ÓBUDAI EGYETEM
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Thesis Booklet

Application of Novel Approaches in Optimal and Adaptive Optimal Control

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Contents

Abstract

In my Thesis I elaborated certain improvements in the subject areas of Optimal and Adaptive controllers with the main aim of realizing their efficient integration. In the traditional mainstream, optimal controllers are based on the mathematical foundations of functional optimization under constraints. The adaptive controllers that tackle strongly nonlinear problems normally use Lyapunov functions for the calculation of the control signal. Both structures have their own inner rigidity that makes their combination not trivial. Recognizing that the mathematical structure of the alternative of the Lyapunov function-based technique, the Fixed Point Iteration-based adaptive control immediately allows the integration of the various particular variants of these methods, I concentrated on the elaboration of adaptive optimal controllers. I have shown that by eliminating the constraint terms in the optimal control by incorporating the dynamic model in the cost functions the computational burden of the method can be significantly reduced in the case of quite sophisticated cost functions. I also elaborated improvement in the FPI-based adaptive controllers by reducing its noise sensitivity using simple filtering techniques, and efficiently tackled the problem of actuator saturation. I suggested separate or optionally partly coupled application of this adaptive method with parameter identification purposes the need of which arose not from the side of control applications. I pointed out the limitation of the evolutionary algorithms in parameter identification issues, and suggested the use of the improved identified model with the same adaptive technique to improve its stability. The statements of my Thesis are underpinned by simulation investigations I made by the use of Julia language programs.

1. Introduction

1.1 Motivations and Goals

In practical control tasks various typical problems must be tackled as e.g., the lack of precise dynamic model of the system to be controlled, the presence of unknown external disturbances and their consequences, limited physical possibilities for introducing control force or other equivalent action into the controlled process, limited possibilities for measuring or at least estimating the controlled system's actual physical state. For tackling at least certain elements of these problems various control methodologies have been elaborated. Some of them were based on particular mathematical formalism that do not seem to be easily combined with each other. In this field of efforts there is a plenty of open problems and a general lack of integration can be observed. The question naturally arose: is it possible to reach certain achievement in this direction? My work was motivated by this simple question. Explanation of the precise mathematical details of which I obtained my motivations can be given only after the state-of-the-art review. In the sequel I give only a short summary of my ideas.

The Model Predictive Controller (MPC) was early idea developed for utilizing the available dynamic model of the controlled system. In order to provide the designer possibility for force limitations or complying with various other, often contradictory requirements, these controllers mathematically were formulated as solutions to the optimization under constraints tasks. Normally, the cost functions represented some weighted sum of various penalty terms that should have been minimized, while the dynamic model of the controlled system appeared in the constraint terms. In the early dynamic programming approach the mathematical background was the minimization of functionals with strong analogy of the variation principles of Classical Mechanics. The computational power -requirements of this approach was considerably reduced by the application of time grid with discrete time-resolution in the Receding Horizon Controller (RHC) that maintained the constraint terms with combination with the Lagrange multipliers. The practical applicability of this approach strongly depended on the dynamics (speed) of the physical process to be controlled, and the technological level of the available processors that were able to realize these control methods. **I realized that in this formalism there is a great freedom for the designer to play with the possibilities for distributing certain details between the cost and the constraint terms. This possibility made me carrying out simulation investigations.**

Whenever the computational resources were not rich enough to apply the complex mathematical framework of optimized controllers, as e.g., in Robotics in the nineties of the past century, the dynamic model was utilized without being placed into the mathematical framework of optimal controllers. The so called Computed Torque Control (CTC) had to scope with the problem of lacking reliable and precise dynamic models. It became clear in the early nineties that no such models can be constructed even within the Classical Mechanics-based framework that does not consider friction effects. In the literature coping with the problems of incomplete and imprecise models generally happens by the use of either Robust design as the Variable Structure / Sliding Mode Controller, or by the application of Adaptive techniques. The Sliding Mode controller often produces dangerous excitation of the controlled system while the mainstream of the finer adaptive controllers is based on Lyapunov's 2^{nd} or direct method. **I recognized that from various points of view this method is very complicated, needs complete state estimation, so the question naturally arose whether is it possible to combine with the optimal control approach its possible, more simple alternative that was based on Banach's fixed point theorem? For this reason I carried out simulation investigations with this mathematically simple approach.**

In the modern control approaches the efficient tool of evolutionary algorithms-based system identification methods can be found. It was a natural idea to investigate how is it possible to combine evolutionary methods-based system identification techniques with the fixed point iteration-based adaptive control.

