

Trajectory Tracking Control for Seafloor Tracked Vehicle by Adaptive Neural-Fuzzy Inference System Algorithm

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Abstract: Trajectory tracking control strategy and algorithm for the tracked vehicle moving on the seafloor has aroused much concerns due to the commonly occurred serious slip and trajectory deviation caused by the seafloor extremely soft and cohesive sediment. An improved multi-body dynamic model of a seafloor tracked vehicle (STV) has been established in a simulation code RecurDyn/Track. A particular terramechanics model with a dynamic shear displacement expression for the vehicle-sediment interaction has been built and integrated into the multi-body dynamic model. The collaborative simulation between the mechanical multi-body dynamic model in RecurDyn/Track and the control model in MATLAB/Simulink has been achieved. Different control algorithms performances including a PID control, a fuzzy control and a neural control, have been compared and proved the traditional or individual intelligent controls are not particularly suitable for the tracked vehicle on the seafloor. Consequently, an adaptive neural-fuzzy inference system (ANFIS) control algorithm with hybrid learning method for parameter learning which is an integrated control method combined with the fuzzy and neural control, has been adopted and designed. A series of collaborative simulations have been performed and proved the ANFIS algorithm can achieve a better trajectory tracking control performance for the STV as its trajectory deviation can be maintained within a permissible range.

Keywords: seafloor tracked vehicle, multi-body dynamic model, adaptive neural-fuzzy inference system (ANFIS), collaborative simulation, trajectory tracking control.

1 Introduction

Tracked vehicles are widely used in the deep seafloor engineering fields, such as seafloor exploration, seafloor cable laying and installation, seafloor dredging, seafloor mineral resources exploitation, etc. The deep seafloor extremely soft and cohesive sediment is completely different from land-surface soils, which makes the tracked vehicle more likely to be involved in serious slip, large sinkage and motion trajectory deviation. Its locomotion performance and control characteristics directly affect the continuous operation performance and operation safety for the tracked vehicle on the seafloor.

Influenced by the seafloor complex and changeable environmental loads, it is particularly difficult to master and evaluate the mobility and locomotion of the seafloor tracked vehicle,

Sup et al. adopted a new technology based on Euler parameters for evaluating the dynamic properties of a tracked vehicle on seafloor [13] and further put forward a subsystem synthesis method to analyse a multi-body model of a tracked vehicle [15]. Kim et al. researched the complicated dynamics of an articulated tracked vehicle crawling on the seafloor inclined and undulating terrain [14]; furthermore the effects of the buoyancy position layout on the dynamics of the vehicle were analysed [16]. Li et al. built a virtual prototype of a seafloor tracked mining vehicle and conducted simulations to estimate the vehicle's locomotion and trafficability [17]. Li et al. studied the effect of the grouser height of a seafloor tracked mining vehicle on its tractive performance through an established relationship between the total driving force and the slip of the mining vehicle [18]. Dai et al. developed new multi-body dynamic models for three types of seafloor tracked vehicles and performed simulations to evaluate their locomotion and trafficability performances [5–7]; besides, the complex integrated dynamic performances for seafloor tracked vehicles connecting to pipeline systems and surface ships were investigated and evaluated [8, 9].

