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MODIFIED ALGORITHM OF NEURAL NETWORK CONTROL FOR NON-STATIONARY OBJECT

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ABSTRACT

A task of automated system control design with non-stationary plant and stochastic signals is observed. A traditional approach suggests permanent and simultaneous adoption of neural networks used for control and identification that leads to extra expenses and loss of control quality.

At the same time in case of rare change of characteristics of the plant it seems reasonable to activate adoption algorithms only if meaningful change of the plant was detected. To detect such change there is a well-known statistical algorithm of cumulative sums. Proposed modified approach can decrease expenses of routine system functioning during periods when plant is approximately stationary.

It's needed to perform comparative experiments to reveal advantages and disadvantages of both approaches. Results will allow to estimate specific behavior and to provide recommendations for application of both methods.

Index terms – Neural network, optimal control system, non-stationary object, cumulative sum.

1. INTRODUCTION

A very actual task in technical systems is an automated control of a plant with non-constant dynamic characteristics which can be changed in arbitrary moment and can't be predicted in advance. A cause of non-stationary plant behavior may be as well spontaneous technical object change (due to wear, for example) as external conditions influence to the processes in the system (season and weather, for example).

Change of dynamic parameters of the plant with constant parameters of controller usually leads to worse control quality. To avoid decrease of control quality and related losses which can be represented as descent of economical efficiency one needs to adopt controller according to new conditions. It's technologically convenient and reliable to solve this task automatically instead of drawing in a human as an operator of control system.

Let's observe a task of neural network control of non-stationary plant in stochastic conditions. The last term means the reference signal and noise are suggested as stochastic processes in discrete time. We will consider also that change of plant parameters are rare enough to have long period of steady plant parameters. The change of parameters is suggested as very fast, stepped manner. So, neural network of the controller (NN-C) is to be tuned to decrease control error.

In computational experiments linear plant models were used, but described methods themselves do not imply plant linearity.

2. PERMANENT ADOPTION APPROACH

The most commonly used solution of the posed task is permanent tuning of neural network of the controller to adopt to any possible changes. In this case the neural network will follow change of dynamic characteristics of the plant as well. Such mode of system control evidently causes extra expenses when changes is not taking place. Also this may decrease general control quality due to inevitable stochastic signals fluctuation.

Such approach may be implemented on the basis of neural network control algorithms which use direct or indirect inversion of the plant [1]. Let's realize traditional neural network controller for non-stationary plant by extending algorithm of indirect adaptive control [2] appropriately.

Indirect adaptive neural network control requires a special neural network for plant identification (NN-P) which should be tuned in advance to behave as well as the object of control — plant. This plant-equal behavior is used to train neural network controller by implementing online estimation of plant's Jacobian. In case of steady plant parameters a neural network identification as a process of NN-P training may be performed once. After training NN-P is ready to predict plant output in feed-forward mode and estimate Jacobian in back-propagation mode.

But if dynamic characteristics of the plant become changed then the neural network plant modeling and Jacobian estimation become wrong therefore identification has to be performed again to adopt new plant parameters. The controller may be trained simultaneously with the neural net plant identification. So, in case of permanent activity of adoption algorithm both neural networks NN-C and NN-P are in state of training. The schema of control system with permanent neural networks adoption is shown on fig. 1.

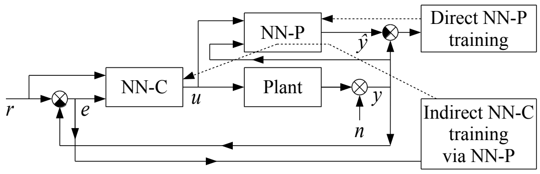


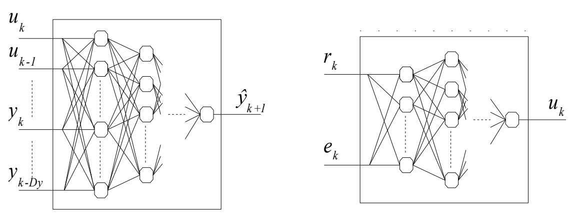
Figure 1 Control system with permanent neural networks adoption

External input signals of the control system are reference signal *r* and noise *n* in the observable output of the plant. Neural network controller (NN-C) influences the plant by signal *u* aimed to minimize control error $e=r-y$. In parallel to the plant a neural network identification model (NN-P) operates. It predicts plant observation output at next time ($\hat{y}$) using several delayed values of controller influence signal *u* and previously observed outputs of the plant *y*.