In dynamic control problems the presence of observation or sensor noise is a general problem. Due to the structure of the fixed point iteration-based approach it was expected that the noise issues have enhanced significance in this case. Therefore, I felt strong motivation to consider noise filtering possibilities. The success of the Acceleration Feedback Controllers that have to cope with similar problems convinced me that it is not hopeless to make investigations in this direction.

1.2 State of Art

In control technology, various control methods are present in the inventory of possible solutions. The appropriate choice can be selected according to various particular and practical aspects related to a given task, and there is no way to generally state that a given method would be superior in comparison with others. Such properties as mathematical complexity, the need for computational power, the need for a more or less precise dynamic model of the controlled system, robustness against modeling errors and external disturbances, adaptivity, and possibilities for implementation can be considered when a control approach is chosen to tackle a given problem.

The wide set of model-based controllers belong the (MPC) (e.g., [1]) in which beside the dynamic model of the controlled system various force limitations and other restrictive factors can be taken into account that originate from sources other than the model. It was successful especially in the control of slow processes as e.g., crystallization, that can be traced by computers of limited computational power. For finding the optimum a computationally greedy approach was suggested in the late Fifties of the past century as Dynamic Programming that aimed at the minimization of functionals [2, 3]. The computational power of this approach later was reduced by solving this problem over a discretized time-grid and using numerical approximations under the name Receding Horizon Controller [4]. However, the original elegant structure in general was maintained. The analogy with the Canonical Equations of Motion of Classical Mechanics were maintained with related issues as the flow of incompressible fluids and conservation rule for the Hamiltonian (or artificial Hamiltonian) of the controlled system (e.g., [5]). These controllers generally applied Lagrange's Reduced Gradient Algorithm [6]for problem solution. In special cases as linear time-invariant system models and quadratic cost functions, also utilizing the theoretical results by Riccati [7] and Shur [8, 9], considerable mathematical simplifications were achieved under the name Linear-Quadratic Regulators [10]. This approach was able to treat modeling errors in a very simple manner: the optimized motion was designed for a whole horizon, but normally only one step of this optimized force was exerted on the system, and in the next step a new horizon have been calculated again.

Whenever the computational resources were not rich enough to apply the complex mathematical framework of optimized controllers, as e.g., in Robotics in the nineties of the past century, the dynamic model was utilized without being placed into the mathematical framework of optimal controllers. The so called Computed Torque Control (CTC) [11] had to scope with the problem of lacking reliable and precise dynamic models. It became clear in the early nineties that no such models can be constructed even within the Classical Mechanics-based framework that does not consider friction effects [12]. Various friction models were considered with regard to slow velocity motion where the phenomenon stick–slip' typically occurs (e.g., [13, 14, 15]). It was also realized that building in even the simplest friction models leads to observation or identification problems (e.g., [16]). High complexity friction models need the introduction of complementary degree of freedom (DOF) as in the LuGre model [17].

In many cases, a simple PID-type controller invented in the 1940s [18] can do well. In robotics, the direct use of the dynamic model without inserting it into the mathematical framework of optimal controllers was initiated in the 1980s [11] in the concept of (CTC). In this approach the inverse dynamic model is directly used for the calculation of the control signal without using the mathematical complexity of the optimal controllers. However, it became clear very early that practically it is impossible to develop precise dynamic robot models (e.g., [12]), and that the identification of important parameters related to modeling the friction effects has limitations, too (e.g., [16]).