To control the locomotion state and trajectory of the tracked vehicle on the seafloor, Herzog et al. established an automatic hydraulic drive mode with slip control of the driving track for a seafloor tracked vehicle; meanwhile an experimental system for the slip control development along with the logic of the automatic driving model was presented [12]. Yeu et al. proposed a path tracking method for tracked vehicle on the seafloor with a vector pursuit algorithm to make the vehicle's motion following the specified path [28]. Yeu et al. further based on the kinematics of the seafloor tracked mining vehicle to propose two navigation algorithms, known as dead-reckoning and extended Kalman filter [29]. Yoon et al. used the indirect Kalman filter method with the inner measuring sensors to underwater localization of a seafloor tracked mining vehicle [30]. Zhang et al. presented a control method for a straight-line path tracking of a seabed mining vehicle based on the ANFIS control; however only a single straight-line path was tracked without comparisons to other control methods [19]. Han et al. proposed a PID control algorithm and achieved an anticipated goal for a seafloor tracked miner moving along a desired path [10, 11]. Wang et al. presented a fuzzy and a predictive controller, further the efficiency of the control method was verified by the computer simulation and experimental results [24]. Li et al. built a hydraulic system model of a seafloor self-propelled tracked mining vehicle, and its kinematic control by a fuzzy algorithm was discussed [20]. Besides, various path tracking control method researches for vehicles or robots have been conducted. Cui et al. investigated a trajectory tracking problem for a fully actuated autonomous underwater vehicle (AUV), and two neural networks (NNs) were integrated into an adaptive control design, the robustness and effectiveness of the proposed control method were tested and validated through extensive numerical simulation results [4]. Sokolov et al. presented a neuro-evolution approach for a crawler robot motion that can autonomously solve the sequences of the navigation and flipper control tasks to overcome obstacles [23]. Bozic et al. based on a combination of neural networks and genetic algorithm to intelligent modelling and optimization of energy usage for a wheel-legged (Wheg) robot running; simulation of neuro-fuzzy control system was developed for minimization of energy usage during the Wheg's running [2]. Chen et al. proposed a robust adaptive position/force control algorithm to track the desired posture and force in opening a door for a mobile robot manipulator, and co-simulation between MATLAB and RecurDyn were performed to verify the dynamic model and control method [3]. Barai et al. proposed a two-degree-of-freedom fuzzy controller for foot trajectory tracking control of a hydraulically actuated hexapod robot, and the fuzzy pre-filter was designed by a genetic algorithm (GA) based optimization [1]. Wang et al. developed an adaptive position tracking system and a force control strategy for a non-holonomic mobile manipulator robot, which combined the merits of Recurrent Fuzzy Wavelet Neural Networks (RFWNNs), and the simulation and experimental results verified the effectiveness and robustness of the proposed method [25]. Widyotriatmo et al. proposed a control method for a team of multiple mobile

robots, the individual mobile robots tracked the assigned trajectories and also should to collision among the mobile robots by the artificial potential field algorithm [26]. Ngo et al. developed a robust adaptive self-organizing control system based on a novel wavelet fuzzy cerebellar model articulation controller for a robot manipulator, and verified its effectiveness through simulation and experimental results [21, 22].

However, until now, it still remains typical problems need to be further resolved, an optimized trajectory tracking control strategy for the tracked vehicle on the seafloor has not yet been designed; furthermore, a collaborative model with real-time information interactions between the mechanical-control systems has not yet been achieved, so the trajectory tracking control performance and accuracy can not be evaluated and optimized. As it is costly and extremely difficult to perform seafloor in-situ tests, the collaborative simulation for the combined mechanical-control systems is an effective way. An optimized trajectory tracking control strategy and a mechanical-control systems collaborative simulation research were conducted in the paper.

2 Multi-body dynamic model of a STV

The dynamic simulation code RecurDyn/Track, based on a relative coordinate system and a recursive algorithm relative, was adopted to establish an improved multi-body dynamic model of a STV as shown in Fig. 1. Table 1 gives its main structural parameters.