Two neural network training algorithms are activated simultaneously: direct training of neural network identification model and indirect training of neural network controller which uses also current state of neural identification model. NN-P training is based on identification error $y-\hat{y}$ and is aimed to its minimization. Indirect NN-C training procedure inputs control error *e* and propagates it through NN-P in reverse direction. In case of good matching identification model to the plant a desired value of control influence will be produced on the *u* input of NN-P. Further back propagation of error will train NN-C to this desired value. Directions of back propagation process are marked on fig. 1 by dashed lines with arrows.

The method uses feed-forward neural networks without internal or external feedback with sigmoid activation function in neurons. For better modeling of plant dynamics several delayed inputs *u* and *y* from the past are inputted by NN-P. Maximum length of delay for *u* and *y* is marked as D_u and D_y accordingly. For the same reason neural controller has not only control error *e* on the input but reference signal *r* also.

Structure of neural network controller and identification model is represented on fig. 2.



NN-P *NN-C*

Figure 2 Structure of neural networks

Two important notes about described method must be emphasized especially. The first, during indirect NN-C training the control error is propagated in reverse direction through NN-P with delta weights calculation but not application. This is done just because the task of control error minimization must be solved by neural controller, but not by identification model. So, only weight coefficients of NN-C are changed during its training. The second, the training of identification model is performed simultaneously and independently. This means that application of weight coefficients change is used by NN-C training immediately.

3. MODIFIED APPROACH

The schema of control system in modified approach also has two neural networks: controller and identification model. In opposite to traditional method in stationary plant conditions it does not imply any changes in neural networks at all. Additional block of the control system is used for plant parameters change detection (fig. 3). After the change was detected some data are gathered and neural network identification model is trained on that data out of the control system loop. After the NN-P training it is placed into the control loop and the whole system is switched to NN-C adoption mode where NN-P is used the same manner as in traditional approach (fig. 4). It should be noted that structure of used neural networks are completely the same in both methods: traditional and modified. (fig. 2).

For correct functioning of described schema a reliable algorithm of plant parameters change detect should be implemented and proper data gathering is to be performed to train neural network identification model.

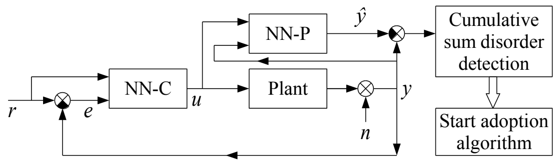


Figure 3 Modified approach to control in steady state

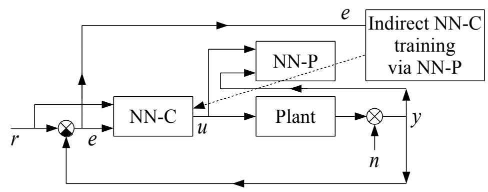


Figure 4 Modified approach in adoption state

The first subtask can be solved with help of cumulative sum algorithm. For more reliable change detection the double alarm event during pre-calculated time range is considered as true alarm. The second task is solved from the point of view that neural network is a general approximation of some unknown function which is defined empirically by the table of observed points. Let's go further for details.

3.1. Cumulative sum method

Algorithm of cumulative sum for disorder detection is to be tuned to provide required efficiency. It's well known that the main control parameter of classic cumulative sum method is a threshold H, and its main characteristics —average time of alarm delay T_{ad} and average time between false alarms T_{fa}. Considering given task they define the time when control system will have losses due to change of plant parameters and inevitable increase of control error.

Cumulative sum method detects change of some control parameter of the stochastic process as a ratio of its current value to the nominal one which was determined in steady state of the process. So, for cumulative sum algorithm setup one needs to select process parameter to control, its steady state value which is nominal one and the value of this parameter considered as meaningful change (so called, nominal disorder). A threshold should be selected also to provide desired values of T_{ad} and T_{fa}.