The robust variable structure/sliding mode controllers that became popular in the 1990s (e.g., [19]) are simple solutions that can solve the problem of modeling errors and unknown external disturbance. In a similar manner, resolved acceleration rate control (e.g., [20]) and acceleration feedback controllers (e.g., [21]) can be considered as improvements of the CTC controllers.

The wide class of adaptive controllers tackle the imprecisions of the models in different manners. The widest subset uses Lyapunov's stability theorems and keeps prevailing from the early 1990s to the present (e.g., [22]) as well as the model reference adaptive control (e.g., [23]). Normally, stability or asymptotic stability of these solutions are guaranteed for a huge set of possible parameters of which the appropriate ones can be selected on the basis of practical aspects often applying various versions of evolutionary computation as genetic algorithms [24, 25], particle swarm optimization [26, 27, 28, 29], simulated annealing [30], and so on.

Strong non-linearity is a natural feature of most physical, biological, economic, and engineering systems. In spite of that most of traditional software packages solving optimization problems can normally handle only linear time-invariant system models with typically quadratic cost function structures because this restricted subject area can be tackled by well-elaborated and efficient mathematical tools as the application of Riccati equations [7] (it provides the solution of special first-order quadratic differential equations by solving second-order linear ones), Schur's decomposition method that obtains the solution of quadratic matrix equations by solving linear ones [8, 9]. For solving linear matrix inequalities in system and control theory a complete program was announced by Boyd et al. in 1994 [31] for which efficient MATLAB program packages have been developed [32]. The mainstream of the engineering research efforts aimed at the elaboration of approximate linear system models and quadratic cost functions for tackling optimization problems by the use of this efficient mathematical apparatus. In [33], the linear matrix inequality (LMI) condition based on slack variables was used to reduce the high gains of control, resulting in using the robust $\mathscr{H}_\infty$ state feedback controllers.

However, for more complex dynamical models and specially structured cost functions the more general mathematical context does not allow such relatively simple solutions. Instead of using ready-made program packages researchers have to develop their own program codes that are not supported by the rigorous and reliable quality guaranties of the MATLAB packages.

From a mathematical point of view, optimization can be formulated by the use of variation calculus. In the 1950s, i.e., in the advent of the appearance of powerful computers, Bellman introduced dynamic programming [2] that computationally is too greedy. The problem was later simplified by the introduction of a discrete, evenly scaled time-grid of resolution δt that is dense enough to allow numerical differentiation and Euler integration over it. The sum of the cost function contributions in the grid points of a horizon of discrete length H was minimized for a first-order dynamical system under the constraint $\frac{q(t_{i+1})-q(t_i)}{\delta t} \approx \dot{q}(t_i)$ in which the function $\dot{q}(t_i) = \mathscr{F}(q(t_i), u(t_i))$ describes the dynamic model of the controlled system, and $u(t_i)$ denotes the control force. By the use of the usual constraint function $g_i(q(t_i), q(t_{i+1}), u(t_i)) := \frac{q(t_{i+1})-q(t_i)}{\delta t} - \mathscr{F}(q(t_i), u(t_i))$, a general cost function (with a simpler notation) $\sum_{\ell=1}^{H} \Phi(q_\ell, u_\ell)$ has to be minimized over the horizon by varying the coordinates $\{q_2, \dots, q_H\}$ (q_1 is given as the initial condition of the motion), and force terms $\{u_1, \dots, u_{H-1}\}$ (because u_H has influence only on the next grid point at time t_{H+1}). The optimization must have done under the constraints $g_i(q_i, q_{i+1}, u_i) = 0$. It traditionally can be solved by the use of Lagrange's reduced gradient method by using Lagrange multipliers for gradient reduction that was introduced in the late 18th century for solving constrained problems in Classical Mechanics [6]. It can well be used for controlling slow processes as e.g., crystallization in chemistry [34, 1] and traffic control [35, 36]. Later, it obtained ample applications from the 1960s with the development of computer technology that provided easy implementation possibilities (e.g., [37, 38]). The scheme description is known as the (RHC) [4] which is a reliable, heuristic realization of the (MPC) (e.g., [39, 40]) that has many applications (e.g., [41, 42, 43, 44, 45, 46]). The adaptive version of RHC were investigated in many cases, such as in [47] wherein the used Adaptive Receding Horizon Controller (ARHC) is based on Lyapunov's adaptation law, whereas in [48], the adaptive controller is based on the set membership identification algorithm, which iteratively calculates at each cycle a set of candidate plant models. The general ARHC is used in [49] along with particle swarm optimization (PSO). Implementing the sliding mode (SM) as an adaptive technique for ARHC is addressed in [50].