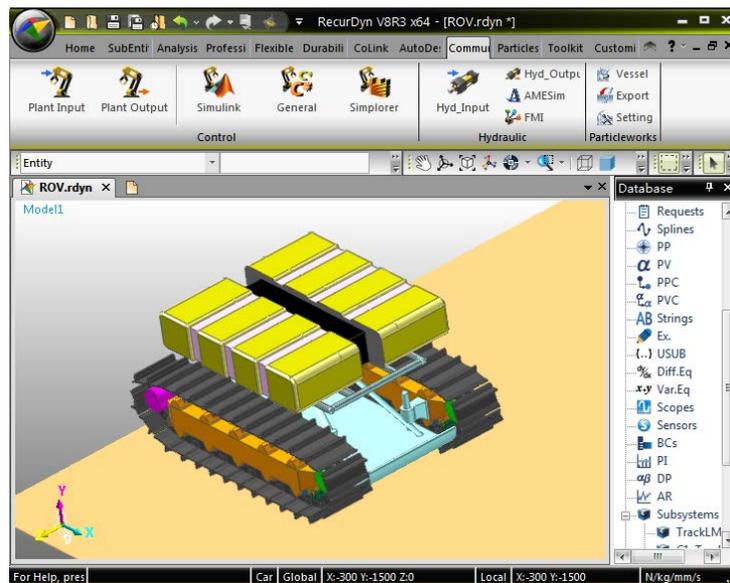


Figure 1: A 3D improved multi-body dynamic model of a STV

A user-written subroutine for characterizing the particular terramechanics model of the seafloor sediment was developed in the C language in the Visual Studio.Net environment and then integrated into the RecurDyn/Track environment. Meanwhile the dynamic processes between the track-sediment interactions were taken into account. Through laboratory simulant experiments as shown in Fig. 2, a pressure-sinkage relationship and a shear stress-shear displacement relationship between the track-sediment interactions have been obtained.

The normal force F_{ni} acting on each track link i th element can be computed by multiplying the pressure with area of each track link as [27]:

$$F_{ni} = p_{x_i} \cdot \Delta A_i = \left[\left(\frac{k_c}{b} + k_\varphi \right) \cdot (\Delta z_i)^n \right] \cdot \Delta A_i \quad (1)$$

Table 1: Structural parameters of the STV

Parameters	Values
Total weight underwater (tons)	2.35
Overall dimension (m): Length \times width \times height	2.3 \times 1.6 \times 1.2
Track contact length (m)	1.6
Track width (m)	0.36
Distance between centre lines of tracks (m)	1.2
Track pitch (m)	0.15
Grouser height (m)	0.15
Diameter of road wheel (m)	0.04
Number of road wheel per track	7
Diameter of support roller (m)	0.04
Number of support roller per track	5

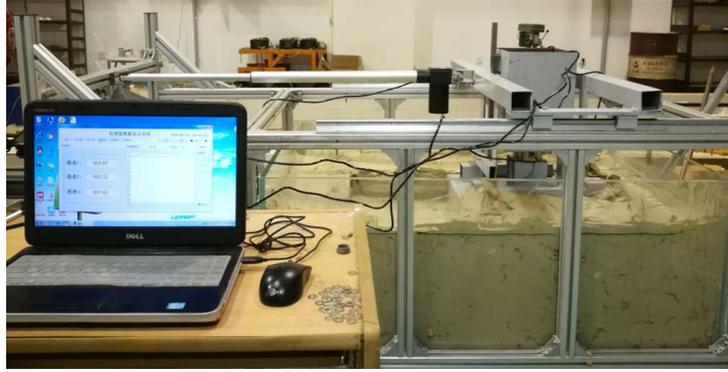


Figure 2: Laboratory experimental system for simulant track-sediment interaction mechanics

Where p_{x_i} is the normal pressure, ΔA_i is the area of each track link, b is the width of track link, k_c is the sediment cohesion deformation modulus, k_φ is the sediment friction deformation modulus, Δz_i is the sinkage, n is the sediment deformation exponent.

The longitudinal shear force F_{long_i} is computed by multiplying shear stress with area of each track link:

$$\begin{aligned}
 F_{long_i} &= \text{sgn}(j_{x_i}) \tau_{x_i} \cdot \Delta A \\
 &= \text{sgn}(j_{x_i}) \tau_{\max} \cdot K_r \cdot \left\{ 1 + \left[\frac{1}{K_r(1 - e^{-1})} - 1 \right] e^{1 - j_{x_i}/K_\omega} \right\} (1 - e^{-j_{x_i}/K_\omega}) \cdot \Delta A \quad (2)
 \end{aligned}$$

Where "sgn" is the signum function, j_{x_i} is the dynamic longitudinal shear displacement, τ_{\max} is the maximum shear stress, K_r is the ratio of the residual shear stress τ_{res} to τ_{\max} , and K_ω is the shear displacement when τ_{\max} occurs.