Preliminary experiments revealed that good disorder detection caused by change of plant parameters is provided by variance of identification error y-$\hat{y}$. The nominal variance is calculated when plant is stationary. The nominal disorder is an increase of variance in selected number of times (two times, for example) relatively to nominal value. Several experiments may show which level of nominal disorder affects control error significantly in exact control system.

The proper choice of threshold H may be result of compromise between desired values of T_{ad} and T_{fa}. The faster alarm (lesser T_{ad}) means faster start of neural network identification model training and therefore faster start of neural controller adoption. However, for the same threshold value this means lesser time between false alarms (T_{fa}), so some random noise fluctuation may be solved as plant parameters change and an expensive adoption procedure will be executed.

For more reliable disorder detection it's suggested to run atomic check procedure of cumulative sum algorithm yet another time after the first alarm. If the second check procedure detected alarm not later than in $3T_{ad}$, then disorder is solved as detected for sure. It should be understood that effective time of alarm delay is doubled.

To make reasonable choice of threshold H it would be desirable to calculate T_{ad} and T_{fa} for every H value, given nominal stochastic process and nominal disorder. There is a reliable method [3] to obtain such characteristics for non-correlated stochastic processes based on their distribution parameters. However computer simulation shows that the mentioned method does not give precise results in our case because observed identification error is stochastic but correlated value. To calculate needed characteristics empirically a number of computation experiments were performed. Their result was a relation between threshold H and characteristics T_{ad} and T_{fa} (fig. 5, 6). These empirical dependencies was used in further experiments and highlight application of cumulative sum algorithm in neural network control system.

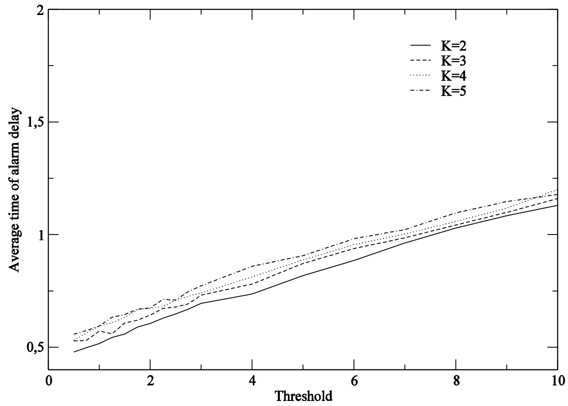


Figure 5 Average time of alarm delay T_{ad} (K is a ratio of changed to nominal variance)

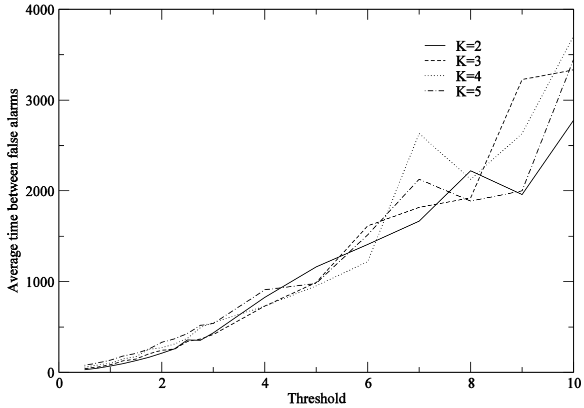


Figure 6 Average time between false alarms T_{fa} (K is a ratio of changed to nominal variance)

After the change of plant parameters and training of both neural networks NN-P and NN-C a new setup of cumulative sum algorithm may be required, especially if variance of identification error in new steady period differs from previous one.

3.2. Training data set gathering

Data set gathering for NN-P training in this case has own specific features related to the length of data set N and the way it should be composed. The standard approach suggests fixed length of training data set but it's not optimal and not even reasonable. The training of neural network identification model should be performed every time the disorder has been detected. Starting from this moment it can be considered that the control system is out of optimal mode and it's highly desirable to minimize the time it lasts. However it's evident that longer data set will provide the better training of neural network identification model and also neural network controller will be trained faster and better. So, we need a method of the shortest reasonable training data set gathering.

