RISE Feedback Control for a R/W Head Track Following in Hard Disc Drives

M. Taktak-Meziou, A. Chemori, J. Ghommam, and N. Derbel

Abstract—**In this paper, the track following problem of the Read/Write (R/W) head of a Hard-Disc-Drive (HDD) is addressed using Robust Integral of Sign Error (RISE) based Neural Network (NN) technique. The proposed control scheme is required to compensate as much as possible the nonlinear hysteresis friction behavior which degrades the HDD performance through generating important residual tracking errors. It is well shown that the RISE technique, along with the NN based feedforward control, is able to guarantee the stability of such a system. Moreover, the boundedness of the closed-loop signals is ensured. To the best authors' knowledge, the suggested control solution, applied at the low frequency region of a HDD, has never been conducted before on such system. Different simulation scenarios are performed including nominal case and external disturbance rejection to demonstrate that the proposed solution is robust and efficient to achieve good tracking performances.**

Index Terms—**Nonlinear systems, hard-disc-drives, asymptotic stability, RISE feedback, neural networks.**

I. Introduction

Recently, since the Hard-Disc-Drives(HDD) technology marks an important development, many works focus on and aim at satisfying the increasing demand of performances. A view of a typical HDD servo-system is illustrated in Fig. 1 . As a mechatronic devise, a HDD consists mainly of rotating platters, driven by a spindle motor, to store data. To read/write information on/from the disc. The system is equipped with several magnetic R/W heads. They are connected to a Voice-Coil-Motor (VCM) which is dedicated to manage their position and move them from a track to another. Therefore, two main functions of a HDD have to be distinguished in describing the general functioning of the considered system: track seeking and track following [1]. The former deals with the displacement of the head from its current position to a target track with a limited control effort, and the latter aims at maintaining the head accurately around the required track while information is being read or written.

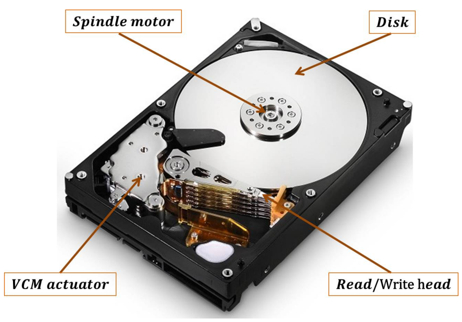

Fig. 1: Main components of a typical hard-disk-drive

The pivot bearing movement, well known as characterized by nonlinear frictions, that can deteriorate the HDD system performance. Accordingly, large settling time, significant overshoots and residual errors can arise yielding the head positioning servo system to be unable to maintain the head tip precisely on the target track. In the literature, different models of HDD frictions behavior have been proposed. In [2], a detailed presentation of the hysteresis behavior is given. Researchers, such as [3]–[5], focused on the nonlinear hysteresis modeling. The LuGre friction model was proposed for the HDD as a good presentation which captures all static and dynamic features [6]. For a complete review of the friction modeling, the reader is referred to [7].

Therefore, many researcher communities were interested in friction effects compensation through different control strategies proposed in the literature. Some of these compensation techniques are based on an accurate modeling of the friction behavior such as in [5], [8], [9]. However, other approaches deal with non-model-based friction estimation [10] [11].

Adaptive neural network techniques were developed and demonstrated as an adequate tool in eliminating the effects of nonlinearities and even external disturbances. For instance, the authors in [12] [13] have shown the effectiveness of these techniques in dealing with friction compensation and tracking performances.

In this paper, the application of the recently developed control method based on Robust Integral Sign of the Error (RISE) [14] is proposed. This technique were firstly tested on a class of uncertain and high order nonlinear systems and have shown good performances. However, since it is a high gain-feedback control, it was more attractive to blend it with a feedforward based on neural networks [15]. Such combination is advantageous since it offers the possibility to reduce, under some conditions, disturbances and uncertainties affecting the system with an improved steady-state performance and minimal control effort [14] [16]. In the RISE-NN based method, the NN weights are adjusted online. Compared with previous works, this technique is able to guarantee the asymptotic stability (AS) of the closed-loop system. This paper will not only treat the compensation of inappropriate responses, but it will also perform a precise and fast desired trajectory tracking of the HDD servo-positioning system which reflects

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the effectiveness of the proposed control solution.
The reminder of this paper is organized as follows. In section 2, the problem statement is presented. The RISE feedback NN controller is developed in Section 3. Section 4 presents a comparative study of the different numerical simulation results to highlight the effectiveness of the proposed control solution. Concluding remarks are drawn in Section 5.