The dynamic longitudinal shear displacement can be expressed as a differential equation:

$$\frac{d}{dt} j_{x_i}(x_i, t) + \frac{r_s \omega_s(t)}{x_i} \cdot j_{x_i}(x_i, t) = r_s \omega_s(t) - v_x(t) \quad (3)$$

Where r_s and $\omega_s(t)$ are the radius and angular velocity of the vehicle's sprocket, x_i and $v_x(t)$ represent the distance and actual velocity of the centre of each track link.

Similarly, the lateral shear force F_{lat_i} acting on each track link is computed as:

$$\begin{aligned}
 F_{lat_i} &= -\text{sgn}(j_{y_i}) \tau_{x_i} \cdot \Delta A \\
 &= -\text{sgn}(j_{y_i}) \tau_{\max} \cdot K_r \cdot \left\{ 1 + \left[\frac{1}{K_r(1 - e^{-1})} - 1 \right] e^{1-j_{y_i}/K_\omega} \right\} (1 - e^{-j_{y_i}/K_\omega}) \cdot \Delta A \quad (4)
 \end{aligned}$$

Where j_{y_i} is the dynamic lateral shear displacement.

While the dynamic lateral shear displacement as be expressed as:

$$\frac{d}{dt} j_{y_i}(x_i, t) + \frac{r_s \omega_s(t)}{x_i} j_{y_i}(x_i, t) = v_{y_i}(t) \quad (5)$$

Where v_{y_i} represent actual lateral velocity of the centre of each track link.

Fig. 3 presents a group of turning simulations trajectories of the STV with different turning velocity ratios (TVRs). The input velocity for the inner track was set to 0.5 m/s, while, the input velocities for the outer track were set to 0.6 m/s, 0.65 m/s and 0.7 m/s, respectively.

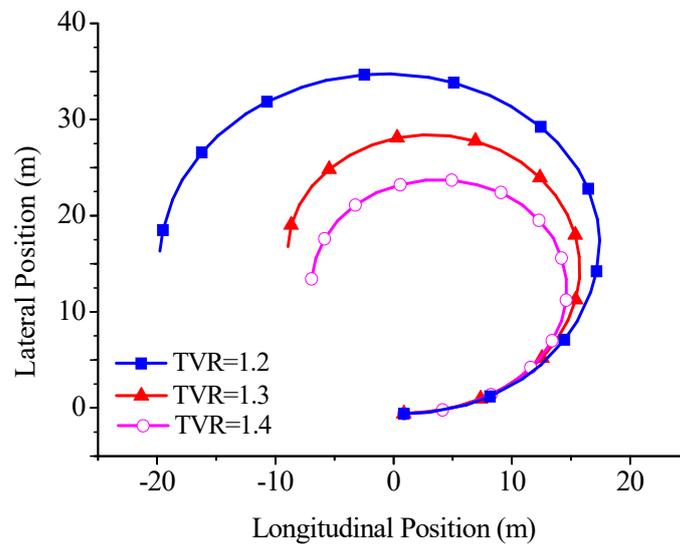


Figure 3: Simulation trajectories of the STV with different turning velocity ratios

It can be seen with the increase although a small value of the turning velocity ratio, the turning radius will increase obviously. According to the requirement of the turning velocity ratio for the STV that should not exceed 1.4, the minimum turning radius for the STV is about 12 m, which is much larger than that on land-surface soft soil and also much larger than the theoretical computational turning radius. Fig.4 presents the slips of the inner and outer tracks when the TVR is only 1.2.

It can be observed a serious slip condition occurred for the outer track of the STV in spite of a low TVR, and further exhibited a serious slip commonly occurred on the seafloor will result in a much larger turning radius for the tracked vehicle compared to move on the land-surface soft soils.

3 Trajectory tracking collaborative control simulations for a STV

A control design code MATLAB/Simulink was adopted to establish different control models for the STV. An interface toolkit RecurDyn/Control was designed to realize the information