Because of the fact that the Lagrange multipliers normally have clear physical interpretation (e.g., [51]), and the strong analogy with the canonical equations of Classical Mechanics [52, 53, 5] that provides solutions similar to the the flow of incompressible fluids, together with the plausible mathematical consequences of this approach, the constraint-based formulation of the problem generally prevailed, though it is not the computationally simplest and cheapest approach. These analogies are derived from considering the auxiliary function of the problem in (1)

$$\Psi(\{q\},\{\lambda\},\{u\}) := \sum_{\ell=1}^{H} \Phi(q_\ell,u_\ell) - \sum_{\ell=1}^{H-1} \lambda_\ell g_\ell(q_\ell,q_{\ell+1},u_\ell) \ . \quad (1)$$

Evidently, $\Psi(\{q\},\{\lambda\},\{u\})$ is not bounded, and at the point where the gradient reduction algorithm stops, it satisfies the equations as $\frac{\partial\Psi}{\partial\lambda_j} = 0$, meaning that the solution satisfies the constraint conditions, $\frac{\partial\Psi}{\partial q_k} = 0$ that can be so interpreted that the reduced gradient is 0, and an additional condition $\frac{\partial\Psi}{\partial u_i} = 0$. These partial derivatives allow the interpretation of the appearance of the numerical approximation of a differential equation for $\dot{\lambda}$, considering the q_i and λ_i pairs as canonical coordinate pairs, and interpreting Ψ as a Hamiltonian with the conservation property $\dot{\Psi} \equiv 0$. The analogy with the flow of incompressible fluids is related to the fact that the canonical state propagation equations are related to symplectic transformations that conserve the volume of the phase space (Liouville's theorem, e.g., [5]).

The numerical algorithm that solves the above problem is commenced by finding a point on the constraint surface by using the Newton–Raphson algorithm [54, 55, 56], then making consecutive small steps along the reduced gradient $\nabla\Phi - \sum_\ell \lambda_\ell \nabla g_\ell$ in which the Lagrange multipliers are so chosen that for the constraint gradients it must be valid that $\forall j \ (\nabla g_j)^T \ (\nabla\Phi - \sum_\ell \lambda_\ell \nabla g_\ell) = 0$ (in this formulation the symbol ∇ contains $\frac{\partial}{\partial q}$ and $\frac{\partial}{\partial u}$ components). Gradient reduction needs the solution of this linear set of equations. The algorithm stops when the reduced gradient becomes zero. It was realized that placing the dynamic model into the constraint term of the optimization task is rather a tradition than a necessity. If we do not insist on the above mentioned elegant formal analogies with classical mechanics, the complexity of the calculations can be considerably reduced. In the original approach the free variables of the optimization are the coordinate values $\{q\}$, and the force terms $\{F\}$ over the horizon, and the quantities that additionally have to be calculated are the $\{\lambda\}$ Lagrange multipliers for reduction of the gradient containing the partial derivatives according to the components $\{q\}$ and $\{F\}$. In [57], the structure of the auxiliary function was investigated in the case of a simple paradigm, and it was found that the appropriate solution is at its saddle point. Furthermore, instead of using a set of individual constraint functions for optimization as $\{g_\ell = 0\}$, the use of a single constraint term defined as $G := \sum_\ell g_\ell^2 = 0$ can be successfully applied with only one associated Lagrange multiplier that can very easily be computed. In [58], the use of the Lagrange multipliers was completely evaded, and the method's operation was illustrated by controlling the dynamic model of two connected mass points that were able to move in a given linear direction. In this approach, the free variables of the optimization are only the force terms $\{F\}$ over the horizon, the gradient in the optimization consists only of the $\frac{\partial}{\partial \mathrm{F}}$ components, and the simple gradient descent method can be applied without any gradient reduction. Following this simple illustration, the method was used for simulating the treatment of illness type 1 diabetes mellitus in determining the necessary insulin ingress rate, and the estimation of the evolution of the not observable internal model variables. In [59], this approach was considered for the RHC control of the Furuta pendulum [60], and in [61, 62] application possibilities were considered in solving the inverse kinematic task of redundant robots.