II. PROBLEM FORMULATION

A. HDD low-frequency modeling

At low frequencies, the Voice-Coil-Motor (VCM) actuator dynamics including the nonlinear hysteresis friction is given by [17]:

$$M(q)\ddot{q}+F(q,\dot{q})=u \quad (1)$$
$$y=q+w_{out}$$

where $M(q)$ denotes the system inertia verifying $M(q)>0$. q, $\dot{q}$ and $\ddot{q}$ denote the position, velocity and acceleration of the VCM-actuator head tip respectively. u is the control input, y is the actual position of the VCM-actuator in presence of the output disturbance w_{out}. This disturbance is induced by external vibrations. $F(q,\dot{q})$ is a nonlinear function representing the pivot bearing hysteresis friction. The behavior of $F(q,\dot{q})$ in HDD applications was investigated in [2] and the LuGre friction model, as introduced in [6], was selected to represent the static and dynamic characteristics of this hysteresis friction as follows:

$$\begin{aligned} F(q,\dot{q}) &= \sigma_0 z+\sigma_1\dot{z}+\sigma_2\dot{q} && (2)\\ \dot{z} &= \dot{q}-\alpha(\dot{q})\mid\dot{q}\mid z && (3)\\ \alpha(\dot{q}) &= \frac{\sigma_0}{f_c+(f_s-f_c)e^{-(\frac{\dot{q}}{q_s})^2}} && (4)\end{aligned}$$

where z is an internal state of the friction model assumed to be unmeasurable. σ_0, σ_1, and σ_2 are the model parameters reflecting the small displacements which are the stiffness, the micro damping, and viscous coefficient respectively. f_s corresponds to the stiction force, f_c is the Coulomb friction force, and the parameter q_s is the Stribeck velocity [18].

B. Control problem statement

Let q_d be the desired track position. The tracking error can therefore expressed as:

$$e_1=q_d-q \quad (5)$$

The control objective is then to ensure the displacement of the R/W head of the HDD such that it follows a given target track. The head must be kept as close as possible to the predefined track while treating data, as such the following objective is obtained:

$$\lim_{t\to\infty}|e_1(t)|=\lim_{t\to\infty}|q_d(t)-q(t)|=0 \quad (6)$$

The recent developed feedback control strategy RISE is proposed to deal with the track following problem of the HDD. This proposed solution is combined with a NN-based feedforward controller which is able to deal with the non-explicit knowledge of the friction model $F(q,\dot{q})$ to compensate the effects external vibrations on the actuator positioning accuracy. Such combination, as shown in [15], is able to ensure the asymptotic stability of the closed-loop system and enhance the steady-state performance with a reduced control effort.

III. PROPOSED CONTROL SOLUTION: A RISE FEEDBACK WITH NN FEEDFORWARD

In this section, the RISE feedback method combined with the NN feedforward control term is proposed for the track-following problem of the R/W head. Fig. 2 illustrates the general structure of the proposed control methodology for the HDD servo-system. The controller is designed based on the nonlinear model and aims at achieving a good performance of the closed-loop system and to ensure a semi-global asymptotic tracking.

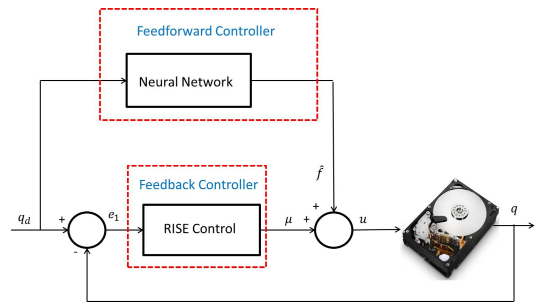

Fig. 2: View of the control structure including the RISE feedback and the NN feedforward