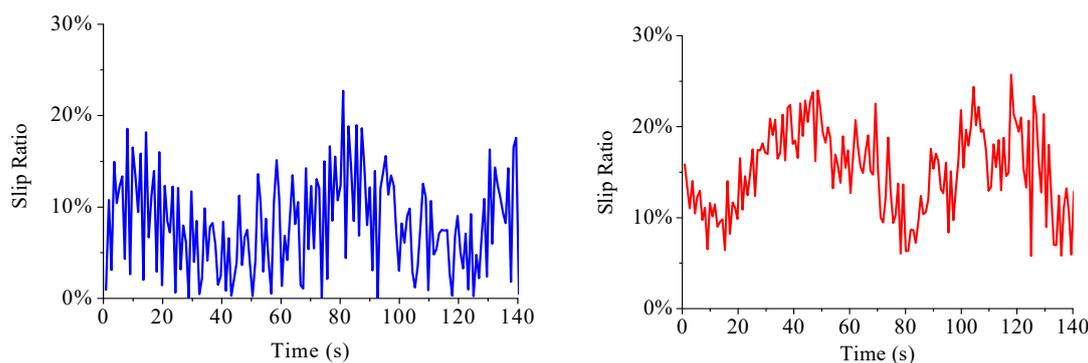


Figure 4: Slips of the left and right tracks of the STV

communication between the control system model and mechanical dynamic model. The MATLAB/Simulink was taken as the main interface. The plant input and plant output of the mechanical dynamic model were set, while, a M file for exporting the mechanical dynamic model was compiled.

3.1 Comparisons of different control algorithms

A RecurDyn/Track plant block representing a mechanical dynamic model of the STV was created in the MATLAB/Simulink; then the mechanical-control collaborative simulation can be achieved. The theoretical input velocity for the STV is 0.6 m/s in the collaborative simulation. Several different control methods including a PID control, a fuzzy logic control and a neural network control were performed and compared. Fig.5 shows the co-simulation model interface of a PID control with mechanical dynamic model, and corresponding simulation results with and without external jamming signal for the input velocity also compared. It can be seen the PID control is insensitive to the external disturbance.

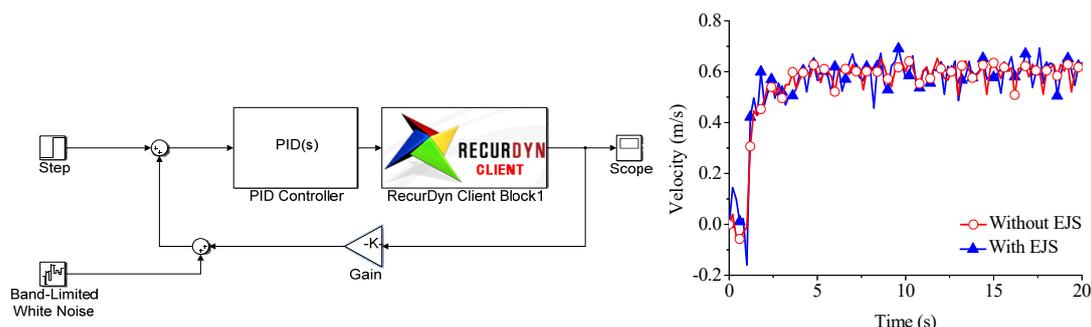


Figure 5: Co-simulation model interface and results of PID control with dynamic model

Fig. 6 shows a co-simulation model interface of an adaptive fuzzy logic control model with mechanical dynamic model, and the simulation results with and without external jamming signal compared. The inputs for the fuzzy logic controller were velocity error (E) and velocity error derivative (EC), which were the difference between the target velocity and ideal velocity. The output was the velocity compensation (U). Compared with the PID control algorithm, the fuzzy logic algorithm has a stronger anti-disturbance ability and better robustness, which was more suitable for the STV motion control. Nevertheless, the control precision of the conventional fuzzy logic is not high.

