains of the PD controllers of local joint. $\boldsymbol{C}$ is a diagonal matrix which consists of the gains of the torque command integration regarding motor-command error and local feedback torque. The term $\boldsymbol{A}\boldsymbol{\theta}$ is optional, and it can be set if it is necessary to specify the neutral position of the joint. In this work, this neutral position is specified only for the wrist joint, because the wrist tends to return to the central position when we relax.

As for local PD feedback, this part corresponds to a local

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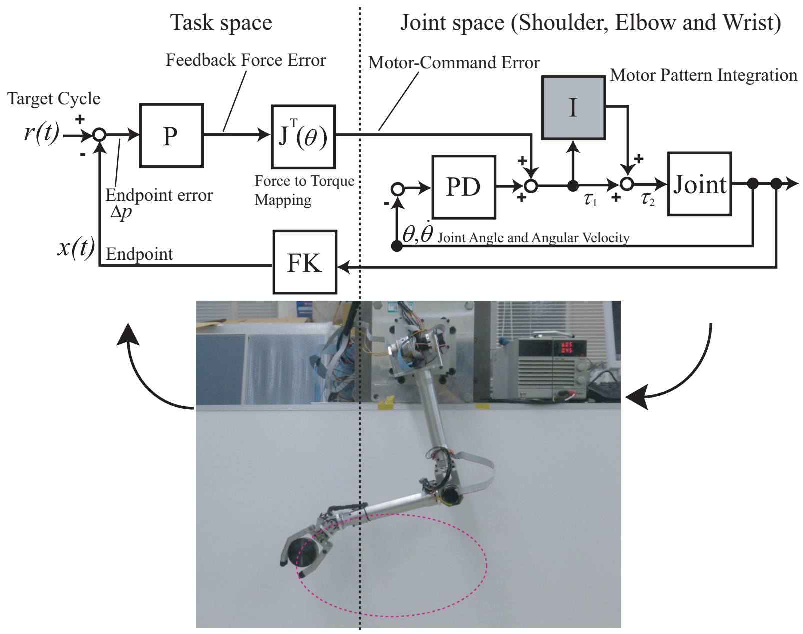

Fig. 2. Synergetic learning control (SyLC) scheme for reaching motion of redundant robotic manipulator. The robot has 3 DOFs of the shoulder, the elbow and the wrist. The task is to track the moving target for 2D ellipsoidal trajectory while holding a load at its hand without the prior knowledge of its dynamics information. P represents Proportional, D Derivative and I the Integral controller, respectively. The box named joint represents the physical joint of the arm. The intentional target is expressed by a force vector in the task space, which represents the direction and distance to the target, using the proportional feedback error between the target and current endpoint. The feedback torque command error at each joint space is computed through the Jacobian of the arm by mapping the feedback force into the joint torque space. Local PD control represents the local reflex loop as a function of a muscle spindle. The motor pattern accumulation part in gray color corresponds to tacit learning.

reflex loop as a function of the muscle spindles [30]. When a muscle is stretched, primary sensory fibers of the muscle spindle respond to changes in muscle length and velocity. The reflexivity evoked activity in the alpha motoneurons is then transmitted via their efferent axons to the muscle, which generates force and thereby modulates the joint angles smoothly.

Note that all joints are controlled independently except the task space operation, then the control configuration has a modular structure. All dynamical parameters, such as segment inertia and mass, and the model itself, are completely blind to the controller. Differently from a typical optimization approach, our method is to produce such optimization process without using cost function, purely with repetitive interactions with the given dynamic environment. The difference between the PD feedback case and SyLC case is only the last term of the command signal accumulation in Eq. 2. Neural integrators are found in many nervous system including our oculomotor system. This term corresponds to a neural integrator in the torque level.

V. Principles in Synergetic learning control

The difference from a typical FEL configuration is first the point where the motor-command error is created by the mapping between the task space force and the joint space torque. In FEL, the optimized desired trajectory of position and velocity in joint space should be prepared in advance by optimizing some criteria specifically for the arm with redundant degrees of freedom [29]. Here, the necessary joint position and velocity are unknown, and the task to follow the moving target is directly given keeping joint redundancy. Even if we use the Jacobian information, we do not perform inverse kinematic (IK) and inverse dynamics (ID) computation explicitly. The pseudo-inverse of Jacobian is not computed in this method, different from the typical methods in the robotics approach. Thus, the dimension reduction is not explicitly performed. The Jacobian itself can be obtained with the knowledge of the FK model. Thus, only FK information is assumed in this method, and the IK and ID models are unknown, here how to take the dynamics into account should be learned by the repetitive interactions with the environment. Along with the adaptivity originating from the FEL architecture, the energetic optimization manageability is a contribution of this method without using explicit model-based structure.

As for the mechanism on how motor performance can be optimized over time, Eq.1 is basically for the end-point error minimization purpose. The motor command accumulation part in the added term in Eq.2 serves as an energy feedback considering the task space directional information to the total system. The torque integration can account for the energy consumption of the robot arm for the cyclic motion as it is employed in [33]. In general error feedback control, when the error is fed back, the systematic error can be minimized. Similarly, the integrated torque command contains an energy measure since it accumulates the past torque generation history during cyclic reaching task. Thus the energy of total system can be naturally minimized as it is both in a feedback loop through the repetitive interactions with the environment. Even the torque accumulation feedback is performed in each individual joint, the total system receives the all energy consumption information from the associated joints. The modified joint torque is feed to the coupled link dynamics and results in the new joint coordination as a total system.