With regard to the significance of the effects of measurement noises, in the traditional literature, in which normally PID-type feedback terms are used, and in the adaptive control some Lyapunov function-based techniques are prevailing, the noise terms are modeled as additional terms of more or less marginal significance. Generally it is assumed that the physical causes of the noise terms are not identified and individually modeled. It is assumed that the effect of a large number of statistically independent noise sources produce some result of normal distribution with zero mean if the appropriate sensors are well installed. The effect of the lost signals together with the additional Gaussian noise are assumed and, for instance, the Kalman filters are so designed that they are optimized for this Gaussian spectrum (e.g., [10, 63, 64, 65]). However, it can be emphasized that the digital components in the realistic applications do not allow to realize the long tail of the Gaussian distributions, and the originally causal models are treated as really causal ones burdened with the additional noise terms. (The control of stochastic processes is absolutely out of the scope of my dissertation.) Since the Fixed Point Iteration-based method feeds back higher order derivatives than the traditional ones, and the adaptation mechanism of this approach learns from the observations of the recent time instances, any noise filtering technique causes some delay that may corrupt this very special and primitive learning method. Therefor, the use of this method made it necessary to consider noise filtering issues.

Since in the numerical control the mathematical properties of the differentiation can cause high noise-like contribution, the traditional approach simply applies low pass filters as e.g., Bodó and Lantos in [66], in my dissertation I also applied it in one of the theses. For fixed point iteration-based control specific preliminaries as ad hoc ideas can be found in [67, 68, 69, 70].

1.3 Research Methodology

All investigations of the proposed theoretical algorithms and their engineering applications are tested via running the simulation on Julia Language. The reason behind selecting Julia is related to its wide availability as a free and opensource software, capability for providing professional visualization methods that fit the publication requirements. Besides that, its fast processing that reflects the most modern computational technologies against the lack of resources was an important motivation for its use.

The used editions of Julia during the research are v1.4.2-win64 (May 25, 2020), v1.4.2-win64 (July 7, 2021) and lastly v1.8.0 (September 6, 2022). The supporting environments are Python v3.7 and v3.9 so that the visualization in Julia and the possible use of the *qt* back-end (i.e., it applies the Python's Matplot Library) were important facts that motivated my choice.

2. Investigations About Computational Acceleration For Optimization Problems

The Lagrange's method has considerable computational needs that mathematically describe the constrained physical systems in Analytical Mechanics [6]. However, nowadays, in the possession of cheap computers and software products it became a practical problem solving tool for instance in the Solver package of MS EXCEL that can be applied in financial and technical problems (e.g., [71, 72]). In many cases the Lagrange multipliers have important physical meaning, therefore it is necessary to compute them (e.g., [73, 51]), and the Solver package also computes them.

This chapter (in the full version of dissertation), in its first part, investigates the possibility of speeding up the computations of solving constrained optimization problems by avoiding the calculations of individual Lagrange multipliers. While at the second part, the suggested alternative method is tested by using a 7-DOF redundant robot system.