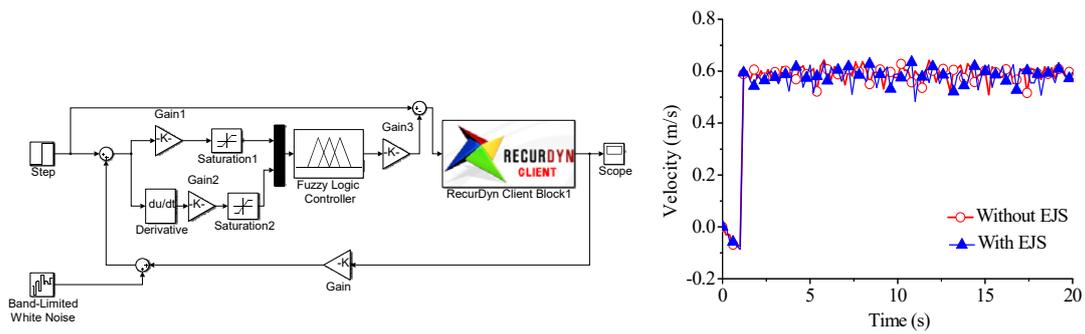


Figure 6: Co-simulation model interface and results of fuzzy logic control with dynamic model

Fig.7 shows a co-simulation model interface of a BP neural network algorithm control model with dynamic model, and simulation results with and without external jamming signal compared. The neural network has the features of self-adapting and self-learning; however, it is weak in expressing the rule knowledge. As it can be seen the neural network algorithm has a weak anti-disturbance ability compared to a fuzzy control method.

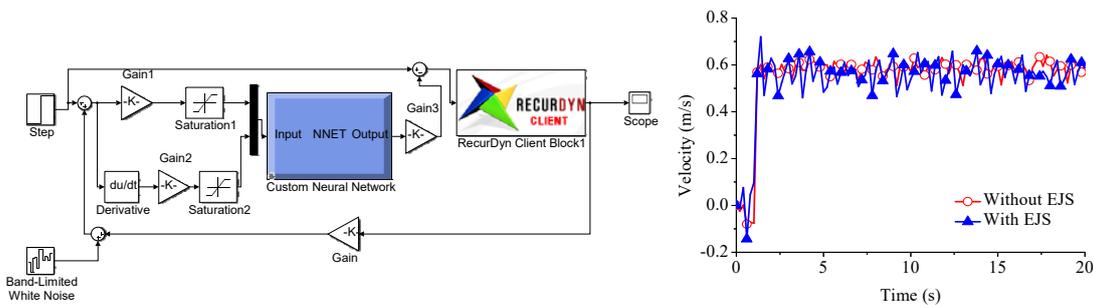


Figure 7: Co-simulation model interface and results of neural network control with dynamic model

In order to overcome the shortcomings of a single fuzzy control or a single neural control, a Fuzzy-Neural control method that incorporates the fuzzy control and the neural control was adopted and designed. The fuzzy Takagi-Sugeno (T-S) model that is more simple for calculation and better for mathematical analysis, was combined with an adaptive neural control systems, then an Adaptive Neural-Fuzzy Inference System (ANFIS) was presented for controlling the STV motion state in the paper. The critical step in this ANFIS architecture is to realize the self-learning and adaptive of the control parameter. Hybrid learning algorithm, namely, a combination of least-squares estimation and back-propagation, was developed for the parameter learning of the membership function.

The simulation model interface of the ANFIS collaborated with the dynamic model for the STV was presented in Fig. 8. It can be seen a desirable control effect can be obtained by using this control scheme. However, this hybrid algorithm method required more computation and analysis.

3.2 Trajectory tracking collaborative control simulations and comparisons

Actually, mechanics properties of the seafloor sediment are always uneven distribution, which will cause the differences of the shear forces and traction forces under two tracks. As a result, a turning moment will be generated, and make the STV move deviate from its predetermined

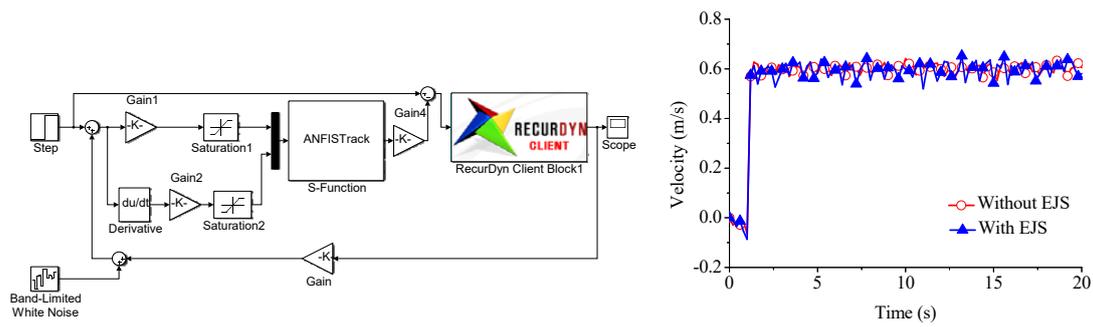


Figure 8: Co-simulation model interface and results of Neural-Fuzzy control with dynamic model

