

Looperless Tension Control in Hot Rolling Process Using SVR

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Abstract: This paper proposes a looperless tension control algorithm which is robust to disturbance and tensional variation in rolling process using SVR(Support Vector Regression). Hot rolling process which is global technology to coil steel after continuous finishing process for welded bars followed by roughing mill process, becomes hot issue. Finishing mill process not only makes it possible to produce ultra thin steel strip(0.8 mm) but enhance the quality of terminals of coil, which increases the productivity due to faster process. Constant tension control between stands in hot rolling process is essential to enhance the quality of steel. Sensorless tension control is under research by some advanced companies to replace the conventional tension control method because in continuous finishing mill process, it is impossible to install the looper used in conventional control system. Simulation results show the effectiveness of the proposed algorithm.

Keywords: Looperless, Support Vector Regression, Rolling Process, Sensorless Tension Control.

1. INTRODUCTION

The tension between stands should be kept constant by operating the whole rolling line in target pattern speed by controlling a motor speed based on the measured tension information of the strip to enhance threading stability in rolling process. However, speed error by load condition of each roll or characteristic difference of the strip results in variation of tension, which brings a quality deterioration of the product. Therefore, it is essential to maintain the tension constant between the roles in rolling process. In case of permanent-magnetic-type motor, the correct torque can be calculated by measuring current, differently from other types of motor which use torque sensor to measure the torque. However, it is not easy to calculate 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 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 continuous rolling process. An alternative method where sensors(torque sensor, load cell etc..) are attached on multiple points in necessity to measure torque of each motor has limitation in use because of sensor price and set-up cost as well as difficulty in maintenance.

Wolfemann proposed a sensorless tension control method which estimates tension from the model directly without measuring tension between stands in 1997.[1-2]

This method relies on observer using accumulated error and variable outputs calculated from internal model by considering variables of coupling with adjacent section as disturbances.

However, since the modulus of elasticity(MOE) of material included in tension model equation in this method is in general very big and changes according to environment, correct estimation of tension is difficult. Moreover, it is impossible to consider connections of forward and backward sections simultaneously. As a result, the experiment results in this paper doesn't depend on the measured information of motor but show estimated tension by receiving tension and speed of fore and back span respectively.

In continuous rolling process, the load cell 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. We propose a new tension estimation model using Support Vector Regression (SVR) to compensate for the above problems to obtain correct information on tension.

2. MATHEMATICAL MODELING OF THE TENSION

Tension control is applied at finish rolling process of rolling process. Finishing mill which consists of 6 or 7 stands for precise thickness control, rolls the strip from roughing mill process until it gets target dimension. Fig. 1 shows mechanical relationship between two rolls that is basic unit for tension generation. Dynamic model for material tension is derived for the plant which consists of 2 rolls and strip material in Fig. 1, for which some necessary assumptions are imposed as follows:

- (1) The distortion of the strip is very small and evenly distributed.
- (2) Density of the strip is constant.
- (3) More forces is imposed for direction that strip flows.
- (4) There is no slip between roller and strip.
- (5) Density and MOE of material are constant.

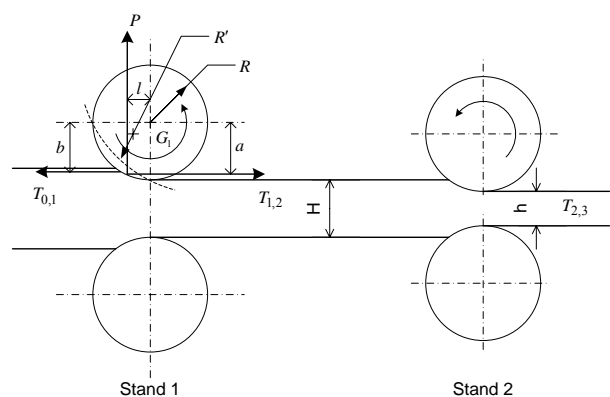


Fig. 1 Mechanical relation of force that appear between roles

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 roles. [3-4]

$$G_f = P \cdot l - b \cdot T_{i-1,i} + c \cdot T_{i,i+1} \quad (1)$$

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

$$T_{i,i+1} = -\frac{l}{c} \cdot P + \frac{G_f}{c} + \frac{b}{c} T_{i-1,i} \quad (2)$$