In human motor control, the usage of feedforward control is well known, and it is a key to arrive at energetically efficient solution. Feedforward movements are made without sensory feedback, which have predictive nature of the given dynamics. Feedback control, in contrast, involves modification of the current movement using information from sensory receptors and error detection. If we rely on the feedback control and to perform certain accurate motion, local joint feedback gain tends to high resulting in a high joint stiffness, which is a source of increased energy consumption [13]. The phase shift between feedback control and feedforward control during motor learning is well justified by obtaining the internal model in the cerebellum in previous papers [17],[19]. In general, optimal movement control likely reflects a combination of both feedback and feedforward processes [10].

VI. Results

A. Energy and Error Coupling Minimization

To evaluate the performance of the proposed SyLC control in redundant robot, we compare the control results of vertical tracking for 2D ellipsoidal trajectories between (a) PD feedback controller and (b) SyLC controller. The task of vertical reaching is to drive the endpoint of the arm following the dynamically moving target while holding a load at its hand under the gravity. The hand load was in two conditions, 450g and 600g respectively. These loads were given as an unknown object, as this controller doesn't have the dynamics information. The cycle frequency f to draw an ellipse is given with $1/T$, where T is the time to draw one ellipse.

The moving target $\boldsymbol{r}(t)$ is given as follows:

$$\boldsymbol{p}_c = \left[\begin{array}{cc} 0.0 & -0.4 \end{array}\right]^T,$$
$$\boldsymbol{r}(t) = \boldsymbol{p}_c + \left[\begin{array}{cc} -0.15sin(2\pi ft) & -0.075cos(2\pi ft) \end{array}\right]^T. \quad (3)$$

At the beginning, the arm is stopped with extended posture to the gravity direction with zero joint angle for all the joints as in Fig.1(b).

Fig. 3(a) represents a control result for endpoint transition only with feedback control. The target was moving in an ellipsoildal orbit in 1/4 Hz with 0.45kg load at hand. Fig. 3(b) is the endpoint with SyLC controller. The feedback control gains are kept same for the both type of controllers. The time sequential transition is illustrated using color map which changes depending on the time progress. A cool color map is used for (a) PD feedback control, a jet color map is used for (b) SyLC. This colormap configuration is used also in the other following figures.

Fig. 3(a) shows that PD control is largely affected by the gravity and the interaction torques. The fact that the control gain is set low, can be also observed. There is no learning effect then the endpoint loop is unchanged after the initial dynamic transition from the stopped straight arm configuration to the dynamic motion phase. On the contrary, we can find that the trajectory is being corrected in time in the case of Synergetic learning control minimizing the effect of the gravity and interaction torque. Initially the trajectory was similar to the one of (a), but improves the tracking performance as indicated in Fig. 3 (c), which shows the transition of endpoint error. The average endpoint error is calculated as the root-mean-square (RMS) error between the target point and current endpoint during one cycle.

Energy consumption in one cycle of reaching was measured as an average power, which is plotted in Fig. 3 (d). The target is moved in the ellipsoidal orbit in the frequency 1/4Hz. Therefore, the energy consumption during every 4 seconds was calculated by summing up each joint energy consumption $\tau\dot{\theta}$ and computed as a temporal work rate scale (power). The transition of energy consumption in learning control can be observed as in Fig. 3 (d). In Eq. 2, the torque component of PD feedback was regarded as feedback (FB) controller, the integration term was regarded as FF controller. Because it is independent from the feedback signal status and it converges into an open loop cyclic torque pattern for a given task. The energy consumption by each torque component is also visualized as in Fig. 3 (d). The energy rate is not much changed in the course of learning, but we should note that the tracking error is being improved. Considering the fact that more energy is naturally necessary to make the motion with less error to the target. The Synergetic controller is managing dual conflicting criteria of error and energy as a coupling. Balance of these two criteria can be potentially manageable to adjust the learning gain and the feedback gain. However, we employed a fixed gain in this first robot trial to verify the systematic feasibility of the proposed method in the real robot. In addition, it was possible to observe the contribution ratio was switched between FB and FF controllers. Initially FB was mainly used, and with learning progress, the energy consumption with FB is minimized, while FF contribution is significantly increased.

Next, motor control result to track the moving target in an ellipsoildal orbit in 1/4 Hz with 0.6kg load at hand is summarized in Fig. 4. The hand weight is increased by 33 percent. The added moment of inertia in respect to the hand weight concerning the shoulder joint should have been increased by 33 percent. This test is to verify the control performance in different dynamic conditions. As the proposed method does not use the prior plant dynamics information, the exactly same controller is rerun including the control gains and learning gain. We have only changed the weight from 450g to 600g in a real world.

We can observe in Fig. 4 (a)(b) that endpoint only with feedback control is affected more by larger inertial effect caused by the added hand weight, in contrast the endpoint in Synergetic learning control is converged in similar way to the case of 450g toward tracking the ellipsoidal target by compensating the gravity and the interaction torques. The Synergetic control case converged to very close endpoint error which is only the difference of 3mm compared to the case of 450g as observed in Fig.4 (c). It successfully deals with the different dynamic condition. Keeping average endpoint error for different loads with exactly same controller is already not trivial in conventional robotics, when the joints of the arm have high compliance. The fact of high compliance of the manipulator can be confirmed from the feedback case performance of Fig. 4 (a). As the feedback gain is low, the