It's proposed to start training data set $\{u_k\}_N$ and $\{y_k\}_N$ gathering just at the beginning of the last successful check procedure of cumulative sum algorithm t_0 until the signal of disorder detection at moment t_1 (let's designate length of this series M). Also we can add series of length M just before t_0 because that check procedure was also successful and it was true disorder detection as we found later, after the second check. Since the length of t_1-t_0 is a stochastic value then the resulting data set will have random volume N=2M. This length defines the minimal data set we can obtain from the past and can use to train neural network identification model immediately after disorder detection.

However this length may be not enough for quality training if the range t_1-t_0 was too small. It's suggested to estimate two-dimension (u,y) distribution parameters and gather observed values u_k,y_k further to the data set to fill selected two dimension area with desired density. For Gaussian distribution it is convenient to select target area of radius 3σ around point with mean coordinates. Since neural network training may be considered as fitting empirically described function then the better fill will provide the better fit of target function.

Described algorithm allows to compose data set dynamically and to guarantee reliable neural network training to approximate unknown function. In our case this unknown function predicts plant output and gathered data set is used to reveal its properties during NN-P training out of control system loop.

4. EXPERIMENTS

Both described methods were realized in computer simulation software specially designed for neural network control system modeling. A number of simulation experiments were performed for investigation of general characteristics and control quality of neural control in both cases. To estimate control quality two different criteria was used: mean squared error (MSE) which gives presentation of integral losses and standard distribution parameters which allow to reveal probability of dangerously large control error, sometimes leading to crash of technical system.

4.1. Steady plant conditions

In series of experiments with stationary plant the behavior of neural network control was examined in conditions when no actual adoption was needed.

The traditional neural network controller with permanent adoption (PA) causes meaningful oscillations of control quality with the period ~2-5×10^5 time samples and amplitude from 0.05 to 6. This behavior can be clearly seen on the diagram of mean squared error of control (fig. 7).

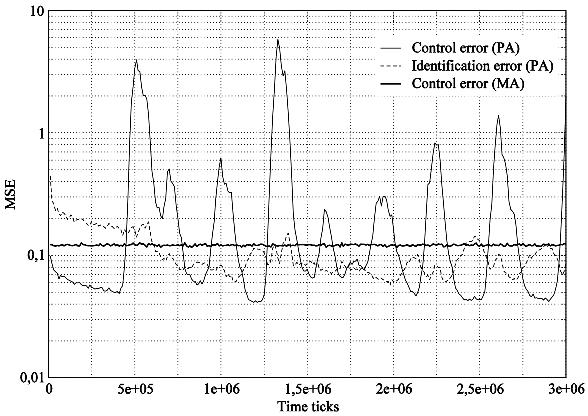


Figure 7 Mean squared errors for permanent adoption (PA) and modified approach (MA) in steady plant conditions

A diagram of identification error also demonstrates oscillations since NN-P is trained simultaneously with NN-C. However in general its diagram looks reversed to the control MSE diagraph. Such specifics may mean that increasing quality of identification means better Jacobian estimation not every time. Possibly, some level of identification quality is optimal and should not be improved further.

Neural network controller in modified approach case (MA) demonstrates very small oscillations of control error around mean value 0.121.

During experiments with statistical distribution properties determination it was found that control error was distributed by normal Gaussian law. (fig. 8).

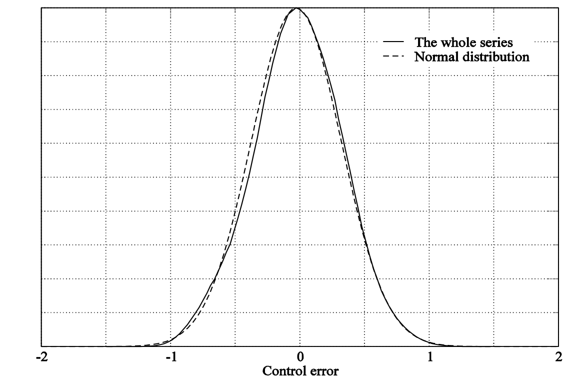


Figure 8 Distribution of control error in modified approach for steady plant conditions

During permanent adoption of neural network controller it was found that statistical distribution was variable and in periods of the worst control quality the mean value of error differs from zero significantly. Diagrams of error distribution in two consequent time ranges and for the whole series are shown on fig. 9. One can see that during period of good control quality [0, 4×10^5] (see fig. 7 also) the distribution is close to Gaussian, but in periods of bad control quality (for example, [4×10^5, 8×10^5]) the distribution is multimodal.