straight-line and circle trajectory. The shear strengths under the left track were set to 3.0 kPa and 4.0 kPa respectively, while the shear strength under the right track was set to a constant value 5 kPa. Fig.9 shows the simulation trajectories of the STV under these two conditions. While the green dashed lines both in Fig.9 and Fig.10 represent the predetermined straight-line paths. It can be seen the actual motion trajectories will deviate from its predetermined straight-line trajectory due to the uneven distribution of the sediment mechanics properties. With the longitudinal displacement increases, the deviations will continuously increase. According to the trajectory deviation control requirement for the STV, the deviation should within the allowable range of $-1m$ to $1m$. So, it is necessary to perform an effective control for the STV to keep its actual motion trajectory to tracking a predetermined path.

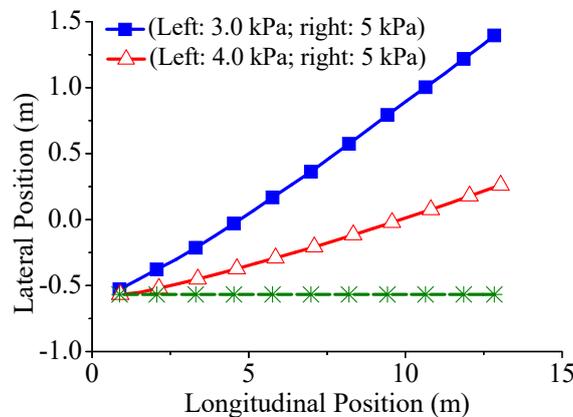


Figure 9: Straight-line motion trajectory deviation simulations of the STV

Straight-line motion trajectory control simulations comparisons between different controls

The above used fuzzy logic control, neural control and ANFIS control were carried out respectively for the trajectory control as shown in Fig. 11. It can be seen obviously that with the ANFIS control, the trajectory deviation is the minimum; when the longitudinal displacement is about 16 m, its lateral trajectory deviation is just about 0.01 m, which indicate the ANFIS control has a better effect for the STV compared to other control methods. If without an optimized or proper control for the STV, its lateral trajectory deviation will continuously enlarge along with its longitudinal motion.

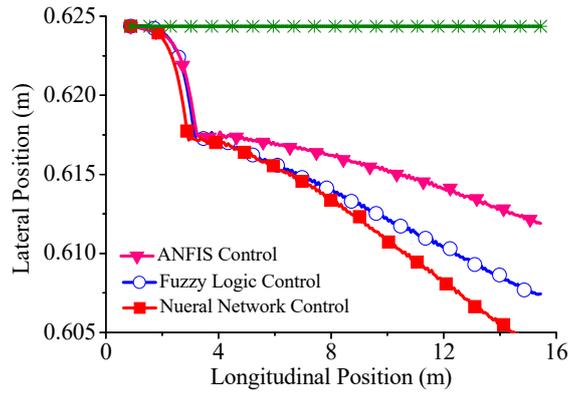


Figure 10: Straight-line motion trajectory control simulations comparisons between different controls