Thesis Statement I

I have recognized that in contrast to the traditional approach of optimal controllers, in which the optimization of a cost function happens via individually dealing with each dynamic model term as a constraint equation, it is possible to construct a single constraint equation that guarantees the fulfillment of each original constraint. In this new approach, similarly to the traditional one, the Newton-Raphson algorithm is used for finding a point on the embedded hypersurface that contains the possible solutions, and Lagrange's Reduced Gradient Algorithm is used for moving along the hypersurface, but in our case only one Lagrange multiplier can be used. By directly using the Gram-Schmidt algorithm for gradient reduction, in this manner considerable decrease in the computational efforts became possible.

I have observed that in application areas that contain singularities (e.g.,

in solving inverse kinematic task of redundant robot arm) this approach is sensitive to the presence of kinematic singularities as well as the Moore-Penrose pseudoinverse-based solutions that need the application of complementary tricks for dealing with near singularity solutions. I have recognized that the common reason of this sensitivity is that the constraints are exactly taken into account in both cases.

Related publications to Thesis I:
Related own publications: **[A. 1] and [A. 2]**

3. Improvement of the Fixed Point Iteration-based Adaptive Receding Horizon Controller

In this chapter (in the full version of dissertation), I have investigated the applicability and limitations of using “Adaptive Receding Horizon Controller (ARHC)” in various engineering applications. Because the Fixed Point Iteration-based Adaptive Control method is considered in the Thesis, it is expedient to briefly summarize its essence in the sequel.

Thesis Statement II

I have elaborated further modification of the Receding Horizon Controller. By directly incorporating the dynamic model into the cost function calculated over a horizon, I have completely eliminated the use of the constraint term from the formalism. I have shown that by the application of a transition between the simple Gradient Descent and the fast Newton-Raphson Algorithms an efficient method can be developed for finding the local minima. In this manner strong penalization of high forces became possible, however, the method did not guarantee the evasion of actuator saturation and windup problems in the Fixed Point Iteration-based adaptive control.

To tackle actuator saturation and windup problems I have elaborated a complementary method in which a hypothetical heavy device model was applied in the optimization of the trajectory, and the so obtained optimized trajectory was adaptively tracked by a realistic not heavy approximate dynamic model. The main benefit of this approach is that the optimization's mathematical structure can be completely separated from that of the adaptive tracking.

Related publications to Thesis II:
Related own publications: **[A. 3], [A. 4], [A. 5] and [A. 6]**.

4. Investigation of the Cooperation of Noise Filtering Methods With Fixed Point Iteration-based Adaptive Techniques

In chapter. 2 (in the full version of dissertation) I briefly mentioned that in dynamic control problems the presence of observation or sensor noise is a general problem. The special structure of the Fixed Point Iteration-based approach makes one expect that the noise issues have enhanced significance in this case. The success of the “Acceleration Feedback Controllers” (e.g., [74]) that have to cope with similar problems also confirm the idea that useful investigations can be done in this direction. Fixed point iteration-based control specific preliminaries as “ad hoc” ideas were already published in [67, 68, 69, 70]. I already applied -in previous chapter (in the full version of dissertation)- the traditional low pass filter technique that was borrowed from [66, 75]. In this chapter (in the full version of dissertation) I summarize the results of my own novel investigations.

The first part investigates a very drastic noise filtering technique that was introduced to support the operation of the adaptive control. Its basic idea is affine approximation of the various derivatives within successive moving windows. This idea was checked in cooperation of a special “continuous variant” of fixed point transformations. The investigations were made for the modified van der Pol oscillator that had an additional quadratic drag force term also used before.

The second part outlines the comparison between Unscented Kalman Filter (UKF) and two methods based on Fixed Point Operation-based adaptive controllers.

<u>**Thesis Statement III**</u>

By the use of simulation results I have shown that the FPI-based adaptive technique can well cooperate with the simple noise filtering techniques as the cascade of moving windows with affine signal approximation and the simple low pass filter, that do not apply any assumption on the statistical nature on the measurement noises. I have also shown that it is difficult to combine this method with the more traditional UKF that was found less effective. As possible reason I identified the fact that the mathematical structure of the UKF cannot be so well fitted to that of the FPI-based adaptive approach.

