Fast Predictive Inverse Neurocontrol: Comparative Simulation and Experiment

K.V. Zmeu, B.S. Notkin, P.A. Dyachenko, V.A. Kovalev
Industrial Engineering Department
Far Eastern Federal University, FEFU
Vladivostok, Russia
k.zmeu@ieee.org, boris_notkin@mail.ru, dyachenkopasha@mail.ru, daria3000@mail.ru

Abstract—There has been proposed a new approach to a neurocontrol synthesis under conditions of uncertainty. It does not directly use an optimization procedure. In terms of a synthesis technique, the proposed solution is close to inverse neurocontrol, but regarding its functions, the system has properties of a fast predictive control. There have been presented the comparison of the proposed approach with classical and modern proportional-integral-derivative (PID) systems that were obtained based on a numerical simulation and an actual control of complex plants.

Keywords—predictive control; inverse control; neural network; PID-control; neurocontrol

I. INTRODUCTION

Artificial neural network (ANN) is one of the fundamental components of the intelligent control. Now, the ANN in control systems exist just in the form of separate blocks (controllers, plant models, adjustment mechanisms, etc) [6, 7, 20, 25, 27]. In itself, ANN does not create a special control strategy and success of a neurocontrol system depends on the most appropriate way of using ANN capability as a structural unit of the control system.

The predictive control existing so far in technical spheres officially has nothing to do with a paradigm of intelligent control. On the other hand, a predictive control can serve as an example of a fast move from theoretical evidence to practical use and market promotion. It has achieved such success in practical application that some researchers view it as an alternative to proportional-integral-derivative (PID) control for complex non-linear slow processes.

The new approach is close to explicit model predictive control (MPC) [1] and addresses the problem of removing one of the main drawbacks of MPC, namely the need to solve a mathematical program on line to compute the control action. Utilization of an advantages of the predictive control and applied neurocontrol for fast processes is the objective of this paper.

II. PREDICTIVE INVERSE NEUROCONTROL: MAIN PRINCIPLES

It is not possible to implement a strategy of a model predictive control without plant mathematical model. A type of the model and a method of development are the most essential MPC problems [2, 3, 4, 5].

The solution suggested for a predictive control uses ANN. It should be mentioned that neurocontrol quite widely use the principles of a predictive control [6, 7, 28], and the idea of training the neurocontroller using the examples of the predictive control law underlies the neurocontrol [17]. However, this solution suggested more than 10 years ago and survived to this day virtually unchanged [15], as well as a conventional MPC technique requires the plant model and implementation of a numerical optimization procedure to generate control samples in order to train the neurocontroller.

The suggested technique of automatic control system synthesis enables to extract examples of the predictive control law directly from the input/output experimental data obtained from the plant bypassing of a plant modeling and a repetitive on-line solution of a numerical optimization problem.

Neural network training requires a training set. Training of a neurocontroller requires that each sample of a training set have: "current" and "reference" state of a plant – at the input; and "a control variable" – at the output.

The point of the suggested approach is as follows. Let a plant be in a certain initial state. It is assumed as a "current state". A variable "control action" is given to the input of the plant. The state that the plant will acquire after a while by the action of the control is assumed as a "reference" state. Consequently, the "control action" received virtually transfers the plant from a "current" state to a "reference" one. The scope of the evidence is regarded as a control example. A great number of the examples obtained in this way create a training set of a neurocontroller.

The "current" state $y[i]$ and "reference" state $y[i+\lambda]$ in Fig. 1 are separated by time at interval $\lambda$, which defines a value of a predictive horizon in the suggested solution. In addition, as is the case with a conventional MPC strategy [13, 4, 5], a principle of a receding horizon is applied, that is, only the first value of the sequence consisting of $\lambda$ control actions is actually used.

Fig. 2 shows a block diagram of training of a predictive inverse neurocontroller. The current and reference states of a plant in this picture are clearly presented as vectors with a dimension of $v^+1$. 

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Interpretation of delay values of the output variable as elements of the state vector defines their relation with a plant order \((v = n-1\), where \(n\) is the plant order). Within the framework of the suggested technique, this dimension is interpreted only as required minimum.

In this approach the training set is produced by arbitrary plant inputs. Thus the training set may contain some conflicting samples. But the nature of conflict is not fatal because each of training sample satisfy the control goal. Properly trains ANN has good generalization and satisfies the same goal.

