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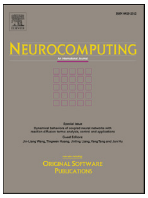

Dynamic neural networks aided distributed cooperative control of manipulators capable of different performance indices[☆]

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ABSTRACT

This paper presents a distributed scheme for the control of multiple redundant manipulators to simultaneously achieve four objectives, i.e., the task to reach global cooperation, joint-physical limits compliance, limited communications among manipulators and optimality in terms of a specified performance index. In addition, corresponding theoretical analyses are provided, which guarantee that, with the communication network being connected, all manipulators can jointly obtain the same desired motion information. Then, the proposed scheme is converted into a quadratic program (QP) formed formulation and solved by a dynamic neural network with rigorously provable convergence. Furthermore, simulations and comparisons are provided to illustrate the effectiveness of the proposed distributed scheme as well as the presented dynamic neural network.

1. Introduction

Robotics research has made impressive progress in the past decades, which is widely found in academic researches and industrial applications. Much effort has been devoted to it, and various types of robots have thus been invented and employed [1–6]. Redundant robot manipulators, providing increased flexibility for complicated tasks, have been playing an increasingly important role in performing boring and cumbersome tasks [1,2]. Recent progress has shown the advantages of quadratic program (QP) based formation for handling various constraints of manipulators' redundancy resolution, which incorporates equalities, inequalities and bound constraints simultaneously [1,2]. In generally, schemes aiming to motion generation of robot manipulators with additional constraints can be cast into a QP-based formulation, wherein different problems have different performance indices (i.e., the cost function) [1,2,7,8].

Neural networks have been successfully applied in various control systems, such as, control of robots [9–12], adaptive control of nonlinear systems [13–22], impulsive control [23,24], and so on [25–31]. In particular, the control of single-arm robot manipulators aided with recurrent neural networks has been investigated widely and numerous control schemes have thus been presented and investigated [32,33,44]. Zhang et al. present two neural networks for the repetitive motion generation of single-arm robot manipulators in [7], which do not incorporate the bound constraint and thus the joint physical limits in manipulator applications may be violated. By considering and solving inequality-constrained quadratic programming problems in their dual spaces, various neural networks based on the dual-space related techniques with different architectures have been presented [32,34]. These models are highly efficient for real-time processing and have been successfully used in the motion planning and control of redundant manipulators.

Compared with the great successes achieved for the redundancy resolution of single-arm manipulators, the research on the coordination control of multiple manipulators is less than desirable

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[35–38]. An adaptive neural control scheme is presented in [39] for general dual-arm robot systems, in which the RBFNN is employed to approximate the unknown dynamics of both the robot arms and the manipulated object. An energy consumption optimization method is discussed in [35] for multiple-robot production systems, which is constrained by externally given or currently existing robot hardware limitations and production rates. In order to create an adaptive and intelligent multi-robot system, La et al. present a hybrid system integrating reinforcement learning and flocking control in [36]. Schemes for the cooperation control of multi-agent problems can be divided into three classes: centralized, decentralized and distributed approaches, respectively [40]. For a centralized scheme, all of the agents involved should be able to exchange information with the central station, thereby making the central station a fragile point. Therefore, the breakdown of the central station may give rise to the global collapse of the network. Decentralized approaches remedy the weakness of centralized ones, but still have the requirement of all-to-all communication for information exchange. On the contrary, a distributed scheme only needs limited communication and dramatically saves overall communication expenses, which still works well even when some agents fail. By considering the advantages that the distributed schemes possess, it is worth developing a scheme for the cooperation and consensus control of multiple manipulators in a distributed manner.

A centralized scheme is presented in [38] for the synchronous manipulation of two redundant robot arms, which only considers a dual arm system and the generalization to a network of manipulators remains unclear. A decentralized scheme is presented in [41] to address kinematic control of a class of collaborative redundant manipulators, which is derived under the assumption that all manipulators are able to access global command on the desired velocity in workspace. This result is further extended to the situation with a hierarchical organization of all manipulators [42]. A fully distributed scheme is presented in [40], which remedies the weaknesses existing in [38,41,42] by formulating the problem from the perspective of game-theory. However, this scheme does not exploit the position information of the desired trajectory, thereby requiring that the initial positions are accurately set at the theoretical ones. Moreover, for the consensus problem regulated to a desired static position, such a scheme fails to complete it [45].