Related publications to Thesis III:
Related own publications: **[A. 7], [A. 8] and [A. 9].**

5. Implementing Fixed Point Iteration-based Adaptive Control and Particle Swarm Optimization

In comparison with the classical Lyapunov function-based parameter identification-based techniques, the advantage of the fixed point iteration-based techniques is that they do not require the identification of the model parameters. However, for other purposes, especially in life sciences, certain parameter values have definite significance and their identification is required independently of solving the control task. This naturally make the question arise if is it possible to identify the system's parameters (or at least certain parameters of the system) while the FPI-based adaptive controller is in operation. It is well known that the early adaptive controllers in robotics [76] the dynamic model of the controlled system was so formulated that an array of the identifiable dynamical system parameters were separated from an array of kinematically precisely known components, and the approximate system parameters were slowly tuned by Lyapunov functions-based constructions. At beginning of the tuning process this method worked with large trajectory tracking error since it always used an only slowly improved parameter set for the calculation of the necessary control forces. Later Dineva combined this learning method with the FPI-based adaptive controller in [77, 78, 79]. The main idea was that the FPI-based control signal was used for realizing the adaptive control, but instead of the original PID-type feedback terms used by Slotine and Li, she utilized the FPI-based terms for parameter tuning. This method resulted precise tracking from the beginning, and the use of the improved parameters in the approximate model in the adaptive control was only "optional". In this research I investigated a similar problem: while the adaptive controller worked on an FPI basis, for the identification of the system parameters more general, evolutionary computation-based methods could be used. Utilization of the improved parameters in the adaptive control remained rather a "free option" than a must, as well as in the case of Dineva's investigations. For the simulations I have chosen a strongly nonlinear model with limited number of parameters, and a particular evolutionary method, the simple and elegant Particle Swarm Optimization method [26].

The first part investigates the limitations of the applicability of Particle Swarm Optimization (PSO) with Fixed Point Operation-based adaptive controllers in case of on-line mode. For this purpose a simple but strongly nonlinear dynamic model was chosen by the use of which the problems of the parameter identification tasks can be well illustrated, expounded, and understood. Especially the limitation of this method was pointed out when the identified model in certain steps replaced the originally used initial one (this is the meaning of the term "on-line mode").

In the second part I made studies on the off-line combination of Fixed Point

Iteration-based adaptive controllers with Particle Swarm Optimization (PSO) using a more complicated, realistic robot model. In this approach the (FPI)-based adaptive controller is used for tracking a nominal trajectory while the Particle Swarm Optimization (PSO) used to refine the model, without using the improved model in the control.

<u>**Thesis Statement IV**</u>

I have elaborated a cooperation between the Fixed Point Iteration-based adaptive control and a system parameter identification process using Particle Swarm Optimization. The method allowed online and offline modes. In the offline mode the adaptive control and the model identification tasks were completely decoupled, and the quality of trajectory tracking was independent of the actual phase of identification, and was precise from the beginning of the controller's operation.

I have shown that due to balancing problems in the online case no asymptotic convergence of the identified model can be expected. The fact that the use of the online mode is not compulsory in the novel approach is an advantage over the traditional ones that cannot avoid the application of the not well identified model from the beginning of the control.

Related publications to Thesis IV:
Related own publications: **[A. 10] and [A. 11].**