A. Background on Feedforward NN control

Dynamical neural networks present an effective tool for estimation and control of nonlinear and complex systems. The universal approximation remains the feature of the NN-based controllers [19]. Consider $\mathbb{S}$, a compact set and $f(x)$ a smooth function defined as $f:\mathbb{S}\to\mathbb{R}^n$. There exists always three-layer NN able to represent $f(x)$ [15] such that $f(x)=W^\top\sigma(V^\top x)+\varepsilon(x)$ for given inputs $x(t)\in\mathbb{R}^{a+1}$. $V\in\mathbb{R}^{(a+1)\times L}$ are bounded constant weight matrix for the first-to-second layer and $W\in\mathbb{R}^{(L+1)\times 1}$ is the ideal weight matrix for the second-to-three layer. a is the number of inputs and L is the number of neurons in the hidden layer. $\sigma(.)\in\mathbb{R}^{L+1}$ is the activation function and $\varepsilon(x)\in\mathbb{R}^n$ is the functional error approximation satisfying $\parallel\varepsilon(x)\parallel\leq\varepsilon_N$ where ε_N is a known constant bound. Fig. 3 shows an illustrative description of a three-layer NN principle.

Remark 1: The activation function $\sigma(.)$ can take different forms such as sigmoid, hyperbolic tangent or a radial basis function. In this paper, the considered $\sigma(.)$ is a radial basis function taking the following general form:

$$\sigma(x_i)=\exp\left(\frac{\|x_i-c_i\|^2}{\sigma_i^2}\right) \quad , \quad \forall i\in\mathbb{N}$$

where c_i is the center of the basis function and σ_i is its width, which are chosen *a priori* and kept fixed throughout this work for simplicity.

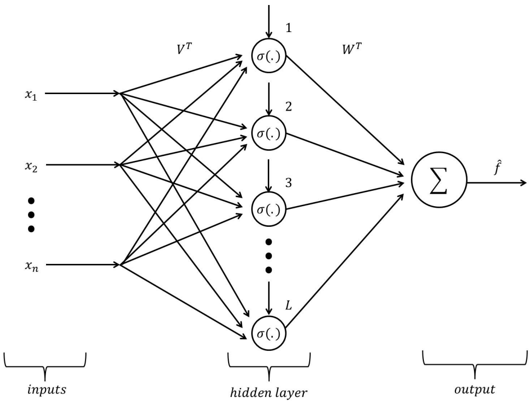

Fig. 3: Schematic view of a three-layer NN

In order to calculate the NN feedforward term, some assumptions and properties have to be taken into consideration.

Assumption 1: The desired position q_d, as well as its first and second time derivatives exist and are all bounded, i. e., q_d, $\dot{q}_d$, and $\ddot{q}_d \in \mathscr{L}_\infty$.

Property 1: The NN quantities are bounded such as $\| W \| \leq W_m$, $\| \sigma \| \leq \sigma_m$, where W_m and σ_m are known positive constants [20].

B. Background on RISE Feedback control

In this work, the main control objective is to maintain the R/W head as close as possible to a predefined desired trajectory in order to perform an accurate track following task. Since unknown nonlinearities of the HDD dynamics are considered, a controller is developed that exploits the universal approximation property of NNs and the implicit learning of the RISE feedback for the identification of the nonlinear effects of frictions. A RISE feedback control approach with NN feedforward estimation is therefore proposed as a good solution which guarantee an asymptotic stability of the controlled HDD model described by (1). The control strategy is developed in this section, introducing the open-loop and closed-loop tracking error systems. Based on assumption 1, the position tracking error $e_1(t)$, the filtered tracking errors denoted by $e_2(t)$ and $r(t)$, are defined as follow

$$e_1 = q_d - q \tag{7}$$
$$e_2 = \dot{e}_1 + \alpha_1 e_1 \tag{8}$$
$$r = \dot{e}_2 + \alpha_2 e_2 \tag{9}$$

where α_1 and α_2 are positive tuning gains.

Remark 2: The filtered tracking error $r(t)$ is a nonmeasurable quantity since it depends on $\ddot{q}(t)$.

1) Open-loop tracking error system: To develop the open-loop tracking error system, the multiplication of (9) by $M(q)$ is made. Then, using the expressions (1), (7), and (8), the resulting system can be expressed as follow:

$$M(q)r = F_d + S - u \tag{10}$$

where F_d is an auxiliary function defined by:

$$F_d = M(q)\ddot{q}_d + F(q_d, \dot{q}_d) \tag{11}$$

and S is a second auxiliary function defined by:

$$S = M(q)(\alpha_1 \dot{e}_1 + \alpha_2 \dot{e}_2) + F(q, \dot{q}) - F(q_d, \dot{q}_d) \tag{12}$$

Based on the NN approximation, F_d can be expressed as follows:

$$\dot{F}_d = W^\top \sigma(V^\top x_d) + \varepsilon(x_d) \tag{13}$$

where $x_d = \begin{bmatrix} 1 & q_d & \dot{q}_d & \ddot{q}_d \end{bmatrix}^\top$ and $\varepsilon(x_d)$ is the bounded NN approximation error. According to assumption 1, the following inequalities hold:

$$\| \varepsilon(x_d) \| \leq \varepsilon_N \tag{14}$$
$$\| \dot{\varepsilon}(x_d, \dot{x}_d) \| \leq \varepsilon'_N \tag{15}$$

where ε_N and ε'_N are known positive bounded constants.