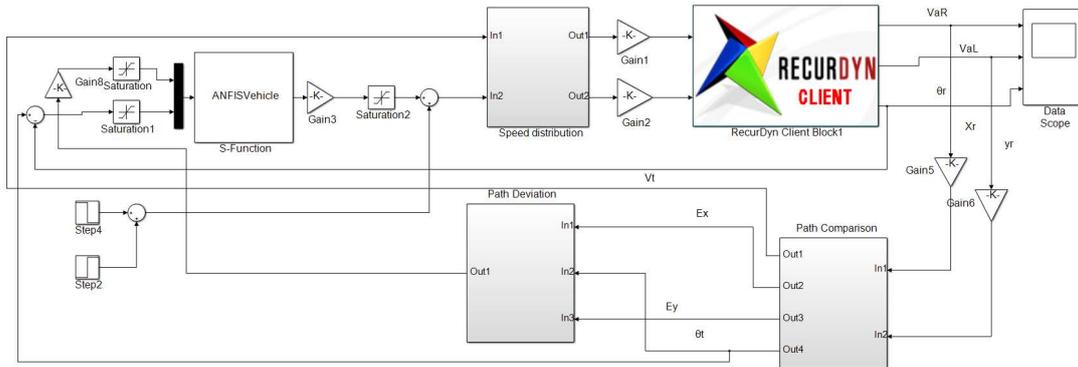


Figure 11: Combined path co-simulation model interface of the ANFIS control model with dynamic model

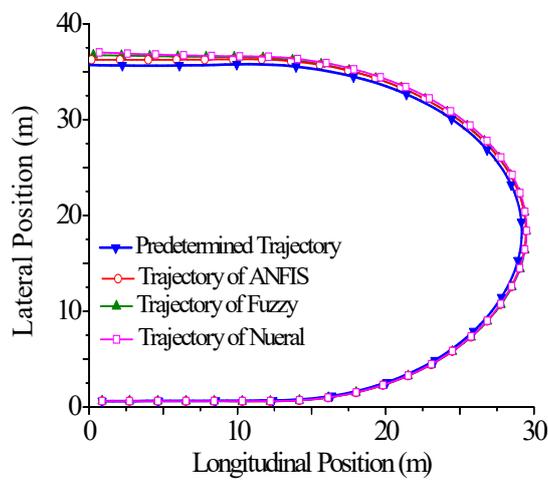


Figure 12: Simulation motion trajectories of the STV with different controls

A predetermined combined path including straight-line and turning paths was set for tracking simulation. The input velocity of the STV was set to 0.5 m/s; the turning velocity ratio was set to 1.2. The straight-line and turning motions time were set to 20 s and 90 s, respectively. The motion trajectories simulations between the fuzzy logic control, neural network control and ANFIS, were conducted and compared relative to the predetermined path in Fig. 12.

It can be seen that with the ANFIS control, the trajectory deviation for the STV relative to its predetermined path was the minimum compared to other control methods. For above one round of the predetermined path tracking, the maximum trajectory deviation under ANFIS control can be maintained around 0.5 m within the allowable range of -1 m to 1m. It can be predicted that with the continuous motions of the STV along with more rounds of above predetermined combined paths, the control effect of the ANFIS will be more obvious and efficient.

4 Conclusions

The major conclusions as follows can be drawn from this work.

(1) An improved multi-body dynamic model of a STV with integration of a dynamic terramechanics model of the particular sediment has been established and verified. A new collaborative simulation model of the STV integrating a mechanical multi-body dynamic model in RecurDyn/-Track and a control model in MATLAB/Simulink has been developed and co-simulations were achieved. Different control algorithms performances including a PID control, a fuzzy control and a neural control, have been compared and proved that the traditional or individual intelligent controls are not particularly suitable for the STV motion control.

(2) An adaptive neural-fuzzy inference system (ANFIS) control algorithm incorporating the fuzzy control and neural network control has been adopted and designed for the STV motion control. A straight-line path tracking controls for the STV by the fuzzy, neural network and ANFIS controls have performed and proved the ANFIS control algorithm can achieve a desired control performance for the STV compared to the other controls.

(3) A predetermined combined path, including the straight-line and turning paths, has been tracked for the STV by an ANFIS control algorithm compared to a fuzzy logic and neural network controls. The collaborative simulations have proved the ANFIS control method can achieve a better control effect among these control algorithms, with its actual maximum trajectory deviation can be maintained around 0.5 m within the permissible range.

Acknowledgment

This research is supported by the National Natural Science Foundation of China (Grand No. 51774324 and No. 51105386), the National Key Research and Development Program of China (Grand No. SQ2016YF010109). The authors would like to thank the comments from the anonymous reviewers that improved the quality of the paper.

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