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SVR을 이용한 Looperless 열연 공정에서의 스텐드간 장력 추정

Tension Estimation of Interstand Strip in Looperless Hot Rolling Process Using SVR

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Abstract : This paper proposes a novel tension estimation of interstand strip in looperless hot rolling process using SVR(Support Vector Regression). The quality of hot coil which is final product of hot rolling process is substantially decided by tension control of finishing rolling in hot rolling process. The fluctuation of the strip tension in conventional hot rolling process is controlled by the strip tension measured by an inter-stand looper. However, the looper can cause a motor trip and tension hunting in hot rolling process, therefore, alternative method is essential to replace it. In this paper, the mathematical modeling of tension mechanism is implemented to estimate the tension using the proposed SVR algorithm without looper in hot rolling process. The simulation results show a reliable estimation performance and a possibility of tension control using SVR technique.

Keywords : hot rolling process, looperless tension control, support vector regression

I. Introduction

To enhance the productivity and quality of coil, Kawasaki steel company adopted endless rolling process which needs multiple high technologies in early 1990s [1]. The interstand tension of the strip in the finishing mill train should be kept constant by controlling the roll gap and speed by using the measured tension information of the strip. However, speed error of the motors caused by load conditions of each roll or different properties of the strip leads to fluctuation of interstand tension, which brings a quality deterioration of the hot coil. Therefore, it is essential to maintain the tension constantly in rolling process by proper control algorithm based on measured or estimated tension. In case of permanent magnetic-type motor, the exact torque can be calculated directly by using the proportional relation between torque and amature current of the motor by measuring current without internal or external sensors to measure the torque. However, it is not easy to extract tension torque based on the measured current because the measured current includes some other components such as roll torque, tension torque, acceleration torque and loss torque. The conventional method to measure tension directly using a torque sensor suffers from data transmission problems by a rolling impact. Therefore, it is very difficult to obtain reliable information on tension based on current of main motor in hot rolling process. An alternative method using sensors attached on multiple points to measure torque of each motor has limitation in use because of sensor price and set-up cost as well as difficulty in maintenance. In hot rolling process, the looper used for detection and control of tension in conventional rolling process can't be installed because of the inherent characteristic of the system. In addition, a reliability of the data through torque sensor could not be guaranteed because of deteriorated signal by a physical impact and external disturbances. In this paper, we propose a novel tension estimator using Support Vector Regression (SVR) technique to estimate exact information on tension for the tension control without looper in hot rolling process [2].

II. Mathematical Modeling of the Tension

1. Modeling of the hot rolling system

In endless rolling process, the consecutive strips should be welded at each frontier parts after sheet bar welder for effective gauge and tension control. Fig. 1 shows structure of endless hot rolling process under consideration.

2. Mathematical modeling of the strip tension

Finishing mill with 6 or 7 stands rolls the strip from roughing mill process until it gets target thickness. Mathematical model for strip tension is derived for the plant with 2 rolls and strip material based on physical model shown in Fig. 2, where some necessary assumptions are imposed as follows [2];

(1) The strain of the strip is very small and evenly distributed.
(2) Density of the strip is constant.
(3) More forces are imposed for the direction that strip flows.
(4) There is no slippage between roll and strip.
(5) Density and MOE(The Modulus of Elasticity) of material are constant.

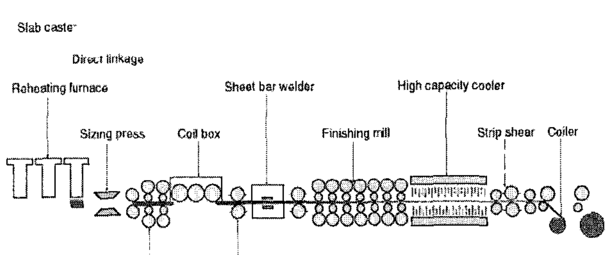

그림 1. 열연공정 구조.
Fig. 1. Structure of endless hot rolling process.