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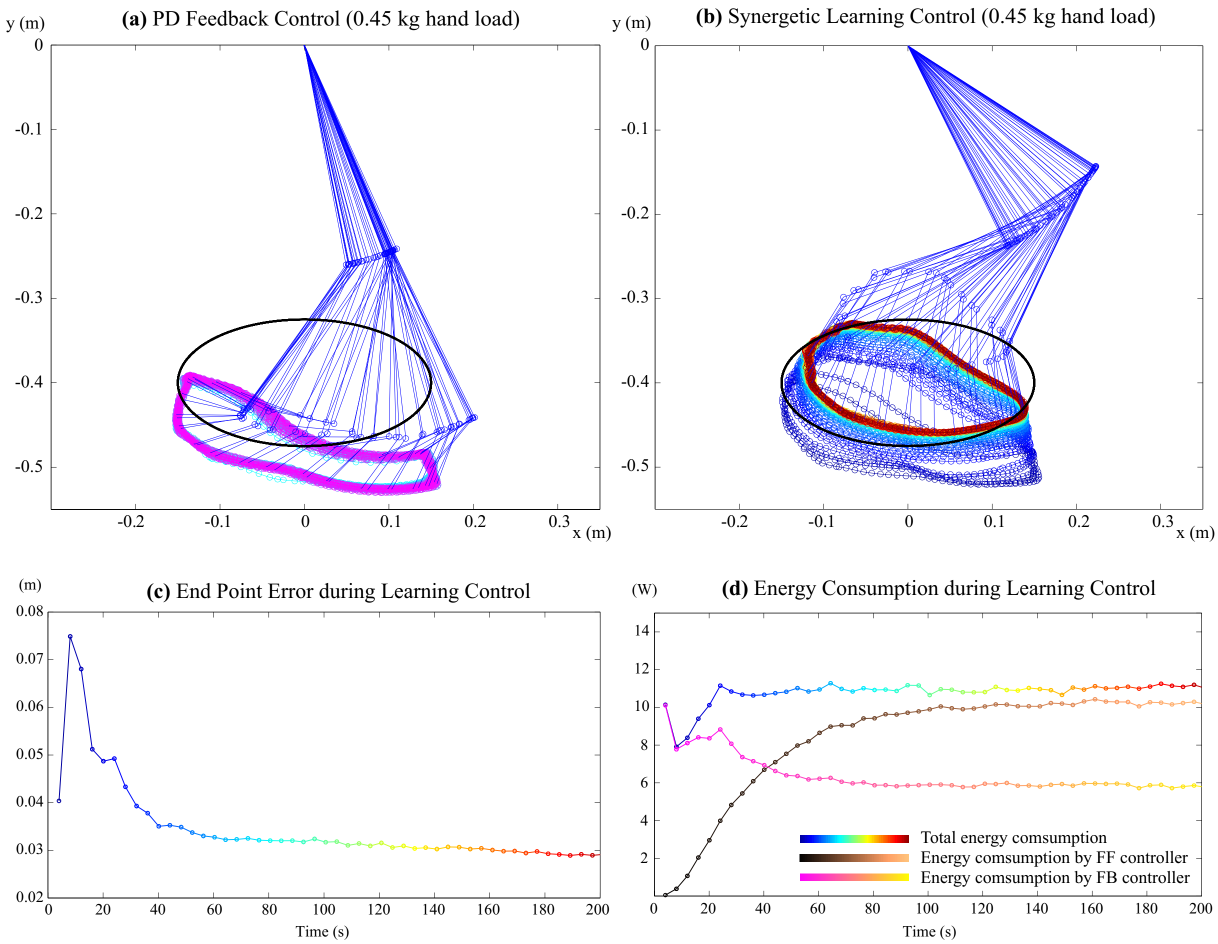

Fig. 3. Motor control result to track the moving target in ellipsoildal orbit in 1/4 Hz (0.45kg load at hand). (a) Endpoint transition only with feedback control and (b) with SyLC control. (c) The transition of endpoint error and (d) the energy consumption in each ellipsoidal cycle of reaching as an average power. Not only improving the target tracking accuracy, but Synergetic learning solutions result in efficient total energy consumption in respect to the tracking accuracy. In addition, it was possible to observe the contribution ratio was switched between FB and FF controllers. Initially FB was mainly used, and with learning progress, the energy consumption with FB is minimized, while FF contribution is increased.

arm is largely influenced by the environment, it indicates that the feedback gain which is employed in this experiment is low then the joint is highly compliant. The energy consumption in each ellipsoidal cycle of reaching as an average power was similar transition to the case of 450g, while increasing the absolute power scale corresponding to 600g hand weight as in Fig. 4 (d).

B. Synergetic Joint Usage

Fig. 5 indicates a phase portrait between the shoulder and the elbow joint angles in different dynamic conditions (a) 0.45kg, 1/4Hz, (b) 0.6kg, 1/4Hz, (c) 0.6kg, 1/3Hz, and both in only feedback control and in SyLC. The task trajectory itself was same, the difference were the hand load and the cycle speed.

The line in the cool color map indicates the joint usage result with only feedback control, and the line in the jet color map is that for Synergetic learning. We see the phase in Synergetic learning converges into the consistent joint angle combinations regardless of different dynamic conditions. In contrast, the joint space usage in only feedback control are different each other as it is significantly influenced by the inertial effect variation due to the motion speed and the hand load changes.