6. Conclusions

In my Dissertation I brought about and investigated the integration of two subject areas in control technology: the optimal and the adaptive controllers. After realizing that both subject areas have their traditional mathematical backgrounds, namely the functional minimization in optimal control, and the use of Lyapunov functions tailored to the particular problem under considerations in adaptive control, that makes their integration mathematically very complicated and difficult, I realized that in a particular slot this integration is not difficult. It was the fixed point iteration-based adaptive control approach. I have shown that its simple mathematical structure offers plausible possibilities for combination and integration with the heuristic optimal controllers in which a great variety of cost functions and constraints can be applied. To utilize the so created freedom I have evaded the traditional optimization approach in which the dynamic model is used as a set of constraint equations. I reduced the number of constraint equations to one, and later completely evaded the use of constraint terms by building the dynamic model into the cost function at the price of little redundancies in the computations. I have shown that these variants were able to cooperate with the adaptive technique I have applied, while allowed simplifications in finding sub-optimal solutions in the case of various complicated cost terms in Receding Horizon controllers. Besides control issues I suggested the application of this method in the solution of differential inverse kinematic task of redundant robot arms to efficiently tame the solution in the vicinity of kinematic singularities. Since the adaptive method applied was expected to be noise sensitive, I suggested its combination with various simple noise filtering techniques. I also improved the adaptive method that originally suffered from some deficiency related to actuator saturation issues.

Finally, I have elaborated the combination and elaboration of the adaptive control applied with parameter estimation task that have significance independently of the need of precise control. I have realized that by the use of the fixed point iteration-based approach the control and identification tasks can be optionally separated from each other, and arrived at the conclusion that due to balancing problems the precision of the estimation has limitations, and in general, it is expedient to use the improved model with some adaptive technique. I have shown that if the adaptation has to make only small corrections, its stability range increases and becomes much more reliable than the original approach using a very rough initial dynamic system model.

Own Publications

Publications Strictly Related to the Dissertation

[A. 1] H. Issa and J. K. Tar, "Speeding up the reduced gradient method for constrained optimization," in *2021 IEEE 19th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*. IEEE, 2021, pp. 485–490.

[A. 2] H. Issa, B. Varga, and J. K. Tar, "A receding horizon-type solution of the inverse kinematic task of redundant robots," in *2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI)*. IEEE, 2021, pp. 231–236.

[A. 3] H. Issa and J. K. Tar, "Tackling actuator saturation in fixed point iteration-based adaptive control," in *2020 IEEE 14th International Symposium on Applied Computational Intelligence and Informatics (SACI)*. IEEE, 2020, pp. 221–226.

[A. 4] H. Issa, B. Varga, and J. K. Tar, "Accelerated reduced gradient algorithm for solving the inverse kinematic task of redundant open kinematic chains," in *2021 IEEE 15th International Symposium on Applied Computational Intelligence* *and Informatics (SACI).* IEEE, 2021, pp. 387–392.

[A. 5] H. Issa, H. Khan, and J. K. Tar, "Suboptimal adaptive receding horizon control using simplified nonlinear programming," in *2021 IEEE 25th International Conference on Intelligent Engineering Systems (INES).* IEEE, 2021, pp. 221–228.

[A. 6] H. Issa and J. K. Tar, "Preliminary design of a receding horizon controller supported by adaptive feedback," *Electronics*, vol. 11, no. 8, p. 1243, 2022.

[A. 7] H. Issa and J. K. Tar, "Noise sensitivity reduction of the fixed point iteration-based adaptive control," in *2021 IEEE 19th International Symposium on Intelligent Systems and Informatics (SISY).* IEEE, 2021, pp. 171–176.

[A. 8] H. Issa and J. K. Tar, "Comparison of Various Noise Filtering Techniques in Strongly Nonlinear Adaptive Control," in *2022 IEEE 16th International Symposium on Applied Computational Intelligence and Informatics (SACI).* IEEE, 2022, pp. 347–352.

[A. 9] H. Issa, M. Al-Bkree, and J. K. Tar, "On Certain Noise Filtering Techniques in Fixed Point Iteration-based Adaptive Control," *SYSTEM THEORY, CONTROL AND COMPUTING JOURNAL*, vol. 2, no. 2, pp. 9–16, 2022.

[A. 10] H. Issa and J. K. Tar, "On the Limitations of PSO in Cooperation with FPI-based Adaptive Control for Nonlinear Systems," in *2022 IEEE 26th International Conference on Intelligent Engineering Systems (INES).* IEEE, 2022, pp. 181–186.

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