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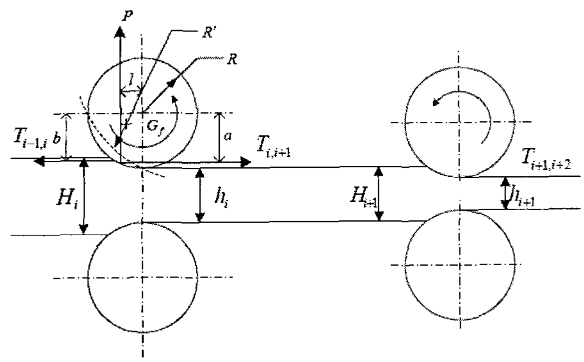

그림 2. 스탠드간의 물리적인 모델.
Fig. 2. Physical model between two stands.

For 1 set of independent stands, the rolling torque on role can be described as $G_f = P \cdot l$ differently from the two stand case where forward and backward tension are considered. The equation of rolling torque has the form of equation (1) by considering the equilibrium of dynamic force between two rolls [3].

$$G_f = P \cdot l + b \cdot T_{i-1,i} - a \cdot T_{i,i+1} \tag{1}$$

where

G_f : rolling torque
P : rolling load
l : length of torque arm
b : length of backward tension arm
c : length of forward tension arm
$T_{i,i+1}$: forward tension (= T_f)
$T_{i-1,i}$: backward tension (= T_b)

Therefore, forward tension $T_{i,i+1}$ to estimate is given by

$$T_{i,i+1} = \frac{l}{a} \cdot P - \frac{G_f}{a} + \frac{b}{a} T_{i-1,i} \tag{2}$$

In addition, the tension between two stands is generated in strip between first and second stand. Therefore, as the backward tension vanishes, equation (2) can be described by

$$T_{i,i+1} = \frac{l}{a} \cdot P - \frac{1}{a} \cdot G_f \tag{3}$$

III. The Tension Estimation Using SVR

A regression method is an algorithm that estimates an unknown mapping between a system's input and outputs, from the available data or training data. Once such a dependency has been accurately estimated, it can be used to predict system outputs from the input values. The goal of regression is to select a function which guarantees optimal approximation of the system's response. A function approximation problem can be formulated to obtain a function f from a set of observations, $(y_1, x_1), \ldots, (y_N, x_N)$ with $x \in R^m$ and $y \in R$, where N, the number of training data, x, the input vector, and y, the output data respectively. The function in SVR has the form of

$$f(x, \omega) = \omega^T K(x) + b \tag{4}$$

Where $K(\cdot)$ is a mapping from R^m to so-called higher dimensional feature space $F, \omega \in F$ is a weight vector to be identified in the function, and b is a bias term. To calculate the parameter vector ω the following cost function should be minimized [6-11]

$$Min \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{5}$$

subject to

$$\begin{aligned} & y_i - \omega x_i - b \le \varepsilon + \xi_i \\ & \omega x_i + b - y_i \le \varepsilon + \xi_i^* \\ & \xi_i \xi_i^* \ge 0, C \succ 0, i = 1, \ldots, N \end{aligned}$$

where C is a pre-specified value that controls the cost incurred by training errors. The slack variables, ξ_i, ξ_i^* are introduced to accommodate error on the input training set.

With many reasonable choice of loss function, ξ, the solution will be characterized as the minimum of a convex function. The constraints also include a term, ε, which allows a margin of error without incurring any cost. The value of ε can affect the number of support vectors used to construct the regression function. The bigger ε is, the fewer support vectors are selected. Hence, ε -values affect model complexity.

Our goal is to find function f(x,ω) that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time, is as flat as possible for good generalization. In other words, we do not care about errors as long as they are less than ε, but will not accept any deviations larger than ε. This is equivalent to minimize an upper bound on the generalization error, rather than minimize training error.

The optimization problem in equation (5) can be transformed into the dual problem, and its solution is given by equation (6).

$$\begin{aligned} & f(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)(K(x_i) \cdot K(x)) + b \\ & s.t. 0 \le \alpha_i^* \le C, 0 \le \alpha_i \le C \end{aligned} \tag{6}$$

In equation (6), the inner product $(K(x_i) \cdot K(x))$ in the feature space is usually considered as a kernel function $K(x_i, x)$ several choices for the kernel are possible to reflect special properties of approximating functions:

Linear kernel: $K(x_i, x) = x^T x_i$

RBF kernel: $K(x_i, x) = \exp(-\|x - x_i\|^2 / 2\sigma^2)$

The input data are projected to a higher dimensional feature space by mapping $K(\cdot)$ [5].