It is interesting to see the phase form is similar for different load conditions in Synergetic learning. The phase portrait is a plot without time dimension, thus it can be an optimized joint synergetic usage regardless of the motion speed for a target trajectory under the given dynamic environment. Then, the unchanged joint space usage is somehow reasonable. As the joint combination usage is common for different dynamic conditions, we can expect that it should be robust also for the case where the robot needs to change the motion speed or hand weight in the course of the motor control. Since it is necessary to change just slightly the joint usage space for dynamical condition changes, this situation helps a lot also for the adaptivity to the time-variant unknown environmental dynamics. If we carefully check Fig. 5, we can also find that the very initial phase portrait of learning case is very close to the one of feedback case as it is initially fully driven by feedback component of the controller. In the course of the learning, the similar Synergetic combination between neighboring joints was found under different dynamic conditions. It is interesting to see such consistent and reasonable solution is

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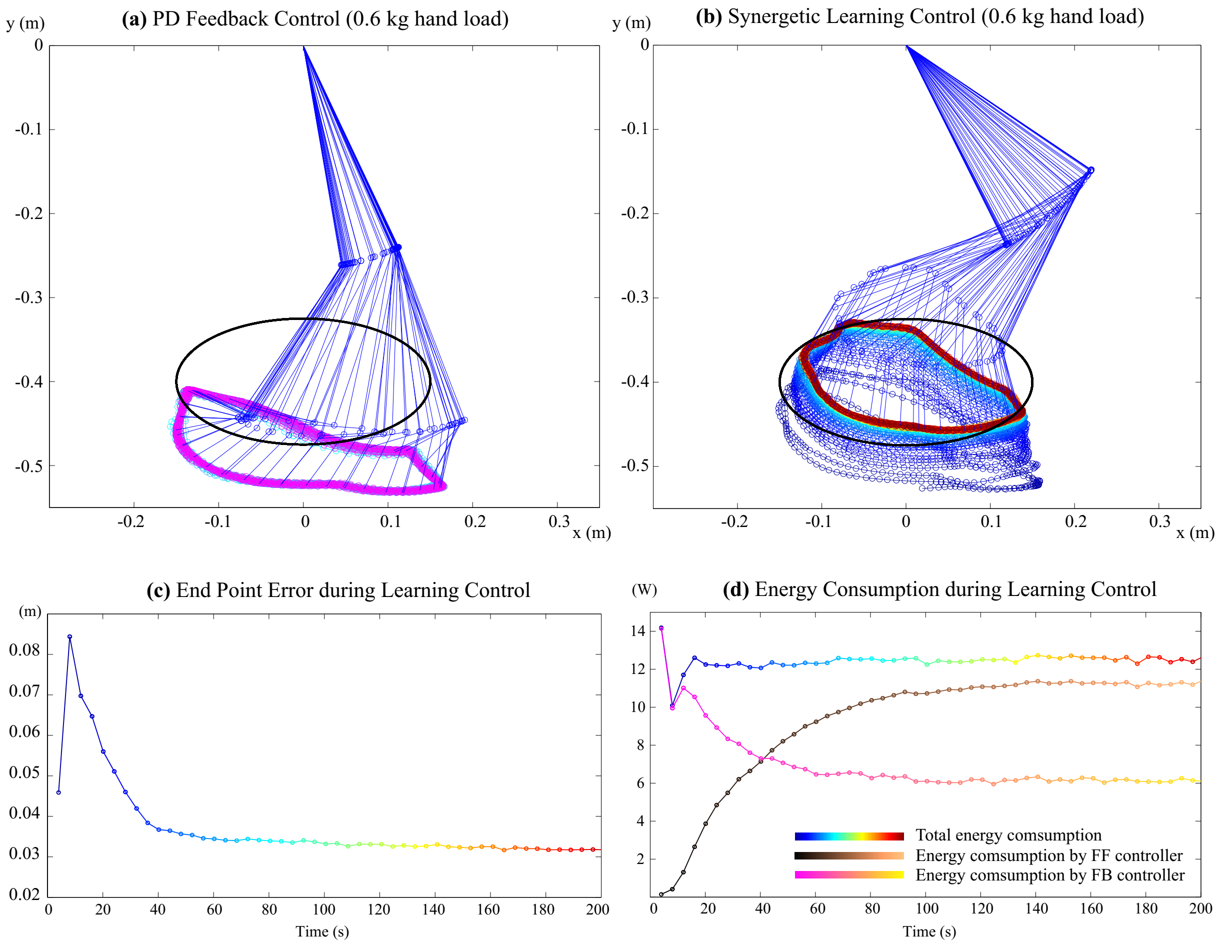

Fig. 4. Motor control result to track the moving target in ellipsoidal orbit in 1/4 Hz (0.6kg load at hand). (a) Endpoint transition only with feedback control and (b) with SyLC control. (c) The transition of endpoint error and (d) the energy consumption in each ellipsoidal cycle of reaching as an average power. By added load, larger tracking error is observed in feedback control case caused by larger inertial effect in this dynamic motion. In contrast, Synergetic control converged to endpoint error which is only the difference of 3mm compared to the case of 450g. It successfully deals with the different dynamic condition.

gradually found even with the dynamics-model-free and cost-function-free approach.

C. Error-Energy index

As it is previously stated, human motor control employs multiple criteria. If it is an industrial robot, only thinking about the endpoint accuracy may be enough. However, human motor control takes into account also the energy efficiency [16]. Thus, if we look into only the endpoint accuracy of human motor control, it is not necessarily with high precision. For instance, the casual hand move from right to left in front of our body is not that straight, a little curved around the shoulder with the compromised choice of motor command which is easily taken from the given body dynamics. We can not evaluate only with motion accuracy, as it might associate with higher energy usage. So as for only energy consumption measure, as it depends on how the task is accurately performed. A new measure is required to correctly evaluate the rate of motion accuracy per the energetic effort.

Therefore, we propose here a simple criterion to evaluate the coupled index over both error and energy for a moving object following task. We name it as Error-Energy (E-E) index, which is 1/Error/Energy. It is simply the tracking accuracy rate per energy consumption. 1/Error means the accuracy of the tracking, the hyperbolic measure is used to evaluate less error situation as a priority. Zero error situation won't happen in moving object following task. Then $EE_1 = 1/Error/Energy$ represents normalized accuracy rate per energy. Here, we use power (W) as a unit energy. As the proposed controller is not with cost optimization process, this index itself is not used during the control process, it was used only for a posterior evaluation of the performance generated by the proposed learning controller.