In this paper, a distributed scheme is presented with the aid of recurrent neural networks, which can simultaneously complete four objectives. That is, the desired task to reach global cooperation, the specified primary task to reach global cooperation, joint-physical limits compliance, limited communications among manipulators and optimality in terms of a predefined performance index. Then, converted into a QP formation, the proposed scheme is further solved online by a dynamic neural network. Finally, simulations as well as comparisons with other schemes are provided to substantiate the effectiveness of the distributed scheme. The problem is formulated in Section 2 with a dynamic neural network constructed in 3. Section 4 provides simulation examples to substantiate the efficacy of the proposed distributed scheme. Section 5 presents the conclusions. Before ending this introductory section, the main contributions of this paper are presented as follows.

- A scheme capable of different performance indices is exploited for the distributed control of multiple manipulators.
- The redundancy resolution research is extended from a centralized perspective to a distributed one.
- The distributed scheme presented in this paper is able to simultaneously complete four objectives.
- The presented neural controller is of global convergence.

2. Problem formulation and distributed scheme

In this section, we present the problem formulation for cooperative control and consensus of manipulators. Then, a distributed scheme is proposed to handle such a problem.

2.1. Mathematical symbols

For laying a base for further investigation, the mathematical symbols and their meanings used in this paper are listed as follows.

$r(t)$	Cartesian coordinate of end-effector of manipulator
$\theta(t)$	joint angle of robot manipulator with $\theta(t)=[\theta_1(t),\ldots,\theta_m(t)]^{\mathrm{T}}\in\mathbb{R}^m$ for an m-DOF manipulator
$\dot{r}(t)$	time derivative of $r(t)$
$\dot{\theta}(t)$	time derivative of $\theta(t)$
$c_0>0$	feedback gain of disagreement between each manipulator
$\mathcal{N}(i)$	neighbor set of the ith manipulator on the communication graph with $\mathcal{N}(0)$ denoting the neighbor set of the command center
Δ_{ij}	connection weight between the ith manipulator and the jth one, $\Delta_{ij}=1$ for $j\in\mathcal{N}(i)$ and $\Delta_{ij}=0$ for $j\notin\mathcal{N}(i)$
$\delta_i(t)$	$\delta_i(t)=r_i(t)-r_{\mathrm{rp}}$ with r_{rp} denoting the relative constant distance vector between the end-effector and the reference point
ρ_i	$\rho_i=1$ for $i\in\mathcal{N}(0)$ and $\rho_i=0$ for $i\notin\mathcal{N}(0)$
ν_i	$\nu_i=\dot{r}_i$
w_i	$w_i=\dot{\theta}_i$
w_i^-	the lower bound of w_i
w_i^+	the upper bound of w_i
Ω_i	$\Omega_i=\{w_i\in\mathbb{R}^m, w_i^-\leq w_i\leq w_i^+\}$
$\otimes$	the Kronecker product
$\mathbf{1}_p\in\mathbb{R}^p$	a vector composed of 1
$I_n\in\mathbb{R}^{n\times n}$	an identity matrix
$L\in\mathbb{R}^{p\times p}$	Laplacian matrix $L=\mathrm{diag}(\Delta\mathbf{1}_p)-\Delta$ with $\Delta\mathbf{1}_p$ being the diagonal matrix whose p diagonal entries are the p elements of $\Delta\mathbf{1}_p$ with the ijth element of matrix Δ being Δ_{ij}
$\bar{w}\in\mathbb{R}^{mp}$	$\bar{w}=[w_1,\ldots,w_p]$
$\bar{\nu}\in\mathbb{R}^{np}$	$\bar{\nu}=[\nu_1,\ldots,\nu_p]$
$\bar{\delta}\in\mathbb{R}^{np}$	$\bar{\delta}=[\delta_1,\ldots,\delta_p]$
$\bar{\Omega}$	$\bar{\Omega}=\bigcap_{i=1}^{p}\Omega_i$
$\Pi\in\mathbb{R}^{p\times p}$	$\Pi_{ij}=\rho_i$ for $i=j$ and $\Pi_{ij}=0$ for $i\neq j$

2.2. Manipulator kinematics

For an m-DOF redundant manipulator, in mathematics, its $r\in\mathbb{R}^n$ with $m>n$ is determined by

$$r(t)=f(\theta(t)), \tag{1}$$

where nonlinear mapping function $f(\cdot)$ carries the forward kinematics. Note that, the mathematical expression of a PUMA 560 robot manipulator involved in this paper has been presented in [40] and thus omitted here. Based on (1), we further have

$$\dot{r}(t)=J(\theta(t))\dot{\theta}(t), \tag{2}$$

where Jacobian matrix $J(\theta(t))\in\mathbb{R}^{n\times m}$ is abbreviated as J. With the aid of a given control scheme, $r(t)$ is expected to track the desired

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