It should be noted that in the event of a predictive horizon being \(\lambda \geq 1\), a predictive controller acquires a form of an inverse neural network model of a plant [20]. Based especially on this analogy, the suggested solution has been termed a "predictive inverse neurocontrol".

Computational limitations are one of the main reasons of lambda choice in conventional MPC. The proposed approach has no hard lambda bound. In other aspects the lambda choosing is the same as in MPC [1, 4, 5].

The predictive inverse controller is put in a control loop in accordance with the functions of its inputs. Either a reference signal or an output of the reference model can be used as an objective state.

III. NUMERICAL SIMULATION OF LINEAR PLANTS CONTROL

Neurocontrol systems are mostly strong nonlinear, therefore numeric and full-scale modeling are the main tools for their investigation. Unfortunately, in most of the papers on neurocontrol the researchers restrict themselves to proving only operability of suggested solutions on mathematical models leaving their competitiveness unattended. It should be emphasized without going into details of a critical analysis of the aspect that from our experience many neurocontrol techniques that have already become classical do not exceed but even rank below conventional systems in quality of control.

A problem has been set up to show not just operability of the suggested approach but also its advantages. An issue of an adequate selection of a reference base for an investigation of even conventional control systems is not nearly trivial. It was not until fairly recently that a list of test plants has been offered to compare PID-control systems [10]. Whereas PID-control systems occupy a dominant position in industrial control systems -- up to 95% [8, 9], it makes sense to compare the findings with these systems.

The quality of the suggested systems of the predictive inverse neurocontrol (PIN) is demonstrated by the example of control of a series of high order linear plants taken from the list [10] (see Fig. 3). The comparison is performed with one of the modern PID-control systems [26]. The system parameters have been entered in Table I. Synthesis of the predictive inverse neurocontrol systems in question was done by the examples of step input of random amplitude with a frequency of 1 Hz and a total duration of 300 seconds.
Figure 3. Example of control of a series of high order linear plants: a) Control of plant with multiply poles; b) Control of fourth order plant; c) Control of nonminimum-phase plant; d) Control plant with a transport delay.

Fig. 4 shows the results of a predictive inverse neurocontrol of a plant of order 8 with multiply poles as compared to four PID-control systems adjusted by different methods: ES (Extremum Seeking) [21], IFT (Iterative feedback tuning) [16], IMC (Internal model control) [9], ZN (Ziegler-Nichols) [11].
### TABLE I. Parameters of Linear Systems of a High Order

<table>
<thead>
<tr>
<th>Plant Transfer Function</th>
<th>α</th>
<th>PID Controller Parameters</th>
<th>PIN Control Parameters</th>
<th>Order of a delay lines (reference/current)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Kp</td>
<td>Ti (s)</td>
<td>Td (s)</td>
</tr>
<tr>
<td>$\frac{1}{(s+1)^7}$</td>
<td></td>
<td>1</td>
<td>92.1</td>
<td>1.0</td>
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<td></td>
<td></td>
<td>2</td>
<td>1.95</td>
<td>1.61</td>
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<td></td>
<td></td>
<td>3</td>
<td>1.12</td>
<td>2.13</td>
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<td></td>
<td></td>
<td>4</td>
<td>0.83</td>
<td>2.61</td>
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<tr>
<td></td>
<td></td>
<td>8</td>
<td>0.50</td>
<td>4.31</td>
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<tr>
<td>$\frac{1}{(s+1)(1+\alpha)(1+\alpha^2s)(1+\alpha^3s)}$</td>
<td></td>
<td>0.1</td>
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<td>0.5</td>
<td>1.12</td>
<td>0.34</td>
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<tr>
<td>$\frac{1}{(s+1)^7}$</td>
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<td></td>
<td></td>
<td>10</td>
<td>1.65</td>
<td>16.35</td>
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</table>

As a complicating factor in all of the considered experiments, the feedback was supplemented with white noise with a frequency of 100 Hz and amplitude of 1% of the reference signal. Moreover, there was ±10 saturation in the plant.

The following experiment (see Fig. 5) is devoted to a research of a predictive inverse neurocontrol system by a weakly damped non-rigid three mass plant (Threedisk Torsional System, Model 205a) [30]. PID-control system adjusted using a Generalized Kalman-Yakubovich-Popov Method (GKYP) [22] is shown for comparison.

**Figure 4.** Control of a plant of order 8 with multiply poles as compared to four PID-control systems adjusted by different methods.