The endpoint error and the energy consumption transition along with the time progress is summarized in Table I for two hand load conditions. In PD feedback control, there is no improvement for both error and energy. The variation in the initial phase is due to the fact that the robot changes from stopped status to the dynamic motion status. This effect can be seen also in the initial phase of SyLC. Differently from simulation, the real robot has friction in the joint, then some minor value fluctuation can be also observed after the steady-state status.

We can notice that the energy consumption in SyLC is not necessarily decreased, however the endpoint error is minimized to improve the target tracking accuracy during learning

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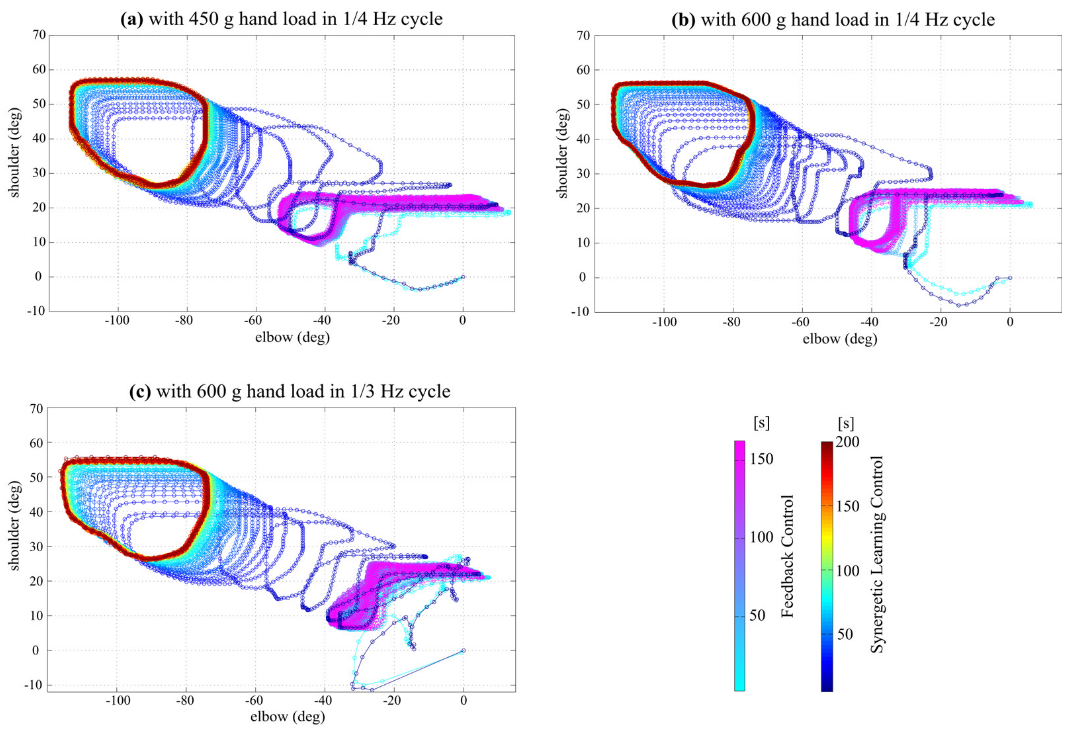

Fig. 5. Phase portrait between the shoulder and the elbow joint angle in different dynamic conditions (a) 0.45kg,1/4Hz, (b) 0.6kg,1/4Hz, (c) 0.6kg,1/3Hz, and both in only feedback and in Synergetic learning control. The line in the cool color map indicates the joint usage result with only feedback control, and the line in the jet color map is that for SyLC. We see the phase in SyLC converges into the consistent joint angle combination space regardless of different dynamic conditions. In contrast, the joint space usage in only feedback is different each other as it is significantly influenced by the inertial effect variation.

control while keeping the energy consumption. If we look the table result closely, from 32s to 200s, the energy increase is only 3% increase in 450g, while the error is significantly minimized with 25%. The error minimization rate was 24% as well for 600g case, while there is no energy increase. This fact supports well the efficiency of SyLC in the tracking accuracy rate per energy. The energy consumption ratio by FF controller is being augmented while the one of FB controller is being decreased. The figures in parentheses in Table I indicate the cycle-to-cycle variability to evaluate the convergence of tacit learning. We can confirm that the error, the energy and the contributions of FF and FB are all converged in the course of the learning process in SyLC. To take into account the Error-Energy balance, the above mentioned E-E index is computed as in the right column of Table I. The left side of Error-Energy index represents the first index (EE_1) as an accuracy rate per energy. In this index, we can observe the clear advantage of SyLC over sole feedback control. From 16s, all the E-E indexes are larger than the case of feedback control, it went into nearly 3. Then, it can measure the motion accuracy in the cost of the energy consumption. In the case of 0.6kg, E-E index was converged even into double of the one in sole feedback control.

The first Error-Energy index as an accuracy rate per energy is newly proposed in this paper. We have verified this Error-Energy coupling aspect also with other exisiting measure as a secondary index, as a reference. It has been shown in neuroscience studies that humans interact with the environment by minimizing error (e) and effort (u) in the normalized scale, which can be modelled as the minimization of the cost function $EE_2 = \alpha e^2 + \beta u^2$, $\alpha + \beta = 1, \alpha, \beta > 0$ [27], [36]. The right side term is to account for the energetic effort, then we replaced here with the energy measure. $\alpha = 0.7, \beta = 0.3$ is employed, to put priority for the object tracking not to have the situation where no motion case is better. This secondary index (EE_2) is more for being minimized. Differently from the accuracy rate, it evaluates the total cost function over the error and the energy. The transition of this secondary index (EE_2) showed very similar tendency to the 1st index (EE_1) except the directional variations. EE_1 is increased with convergence while EE_2 is decreased during the learning process.