2) Closed-loop tracking error system: Using the previous open-loop tracking error system (10), the control input is the summation of the feedforward NN estimation term and the RISE feedback term. As detailed in [21], the RISE control term $\mu(t)$ is expressed as follows:

$$\begin{aligned} \mu(t) &= (k_s+1)e_2(t) - (k_s+1)e_2(0) \\ &+ \int_0^t [(k_s+1)\alpha_2 e_2(s) + \beta_1 sgn(e_2(s))]ds \end{aligned} \tag{16}$$

where $k_s, \beta_1 \in \mathbb{R}^+$ are positive feedback. The time derivative of (16) is given by:

$$\dot{\mu}(t) = (k_s+1)r(t) + \beta_1 sgn(e_2(t)) \tag{17}$$

Since the nonlinearities in the system's dynamics are supposed to be unknown, a new control term, denoted $\hat{F}_d$, and generated by the NN feedforward estimation is added to approximate the uncertainties and cancel out their effects. $\hat{F}_d$ is then expressed by:

$$\dot{\hat{F}}_d = \hat{W}^\top \sigma(V^\top x_d) \tag{18}$$

where $V \in \mathbb{R}^{(a+1)\times L}$ is a bounded constant weight matrix, and $\hat{W} \in \mathbb{R}^{(L+1)\times 1}$, is the matrix of the estimates of the NN weights, which are generated on-line by:

$$\dot{\hat{W}} = K[\sigma(V^\top x_d)e_2^\top - \kappa \hat{W}] \tag{19}$$

where κ is a positive design constant parameter. $K = K^\top > 0$ is a constant positive defined control gain matrix. According to property 1, the upper bound of $\dot{\hat{W}}$ can be formulated as follows:

$$\| \dot{\hat{W}} \| \leq F_N \sigma_m \| e_2 \| \tag{20}$$

where F_N is a known bound constant. The overall control input system is then given by:

$$u = \hat{F}_d + \mu \tag{21}$$

By taking the time derivative of (21) and substituting the expressions of $\dot{\mu}$ and $\dot{\hat{F}}_d$ given by (18) and (17) respectively, we get:

$$\begin{aligned} \dot{u} &= \dot{\hat{F}}_d + \dot{\mu} \\ &= \hat{W}^\top \sigma(V^\top x_d) + (k_s+1)r(t) + \beta_1 sgn(e_2(t)) \end{aligned} \tag{22}$$

Thereby, the closed-loop tracking error system dynamics are formulated by taking the first time derivative of (10)

$$\begin{aligned}M(q)\dot{r} &= -\dot{M}(q)r+\dot{F}_d+\dot{S}-\dot{u} \quad (23)\\ &= -\dot{M}(q)r+\dot{F}_d+\dot{S}-\hat{W}^{\top}\sigma(V^{\top}x_d)-(k_s+1)r(t)\\ &\quad -\beta_1 sgn(e_2(t))\\ &= -\frac{1}{2}\dot{M}(q)r+\tilde{W}^{\top}\sigma(V^{\top}x_d)+\varepsilon(x_d)-(k_s+1)r(t)\\ &\quad +(-\frac{1}{2}\dot{M}(q)r+\dot{S}+e_2)-\beta_1 sgn(e_2(t))-e_2\end{aligned}$$

where $\tilde{W}^{\top}=W^{\top}-\hat{W}^{\top}$ is the estimation error. The equation (23) can then be rewritten as follows:

$$\begin{aligned}M(q)\dot{r} &= -\frac{1}{2}\dot{M}(q)r+\tilde{N}+N_{B_1}+N_{B_2}-e_2 \quad (24)\\ &\quad -(k_s+1)r(t)-\beta_1 sgn(e_2(t))\end{aligned}$$