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

$$T_{i,i+1} = -\frac{l}{c} \cdot P + \frac{1}{c} \cdot G_f \quad (3)$$

3. 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, $(y_1, x_1), \dots, (y_N, x_N)$ 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

$$f(x, \omega) = \omega^T K(x) + b \quad (4)$$

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 [5-10]

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

subject to

$$\begin{aligned} y_i - \omega x_i - b &\leq \varepsilon + \xi_i \\ \omega x_i + b - y_i &\leq \varepsilon + \xi_i^* \\ \xi_i \xi_i^* &\geq 0, C > 0, i = 1, \dots, N \end{aligned} \quad (5)$$

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 $f(x, \omega)$ 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 [8]-[10], and its solution is given by

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

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:

$$\begin{aligned} \text{Linear kernel : } K(x_i, x) &= x_i^T x \\ \text{RBF kernel : } K(x_i, x) &= \exp(-\|x - x_i\|^2 / \sigma^2) \end{aligned} \quad (7)$$

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

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 $\frac{l}{c}, \frac{1}{c}$ variation circumstance is achieved. The tension model is expressed as

$$y = T_{i,i+1} \quad (8)$$

$$x = \{P, G_f\} \quad (9)$$

$$\omega = \left\{ -\frac{l}{c}, \frac{1}{c} \right\} \quad (10)$$

Hence, equation (7) can be depicted as

$$\hat{T}_f = \omega_1^T G_f + \omega_2^T T_b + b \quad (11)$$

Fig. 2 shows the structure of SVR forward tension estimator.



Fig. 2 Structure of the tension estimator using SVR.

4. RESULTS OF SIMULATION AND DISSION

Simulation has been performed for the verification of the proposed control algorithm. The simulator used in simulation is designed under the same rolling conditions in the field. Table 1 shows thickness of the strip in input and output terminal and setting value of target tension in simulation. The flow of tension estimation and control from main model of the system is depicted in Fig 3. [10-13]

Table 1 Simulation conditions.

Entrance · outlet Thickness	$H(1)$	$h(1), H(2)$	$h(2)$
	4.2	3.13	2.53
Reference Tension	$T_{0,1}$	$T_{1,2}$	$T_{2,3}$
	0	1.1	0

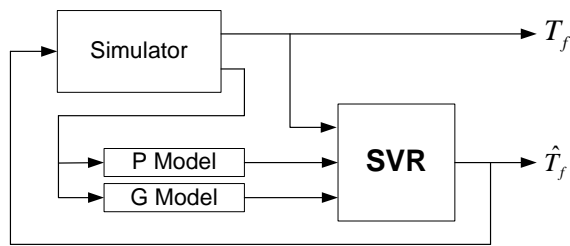


Fig. 3 Configuration of the overall system.

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

Fig. 4, Fig. 5, and Fig. 6 show the state of tension estimation using SVR for step input with reference tension of 1.1[kgf]. The figures show that the outputs of SVR trained with rolling load and torque estimate looper tension with small error. Also they show that the estimation based on the proposed algorithm is robust to sharp change of learning data. Fig. 7, Fig. 8 and Fig. 9 show the controlled results between two stands using estimated tension for step input with reference tension of 1.1[kgf]. Through the simulation results, we know that the tension using the trained result of SVR is controlled based on the estimated tension.

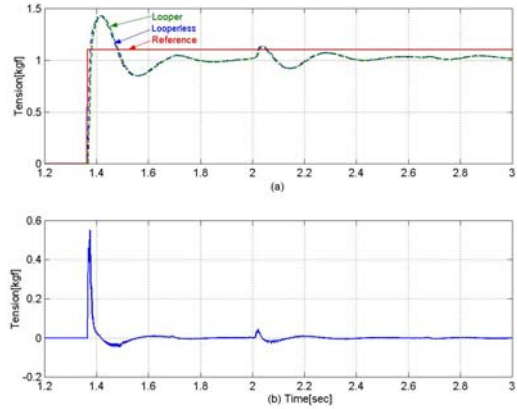


Fig. 4 Estimation of tension behavior at step input (a) under SVR estimator (b) error of tension.