D. Adaptivity for different motion speed

At last, we demonstrate the adaptive nature of the Synergetic learning controller. Differently from the previous tests, we changed the moving target speed suddenly in the course of the robot control.

Fig. 6 shows the motor control result with 0.6kg load at hand, with task speed changes in the order of 1/4Hz, 1/3Hz and 1/2.5Hz. The change is made in a step manner. Simply, the f in Eq. 3 is modified at a time instant. Fig. 6 (a) is endpoint transition with Synergetic learning control. From (a), we can confirm that Synergetic learning control manages well to track moving target even when the target moves suddenly faster. The slight endpoint trajectory change can be observed. Fig. 6 (b) plots elbow joint angle-angular velocity phase portrait, different elbow angular velocity realization can be confirmed by keeping the same elbow joint angle space. Fig. 6 (c) is the transition of endpoint error, we observe slight end-point error changes with 2.8mm increase from 1/4Hz to

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TABLE I
ENDPOINT RMS ERROR (M) AND ENERGY CONSUMPTION (W) IN EACH CYCLE OF ELLIPSOIDAL TRACKING TASK, ALONG WITH E-E INDEX

	PD Feedback Control			Synergetic learning control				
Time	Error	Energy	EE_1-EE_2	Error	Energy	FF	FB	EE_1-EE_2
				0.45kg				
8s	0.078	8.0	1.60-0.756	0.075 (0.0069)	7.91 (2.20)	0.385 (0.682)	7.78 (2.36)	1.69-0.712
16s	0.074	7.73	1.75-0.693	0.051 (0.0025)	9.40 (1.01)	2.04 (0.974)	8.41 (0.30)	2.09-0.468
32s	0.075	8.05	1.66-0.715	0.039 (0.0015)	10.7 (0.16)	5.44 (0.614)	7.36 (0.707)	2.40-0.40
64s	0.073	8.0	1.71-0.686	0.032 (0.00052)	10.98 (0.30)	8.98 (0.335)	6.26 (0.20)	2.85-0.360
120s	0.073	8.05	1.70-0.688	0.032 (0.00064)	10.81 (0.28)	10.05 (0.108)	5.95 (0.166)	2.89-0.356
200s	-	-	-	0.029 (0.00021)	11.02 (0.07)	10.16 (0.13)	5.77 (0.091)	3.13-0.344
				0.6kg				
8s	0.087	9.73	1.18-0.935	0.084 (0.0147)	10.1 (4.10)	0.417 (0.896)	9.94 (4.20)	1.18-0.897
16s	0.086	9.73	1.20-0.919	0.065 (0.0087)	12.6 (0.90)	2.65(1.22)	10.5 (0.975)	1.22-0.696
32s	0.085	9.85	1.19-0.906	0.042 (0.0041)	12.3 (0.21)	6.21 (0.724)	8.06 (0.465)	1.94-0.461
64s	0.086	9.81	1.19-0.921	0.034 (0.00034)	12.3 (0.24)	9.54 (0.307)	6.44 (0.05)	2.39-0.404
120s	0.085	9.73	1.21-0.904	0.033 (0.00055)	12.5 (0.10)	11.1 (0.050)	6.18 (0.231)	2.42-0.403
200s	-	-	-	0.032 (0.00025)	12.4 (0.14)	11.4 (0.25)	6.10 (0.045)	2.52-0.395

*The figures in parentheses indicate the cycle-to-cycle variability to evaluate the convergence of SyLC control.
Between PD feedback and SyLC control, the same gain k of the task space propotional feedback is used as well as local joint PD gains.

1/3Hz, with 2.9mm increase from 1/3Hz to 1/2.5Hz. Especially in 1/2.5Hz, the robot has to manage to follow in a fast speed for an ellipsoid in average speed of 144deg/s while holding 0.6kg weight. In Fig. 6 (d), energy consumption rate can be confirmed. It increases steadily according to the increased motion speed. The contribution ratio between FB and FF controllers is maintained to follow a moving target in higher speed. Thanks to this nature, motor commands are quickly found for new dynamic condition. It is demonstrating adaptivity nature of the Synergetic learning controller.

VII. DISCUSSION

We have applied a human-inspired motor learning control paradigm to the control of redundant robotic manipulators as a first report. First, it is challenging to manage both adaptability and optimizing functionality without using model-based approaches and without prior knowledge of the given dynamics. In fact, the current robotics approach has a separated configuration on motor control and optimization. After model-optimization, the motor actions are normally taken. In addition, the dynamics model is normally required and the redundancy management is performed through the model optimization. Thus, this study has clearly different approach as it manages redundancy without dynamics knowledge of the system and without mathmatical optimization.

We need to point out that there is a common concept regarding its iterative operation with so-called iterative learning scheme [3]. However, the conventional iterative learning is basically to make the motion tracking error into zero. Their solution is looking only for the best tracking performance case. It doesn't address the energetically efficient choice of the motor command. Efficient choice could make it worse for the tracking performance in general. In contrast, while the proposed learning goes, it converges to the solution which is balanced between the error performance and the energy minimization. Another difference is that iterative learning modifies the motor command with the next trial, based on previous trial result. The proposed method has more continuous and seamless adaptation capability. There is no need to separate the learning process with the trial by trial. Fig.6 results show well the new aspect on this feature. After the first learning phase (but computation and control are always online), suddenly the moving object to track became faster. As it is similar type of motion, even for the faster speed case, the controller found the nice solution instantly, almost without FF/FB ratio changes, which means the learning process is not much used. Here, only the task is suddenly changed. There is no need to have relearning process for faster motion. We would say the obtained motor synergy can be used for the faster motion. In iterative learning, it could be complicated when it needs to manage the faster motion with a sudden request in a continuous manner.