where

$$\tilde{N} = -\frac{1}{2}\dot{M}(q)r+\dot{S}+e_2 \quad (25)$$

$$N_{B_1} = \varepsilon(x_d) \quad (26)$$

$$N_{B_2} = \tilde{W}^{\top}\sigma(V^{\top}x_d) \quad (27)$$

As detailed in [21], according to the Mean Value Theorem, $\tilde{N}$ is upper bounded as follows:

$$\| \tilde{N} \| = \| -\frac{1}{2}\dot{M}(q)r+\dot{S}+e_2 \| \le \rho(\| z \|) \| z \| \quad (28)$$

where $z(t)\in\mathbb{R}^3$ is given by:

$$z(t)=\begin{bmatrix}e_1^{\top} & e_2^{\top} & r^{\top}\end{bmatrix}^{\top} \quad (29)$$

and $\rho(\| z \|)$ is a positive nondecreasing bounding function. In order to facilitate the stability analysis, some important inequalities are considered as given in following lemma.

Lemma 1: Consider N_{B_1} and N_{B_2} as expressed respectively by (26) and (27). The following inequalities hold.

$$\| N_{B_1} \| \le \varepsilon_N \quad (30)$$

$$\| \dot{N}_{B_1} \| \le \varepsilon'_N \quad (31)$$

$$\| N_{B_2} \| \le (\tilde{W}_m^{\top}+F_N\sigma_m \| e_2 \|)\sigma_m \equiv \xi_{B_2} \quad (32)$$

$$\| \dot{N}_{B_2} \| \le \xi_1 \| e_2 \| +\xi_2 \quad (33)$$

where ξ_{B_2}, ξ_1, and ξ_2 are positive known constants.
Proof: Inequalities (30) and (31) can be directly determined according to equations (14), (15), and (26). Based on Property 1 and equation (20) which deal with the upper bounds of the NN weights, inequality (32) can be easily justified. Then, by considering the derivative relation $\dot{\sigma}_m=\sigma_m(1-\sigma_m)$ together with the time derivative of N_{B_2} expressed as $\dot{N}_{B_2}=\dot{\tilde{W}}\sigma_m+\tilde{W}\dot{\sigma}_m$, inequality (33) is concluded.

IV. NUMERICAL SIMULATIONS

In this section, numerical simulations are conducted in Matlab/ Simulink framework with a sampling time $T_e=0.05ms$. The 3.5-in HDD-VCM actuator is chosen to test the effectiveness of the proposed control scheme. Therefore, the full used model of the system is as described by (1)-(4). The dynamic model parameters are chosen as: $M(q)=1$, $\sigma_0=10^5$, $\sigma_1=\sqrt{10^5}$, $\sigma_2=0.4$, $f_s=1.5$, $f_c=1$, and $\dot{q}_s=10^{-3}$. The effect of the external vibrations w_{out} will be studied in this section.
Different scenarios have been performed to show the tracking capabilities of the proposed controller.
The first scenario aims at tracking both sinusoidal and constant desired trajectory q_d without external disturbances [22]. The sinusoidal reference is chosen as $q_d=A\sin(\pi t)$ where $A=2\mu m$ and $f=200Hz$, whereas the constant desired trajectory is chosen to be a unit step $q_d=1\mu m$. A general zero-mean Gaussian white noise w_{noise} with a variance $\sigma^2=9\times10^{-9}(m)^2$ is considered for this scenario as well as for the other scenarios.
In the second scenario, for clarity reasons, only the constant reference of $1\mu m$ is considered. Different disturbances are introduced to test if the proposed controller would be able to reject both input and output disturbances. The new system block diagram, for this scenario, is as depicted in Fig. 4. w_{out}

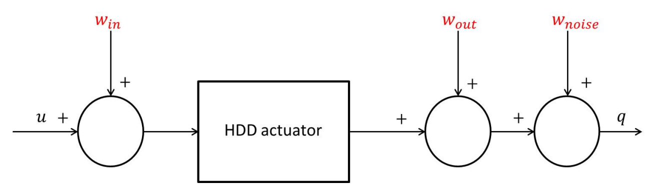

Fig. 4: Block diagram of the system considering input and output external disturbances as well as measurement noise. (Scenario 2)

is an output disturbance assumed to be an impulse with an amplitude of $0.3\mu m$ applied to the system at time instance $t=4ms$. The considered input disturbance w_{in} is an unknown perturbation with $|w_{in}|\le 3mV$. For reasons of simplicity, and in order to have a clear study of the disturbance rejection problem, w_{in} is assumed to be persistent and maintained equal to $-3mV$ [1]. In simulations, all initial conditions are chosen at the origin. The saturation constraint on the control input u has been taken into consideration such as $| u | \le 3v$.
In each scenario, a comparative study between the combined RISE-NN and a classical PD controller is proposed.