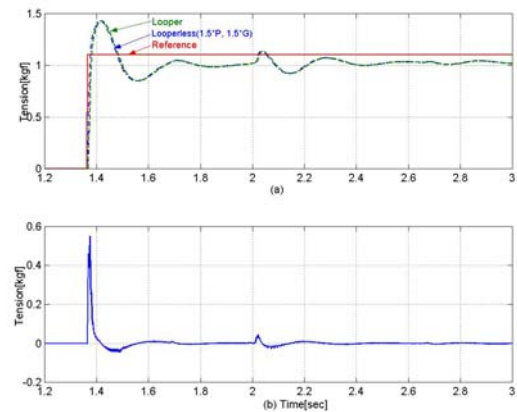


Fig. 5 Estimation of tension behavior at step input $(1.5 \cdot G_f, 1.5 \cdot P)$ (a) under SVR estimator (b) error of tension.

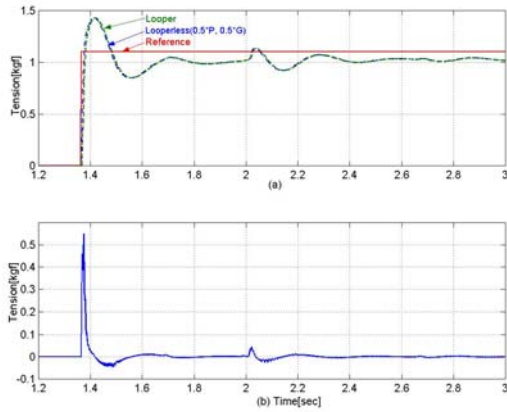


Fig. 6 Estimation of tension behavior at step input ($0.5 \cdot G_f, 0.5 \cdot P$) (a) under SVR estimator (b) error of tension.

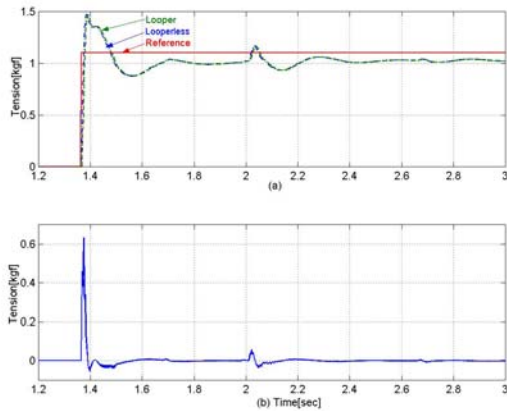


Fig. 7 Tension control behavior at step input (a) under SVR estimator (b) error of tension.

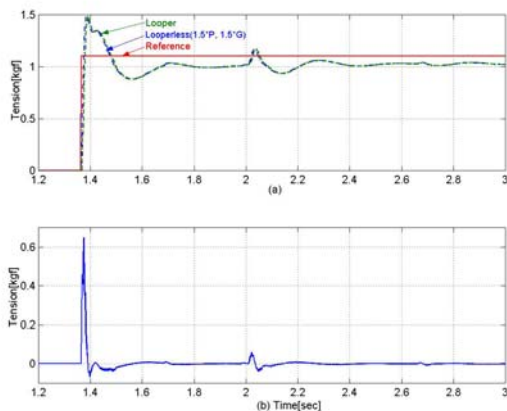


Fig. 8 Tension behavior at step input ($1.5 \cdot G_f, 1.5 \cdot P$) (a) under SVR estimator (b) error of tension.

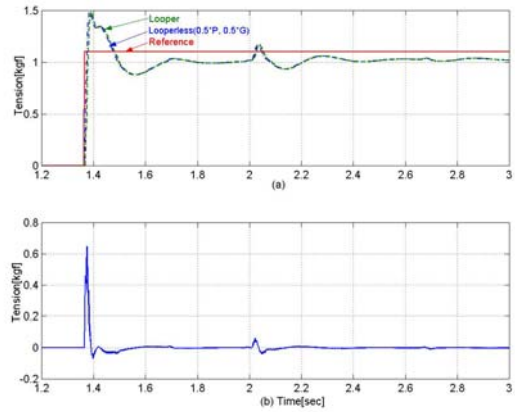


Fig. 9 Tension behavior at step input ($0.5 \cdot G_f, 0.5 \cdot P$) (a) under SVR estimator (b) error of tension.

5. CONCLUSION

This paper proposes a new technique to estimate the tension through looperless control using SVR with information on tension between stands to enhance threading stability in the continuous rolling process. The tension estimation by SVR using rolling load torques as its training data is compared with the calculated torque as reference to observe the tracking trend of the proposed technique. The tension controlled by feedback of the estimated tension to the controller shows the proposed technique based on SVR estimates the target tension with small error and the tension is controlled by the estimated looper tension in the controller. The robust looperless tension control of the actual system is under research using SVR as a compensation technique.

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