In equation (3), target data and training data are defined as $T_{i,i+1}$ and $\{P, G_f\}$ respectively. The basic idea is to minimize error between reference forward tension and calculate $T_{i,i+1}$. Hence, robust forward tension of strip estimation under parameter $\frac{l}{a}, -\frac{1}{a}$ variation circumstance is achieved. The tension model is expressed as equation (7), (8), (9).

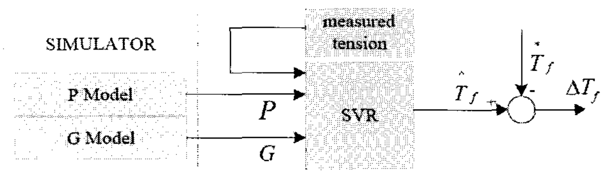

그림 3. SVR 을 이용한 장력 추정을 위한 블록도.

Fig. 3. Block diagram for tension estimation using SVR.

$$y = T_{i,i+1} \quad (7)$$

$$x = \{P, G_f\} \quad (8)$$

$$\omega = \left\{\frac{l}{a}, -\frac{1}{a}\right\} \quad (9)$$

Hence, equation (6) can be depicted as

$$T_{i,i+1} = \omega_1^T G_f + \omega_2^T P + b \quad (10)$$

Fig. 2 shows the block diagram for the tension estimation using SVR. The measured tension can be used as desired value of SVR and compared with the estimated and measure tension [6].

IV. Simulation Results and Discussion

Simulation has been performed to prove the effectiveness of the proposed control algorithm. The simulator used in simulation is designed under the same rolling conditions in the field. Table 1 shows conditions for simulation. The block diagram for tension control using estimated tension is depicted in Fig. 4[6].

The simulation results show the state of tension estimation under the normal condition and under the conditions of the rolling torque with magnitude of 150% and the rolling load of 50% of the reference state respectively. The tension between two stands is controlled by the feedback of the estimated tension.

표 1. 시뮬레이션 조건(i = 1).

Table 1. Simulation conditions(i = 1).

Inlet/Outlet Thickness (mm)	$H(1)$	$h(1), H(2)$	$h(2)$
	4.2	3.13	2.53
Reference tension (kgf)	$T_{0,1}$	$T_{1,2}$	$T_{2,3}$
	0	1.1	0

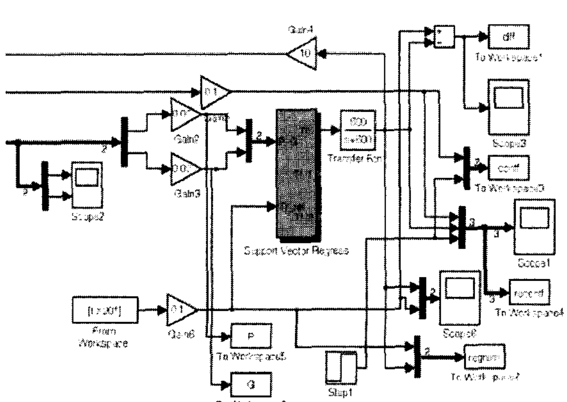

그림 4. Matlab 을 이용한 장력 추정 블록도.

Fig. 4. Block diagram for tension estimation based on Matlab.

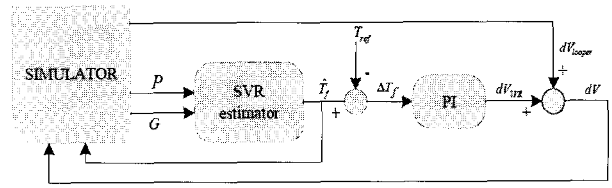

그림 5. 추정 장력을 이용한 장력 제어 블록도.

Fig. 5. Block diagram of the tension control using estimated tension.