This article demonstrated a way to bridge the gap between learning and control, applied in robot control, inspired by seamless learning control nature of human motor control. In a real robot, even if it has backdrivability, there are joint frictions and the internal gear inertia. Then, it is more challenging to apply the learning controller in a real system. In contrast, there was completely no joint friction and gear inertia in simulation as previously reported in [13]. After the learning, FB component ratio against the total energy consumption was less than 20 percent in simulation. However, FB component ratio in the real robot is stayed still around 50 percent against total energy as we can see it in at the right bottom of Figs. 3, 4 and 6. It is advantageous if the dependency on FB could be further decreased in terms of energy minimization, but we think that the geared joint inertia and friction covered the environmental dynamics information

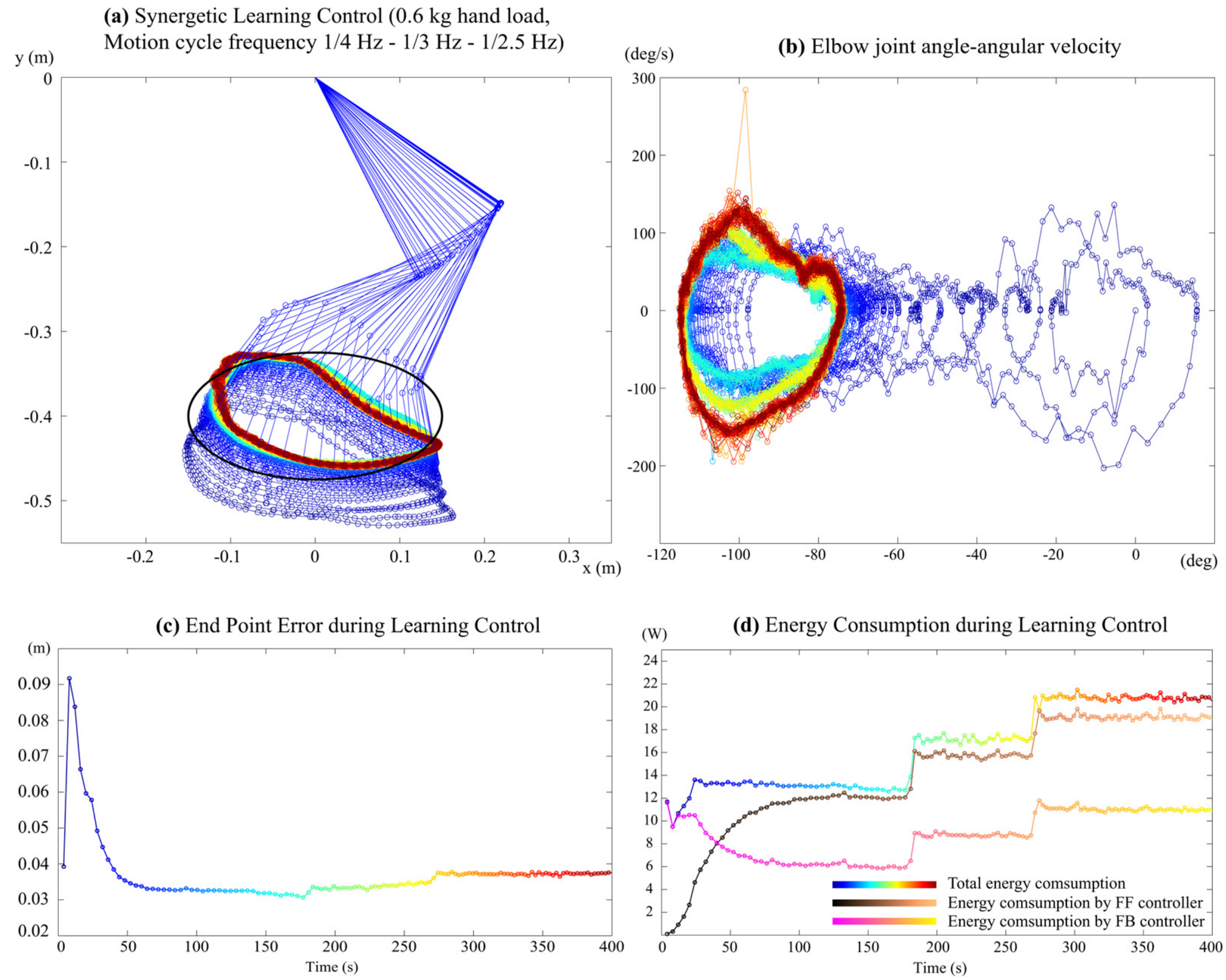

Fig. 6. Motor control result to track the moving target in ellipsoidal orbit with 0.6kg load at hand, with task speed changes in the order of 1/4Hz, 1/3Hz and 1/2.5Hz. (a) Endpoint transition with Synergetic learning control and (b) Elbow joint angle-angular velocity phase portrait. (c) The transition of endpoint error and (d) the energy consumption in each ellipsoidal cycle of reaching as an average power. From (a), we can confirm that Synergetic learning control manages well to track moving target with slight end-point error changes seen in (c). Especially in 1/2.5Hz, the robot has to manage to follow in a fast speed for an ellipsoid in average speed of 144deg/s while holding 0.6kg weight. From (b), different elbow angular velocity realization can be confirmed. In (d), the contribution ratio between FB and FF controllers is maintained for higher speed tracking. Thanks to this nature, motor commands are quickly found for new dynamic condition.

for the learning process. Thus, the unknown friction dynamics in the robot had to be dealt with FB component. The geared joint is served as a noise in the motor learning. It implies high backdrivability in the manipulator helps to correctly perceive the environmental information, which is useful for motor learning. Regardless of this disadvantageous effect, the results in real robot demonstrated a promising performance for learning control of reaching under the redundancy toward improved Error-Energy performance.