A. Scenario 1: Tracking problem in nominal case

The performances of the proposed controllers in non disturbed conditions are illustrated in Figs. 5 and 6. The different control parameters are summarized in TABLE I. It can be clearly seen that for a sinusoidal reference trajectory, the RISE-NN control method gives much more better results than the PD controller in terms of speed and accuracy. The PD controller, as shown in Fig. 5 generates large overshoots and needs a much more time to reach the desired position while the RISE-NN controller shows a rapid compensation of the tracking error to a neighborhood of zero with little overshoots. The time history of the NN weights is displayed in Fig. 6 which shows their boundedness. The closed-loop system's performances are summarized in Table II.

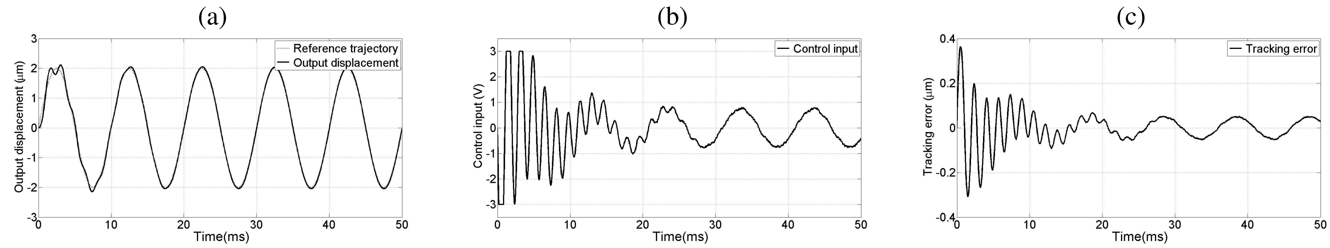

Fig. 5: **Tracking of a sinusoidal reference trajectory in non disturbed case (plots with PD controller)**: (a) Output displacement, (b) Control input, and (c) Tracking error signal.

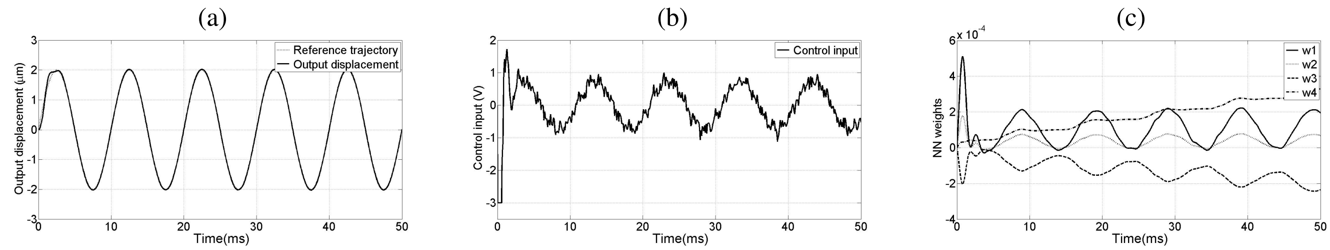

Fig. 6: **Tracking of a sinusoidal reference trajectory in non disturbed case (plots with RISE-NN controller)**: (a) Output displacement, (b) Control input, and (c) Time history of the neural network weights.

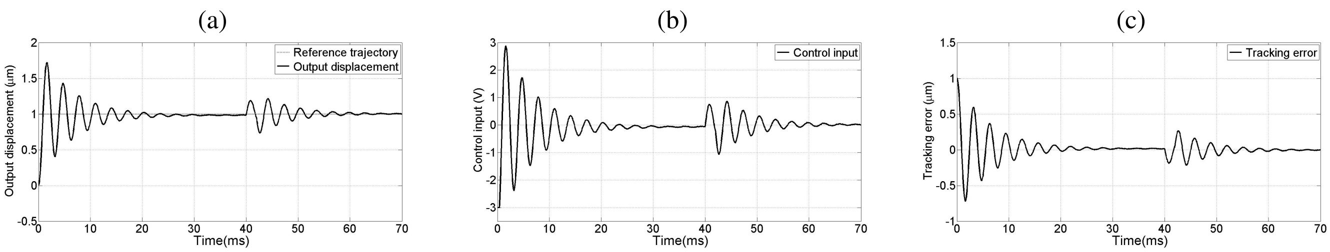

Fig. 7: **Tracking under external disturbances (plots with PD controller)**: (a) Output displacement, (b) Control input, and (c) Tracking error signal.