Fig. 6 shows that the outputs of SVR trained by rolling load and torque estimate measured tension with small error. And error of estimated tension is depicted in Fig. 7. Figs. 8 and 9 show that the estimation based on the proposed algorithm is robust to sudden change of learning data. Fig. 10 indicates that the controlled tension by feedback of the estimated tension converges to the desired tension. Fig. 11 shows an output of the roll speed to control the tension.

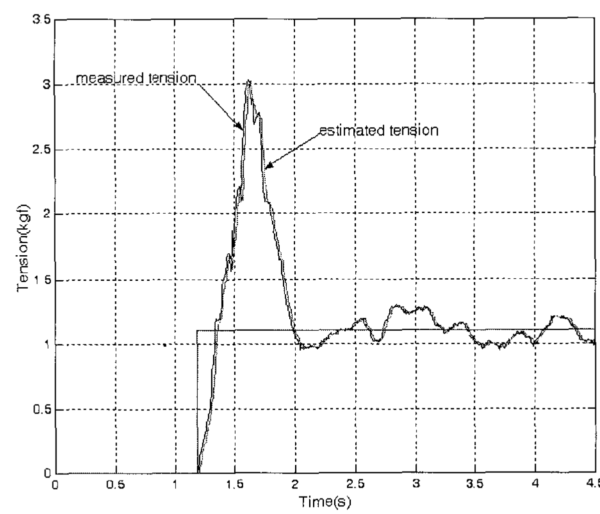

그림 6. SVR 을 이용한 장력 추정.

Fig. 6. Tension estimation using SVR.

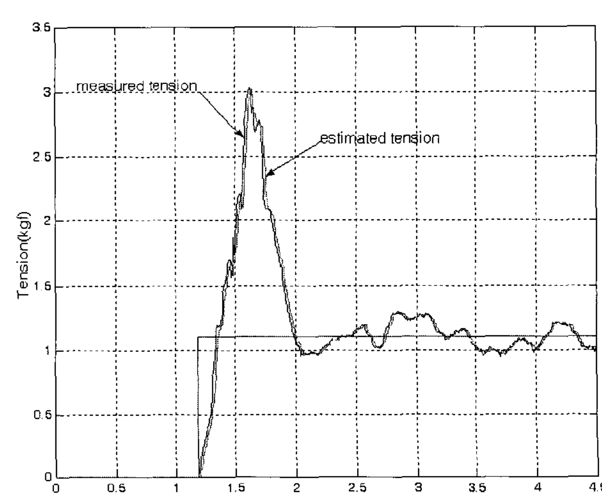

그림 7. 추정 장력 오차.

Fig. 7. Error of the estimated tension.

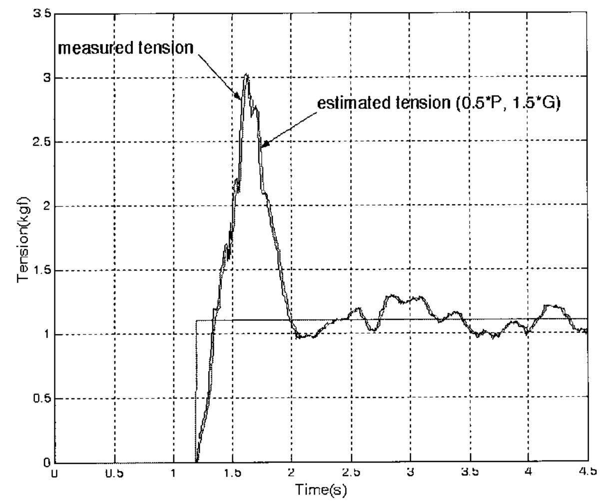

그림 8. SVR(0.5*P, 1.5*G)을 이용한 장력 추정.

Fig. 8. Tension estimation using SVR(0.5*P, 1.5*G).