Motor learning is a process which develops Feed Forward (FF) controller minimizing the contributions from Feedback controller. The motor pattern integration term in SyLC can be considered as FF controller which anticipates the environmental interactions during reaching. We should note that even when the integration term is represented as I in the diagram, this control structure is totally different from so-called PID structure where the joint reference error is normally integrated. Instead, in SyLC, the mapped motor field comprising each joint motor pattern is being integrated in a modular configuration. This integrated motor pattern has cyclic torque signature then this term can still continue to send predictive motor command even if we stop the feedback information. This is the reason why this term can be regarded as FF controller. During the learning, the contribution from FF was increased and the torque from FF was converged into certain pattern. This effect matches well the neurological learning process. We could have this human-like learning phenomenon in real redundant robot control with the proposed Synergetic learning control scheme. The obtained result also gives us an insight into understanding the human motor control, and the FB and FF components can not be measured in humans, but the role of them in relationship to energy efficiency could be quantified from the robot experiment as in Table I.

Dual task of tracking improvement and energy reduction is a well coupled issue, which is conflicting each other. To evaluate the control performance in the dual criteria: endpoint error minimization and energy minimization, we have introduced a new index: Error-Energy index which can measure the error reduction rate in the cost of unit energy. Sometimes improvement in energy consumption measure was not that obvious as in the Table I. However, if we employ Error-Energy index for the motor performance evaluation, we could observe very clear improvement as in Table I. It suggests that the proposed learning control method is well managing dual criteria of improving error performance while minimizing energy consumption. Along with the newly proposed index of EE_1, the existing cost function (EE_2) also supported the advantage of the proposed learning control on the efficiency on error-energy relationship. Evaluating the motion accuracy rate in the cost of unit energy with the proposed E-E index in human reaching study should be also an interesting topic for future.

The vertical reaching task under the gravity involves much complex interaction torques. When the conflicting torques between coupled joint dynamics could be minimized, it can result in energy effective motion. To reduce the conflicts, naturally joints should be synergetically used. The joint angle acceleration in the shoulder involves all the arm segments from upper arm, forearm to the hand. The elbow is nice to be synchronously drived then the forearm is well accelerated by the shoulder. The component of forearm acceleration to be made by the elbow, will be naturally minimized. This phenomenon is well observed in Fig. 5. The shoulder-elbow phase portrait turned into similar circular form for different dynamic task conditions in synergetic learning. As the joint combination usage is common to different dynamic conditions, we can expect that it should be robust also for the case where the robot needs to change the motion speed or hand weight in the course of the motor control. Indeed, our method demonstrated the great adaptive nature for the different task speed condition as in Fig.6. As it is similar task except the motion speed, the robot already knows the effective synergetic joint usage for the given task then the necessary motor commands are quickly found almost without the learning process for a new dynamic condition. Please note that the robot is holding 600g weight, which induces certain amount of inertia. The endpoint accuracy is degraded only slightly. It is demonstrating adaptivity nature of the synergetic learning controller along with Error-Energy index improvement.

At last, we should emphasize that this study is not oriented to compete with the optimization performance against conventional model-based approach. The obtained motor solution itself would be possible to be computed also with the model-based approach. Comparing performances is not our current interest. Moreover, such comparison is not fair as the model-based approach knows dynamics information of the system, then naturally it can potentially give better performance, as the given information is not same. As it is stated in the introduction, our first motivation is to verify a question if we can find a modular computational principle which can handle resultant phenomenological optimization with much simple paradigm. Thus, we have first investigated the point if the solution gives such resultant optimized result or not with the proposed method, in this paper. This point could be successfully confirmed from Table I as we observe the converged motor solutions as it can be seen from the gradually optimized performance in the Error-Energy index along with the development of FF component.

VIII. Conclusion

In this paper, we have verified a novel computational control paradigm ”Synergetic Learning Control” in redundant manipulator. From the control result, we claim that the proposed method is valid for acquiring synergetic motor usage in the system with actuation redundancy. It is verified with Error-Energy index development in different dynamic conditions. This index is newly proposed in this article, which could take into account the error tracking performance per the energy consumption. We should highlight that the SyLC brings computational adaptability and learning for unknown environmental dynamics with dynamic model-free and cost-function-free approach differently from previous studies. Energy efficient solutions could be obtained by the emergence of motor synergy in the redundant actuation space. Increasing the contribution of FF controller matches well the nature of computational motor learning in human being as an infant can improve his motor control ability by repetitions without thinking of something complex. However, there is no function yet to memorize the emerged torque pattern in the current study, which will be solved in our future study.

The result demonstrated in this paper is also concerning to the Bernstein’s DOF problem. Bernstein problem is an issue regarding how Central Nervous System (CNS) finds the optimal solution in the actuation redundancy. The usage of motor synergy was pointed out by Bernstein, but a fundamental motor control principal which can generate motor synergy has not yet been reported in neuroscience except so-called optimization approach. In this article, it is a simplest situation of the actuation redundancy but the proposed SyLC paradigm firstly managed to generate dual aspects of adaptivity and learning by a modular computational principle for redundant robot.

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