**Figure 5.** Control weakly damped of a high order plant.

**IV. EXPERIMENTS ON PHYSICAL PLANTS CONTROL**

As no other technique, the neurocontrol may be complex, diverse and unpredictable when moving from numerical to full-scale experiments. There are quite many problems on the way and it should only be noted that a problem of a successful obtain of a training set using an actual plant is by far more complex than if a model is used.
A. Positional Control of Plane Manipulator Segment

The following considers an example of a predictive inverse system of control of a laboratory model of a vertical plane manipulator link (see Fig. 6). It is based on a widely known Robot Arm, whose mathematical description is stated, for example in [15]. The experiment used a weight of 0.4 kg; distance from the axis of rotation to the center of the weight is 0.5 m; sampling period is 0.01 s. The encoder resolution is 3000 impulses per revolution.

![Figure 6. Single-link robot arm](image)

Results of control of a single-link robot arm are shown in Fig. 7. The neural network of the predictive inverse controller contained 5 neurons in a hidden layer; the input vector consisted of 5 delay values for a current and reference states (5/5). The neurocontroller training was done with a predictive horizon $\lambda=25$.

![Figure 7. Positional Control of Plane Manipulator Segment](image)

B. Fan-and-Plate Control

The appearance of the experimental system is shown on Fig. 8. The prototype of this model was Fan&Plate plant manufactured by "Kent Ridge Instruments" [31]. A significant impact of aerodynamic qualities of the plant makes it quite difficult to obtain an adequate mathematical model. This system should essentially be considered in terms of a system with uncertain dynamics. As regards the conducted research another interesting feature of this plant is its invariably low quality of feedback (position is measured by means of an analog potentiometric transducer).

![Figure 8. Fan-and-Plate](image)

When developing a predictive inverse neurocontrol system, the dimensions of the vectors of the current and reference state were expanded up to 20 delay values ($\nu=20$). This has a positive impact on the training quality of the predictive inverse models and subsequent adjustment in noise conditions. It was quite sufficient for the experiment to use a linear neural network. The predictive horizon $\lambda=50$ of control intervals; discrete interval of the system is 0.01 s. The experiment considered clearly demonstrates a high noise robustness of the suggested technique (Fig. 9).

![Figure 9. Fan-and-Plate Control](image)

C. 2D “Helicopter” Position Control

A far more complex problem must be considered which is a MIMO plant control, for which a model of Helicopter CE-150 was taken as an example (see Fig. 10) [32].

The experiments have been executed by means of a website "Automatic Control Telelab" (ACT) provided by the University of Siena, Italy [29]. The quality of control of a predictive inverse system is compared to the quality of a PID-control system whose settings are suggested by ACT developers.

In order to control each coordinate a separate neural network was used. Fig. 11 shows a diagram of the network input vector forming in one of the channels. As may be inferred from the picture, besides the source data, the second input vector of the neural network is supplemented with information on another coordinate behavior. This additional information resource enables to account the effect of the coordinate mutual influence in the training of neurocontrollers, which has a
positive impact on consistency of their performance in a closed loop and on the control quality as a whole.

As may be inferred from the picture the control quality in the suggested alternative is significantly higher than the basic one.

**CONCLUSION**

The work presents a new approach to synthesis of complex control systems in circumstances of uncertainty, which is a fast predictive inverse neurocontrol. The technique provides the system with features of predictive control not requiring a separate mathematical plant model and the thing of prime importance not requiring a repetitive procedure of a numerical optimization. In a particular case, it reduces to a direct inverse neurocontrol.

A number of model and full-scale experiments dealing with control of different linear plants (of high orders; high multiplicity of poles; nonminimum-phase, with a transport lag, with weakly damped zeros and poles), as well as with non-linear plants, including the plants with uncertain behavior, showed that mostly the suggested approach has significant advantages regarding control and in other cases it yields results comparable with the basic ones.

Results deserving more consideration are those of applying the suggested approach to control MIMO non-linear aerodynamic plant – "helicopter", whose complexity is fully responsible for considering it as a plant with an uncertain behavior. Concerning complex MIMO plants, the predictive inverse neurocontrol can be considered as a successful alternative to decomposition approaches.

The reader can refer to ACT [29] on their own and run experiments to test the neurocontrol using a "helicopter" model suggested in the paper. It would also be not without interest to compare a rating of different “helicopter” control systems presented in the website.

**REFERENCES**