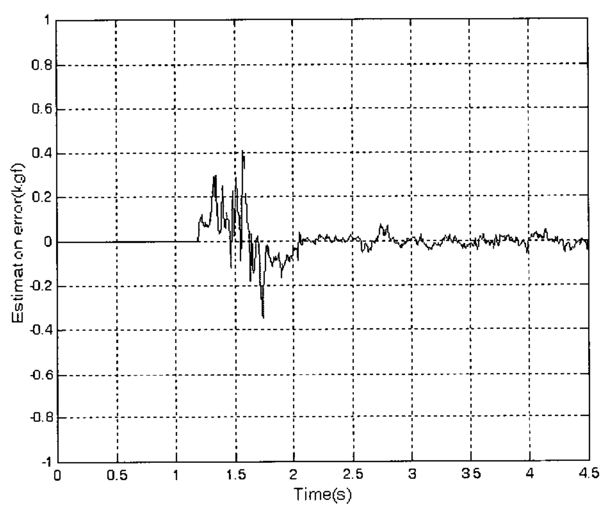

그림 9. 추정 장력(0.5*P, 1.5*G) 오차.

Fig. 9. Error of the estimated tension(0.5*P, 1.5*G).

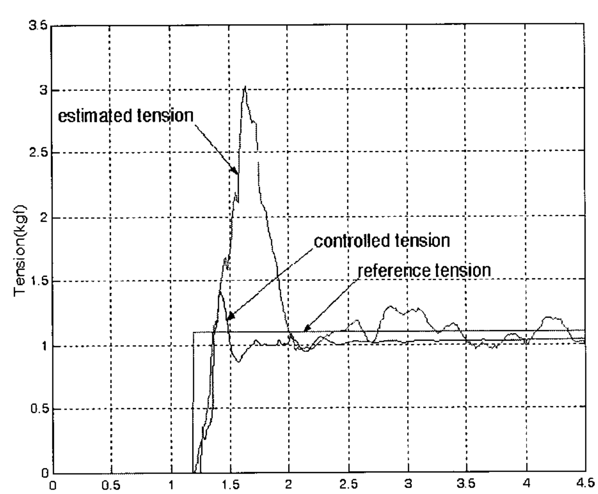

그림 10. SVR 을 이용한 스텝 입력에 대한 장력 제어.

Fig. 10. Tension control behavior for step input under SVR.

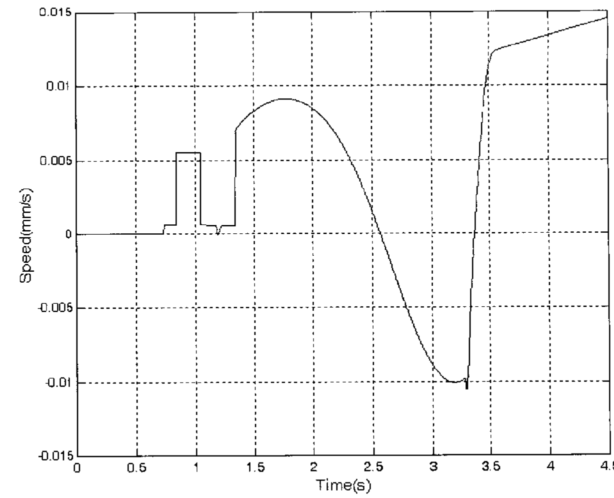

그림 11. 장력 제어를 위한 롤 속도 변화.

Fig. 11. Roll speed change for the tension control.

V. Conclusion

This paper proposes a new technique to estimate interstand tension with using looper based on SVR algorithm to enhance threading stability in the hot rolling process. The tension estimation by SVR using rolling load and torque as its training data is compared with the measured tension in the field to observe the tracking trend of the proposed technique. The proposed technique based on SVR shows that the resultant tension estimates the measured tension with small error. The tension control by the feedback of the estimated tension is under way.

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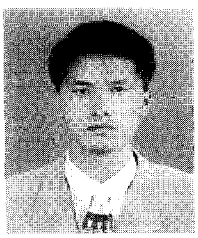

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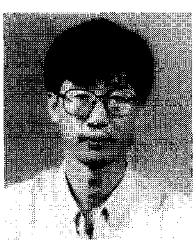

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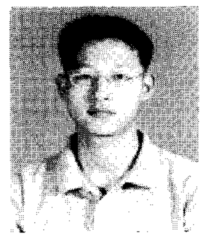

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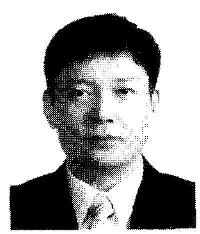

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