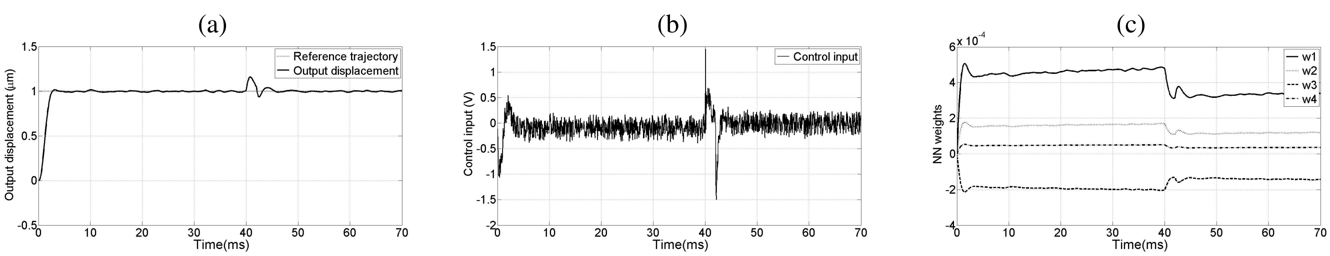

Fig. 8: **Tracking under external disturbances (plots with RISE-NN controller)**: (a) Output displacement, (b) Control input, and (c) Time history of the neural network weights.

TABLE I: Summary of the controllers' parameters

Reference (μm)	RISE-NN				PD	
q_d	α_1	α_2	K_s	β_1	K_p	K_d
$2\sin(200\Pi\ t)$	6000	1500	1850	1	1.5×10^7	0.02
1	1500	1500	1850	1	9×10^6	0.05

B. Scenario 2: Tracking problem with external disturbances

The performance of the RISE based NN controller for the disturbance rejection scenario can be seen in Fig. 7 and Fig. 8. The controller achieves a good track following despite the persistent added input disturbance w_{in} as illustrated in Fig. 4. At time instant $t = 40ms$, it can be seen that the compensation of the external impulse output disturbance w_{out} is successfully performed. The position error signal, as shown in Fig. 8(c) returns quickly to around zero. Therefore, the variation in the R/W head position can be read from the tracking error plot. Moreover, the RISE-NN control input evaluation respects the physical constraint and is kept limited within the interval $[-3,3]\,v$. It is worth to note that the norm of the NN weights can be upper bounded by a constant as depicted in Fig. 8.
Compared with the PD simulation results, the later plots have degraded performances. The 5% settling time and oscillations are much more important than those of the proposed RISE-NN approach. With the PD controller, the recovery time, needed to return to the desired track position after an external

disturbance, is too large which decreases the overall system response. A summary of the closed-loop system's performances for this scenario is presented in Table II.

TABLE II: Controllers performance comparison.

Without disturbances (Sinusoidal Reference)		
	PD	**RISE-NN**
Settling time	3.4 ms	1.62 ms
Maximum overshoot	11%	0.5%
Control input $\mid u \mid$	3 v	3 v
Disturbances Rejection (Step response)		
	PD	**RISE-NN**
Recovery time	15 ms	2.7 ms
Maximum overshoot	27%	16%
Control input $\mid u \mid$	2.88 v	1.5 v

V. Conclusion and future work

In this paper, the recently developed Robust Integral of the Sign of the Error (RISE) feedback controller, combined with a NN-based feedforward term, has been designed. The proposed control simulations are compared with those of a classical PD controller to highlight the effectiveness of the former to perform an accurate and fast tracking of the HDD servo-positioning system. Such control solution was proved to achieve the compensation of uncertainties and nonlinear frictions in the system with the guarantee of asymptotic stability of the closed-loop signals. Therefore, considering NN feedforward term in the RISE approach improves the tracking performance and reduces the control effort such that the NN weight estimates are kept bounded. In a future work, the optimization tools will be introduced for an extended version of the proposed RISE-NN controller.

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