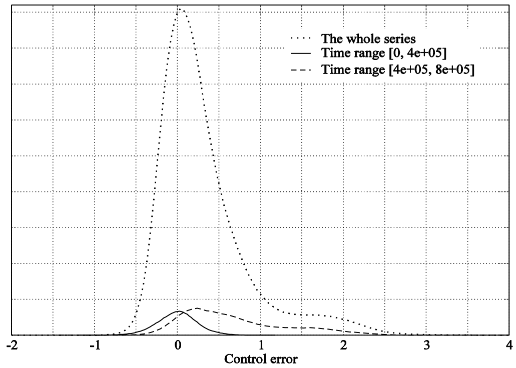


Figure 9 Distribution of control error in permanent adoption approach for steady plant conditions

Statistical distribution properties are listed in tab.1.

	Min	Max	Mean	Variance
Permanent adoption	−2.03	5.43	0.33	0.30
Modified approach	−1.46	1.52	−0.01	0.12

Table 1 Control error distribution in steady plant conditions

4.2. Plant change conditions

In series of experiments with non-stationary plant its parameters were changed at time sample 500. Fig. 10 show diagrams of control MSE for three different control strategies: no adoption of NN-C at all, permanent adoption of both NN-C and NN-P and modified approach to neural networks adoption with use of cumulative sum disorder detection algorithm.

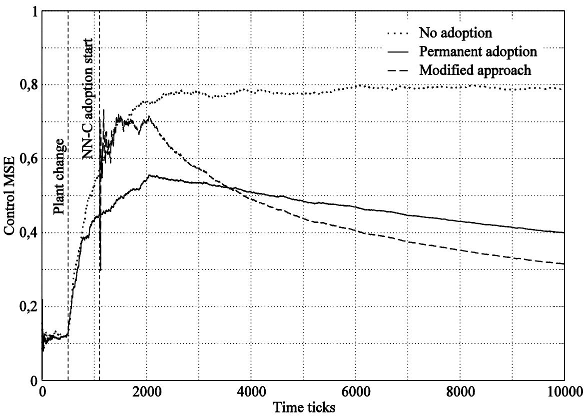


Figure 10 Control MSE in plant change conditions

Time samples when plant change occurred and NN-C adoption started in modified approach are marked by vertical lines and labeled accordingly. Permanent adoption method responds to plant change almost without delay and does not allow control MSE to be greater than 0.55. However after some time of descent (~10^4-10^5 time samples) the control error starts to grow the same manner as it was observed in steady plant conditions (not shown on figure).

Modified approach needs time to gather data for NN-P training. In this experiment the length of data set was determined as 600 time samples. During this time the control MSE reached level 0.6. Let's consider that NN-P training outside the control system loop was performed very fast and new NN-P was ready immediately after data set for its training was gathered. Actually it depends on scale of control system time and performance of computer hardware available for NN-P training. So, at the time sample 1100 neural network controller started to be adopted with help of new NN-P. To this time control MSE reached level 0.7 which is close to original NN-C without any adoption. After beginning of the adoption control MSE started to descent and it was much faster than during permanent adoption.

Statistical distribution properties are given in tab.2.

	Min	Max	Mean	Variance
Permanent adoption	−12.31	3.62	−5.23	10.51
Modified approach	−1.98	2.00	−0.01	0.46

Table 2 Control error distribution in change plant conditions

5. CONCLUSIONS

Simulation experiments displayed key features of two observed approaches of neural network control. Unstable behavior of permanent adoption even while stationary plant control was highlighted. But this method responds faster and provides better control error just after plant change.

Modified approach in general looks more preferable because it supplies stability of control system and provides guarantee level of control quality when plant is stationary. Specific features of the algorithm does not allow it to react on plant change immediately but the quality of out-of-loop NN-P training provides faster learning of neural network controller in the loop to adopt plant changes.

It seems that prospective approach to non-stationary neural network control should combine the best characteristics of both observed methods.

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