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Prediction of Vehicle Trajectory Based on Fuzzy Colored Petri Net

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Abstract

Aiming at the difficulty in establishing model to describe vehicle running state, real road test was carried out to capture data which represent the movement of vehicles. Coordinate transformation method and transform relationship among different variable parameters were used to establishing represent model of vehicle movement. By using Petri net which had well layering and time sequence, vehicle trajectory, speed, side slip angle, and yawrate were treated as parameters to describe the movements of vehicle. Domain of discourse and subordinating degree function were confirmed, and fuzzy rules related to controllability and driving comfort were established. Verification tests results show that the Petri net model can describe the vehicle movement accurately, and the predict results of represent parameters were similarly with the real measured data.

Keywords: *Vehicle Trajectory, Parameter Prediction, Fuzzy Rules, Petri Net*

1. Introduction

Running trajectory is the most directly reflection factor of vehicle movement, and it's also related to the protection of safe driving and foundation to definition the responsibility of traffic accident. Besides, relationship between running security of vehicle and effective work of driver assistance system was closely. Vehicle trajectory determines the direction of motion directly, and to gain the vehicle trajectory in advance can not only provide the fundamental data which is necessary to assistance system, but also provide theoretical references to the valid prediction of traffic conflict which is potential.

Some researchers proposed some prediction algorithms of vehicle trajectory. Yoshihiro Nishiwaki proposed an algorithm to generate lane change trajectory, and he assumed that different lane change trajectory was based on the movement of vehicles which around own vehicle. By using Hidden Markov Model to imitating the way of lane change of different driver, and taking longitudinal speed, the lateral position of the vehicle and the changing characteristics of this parameters as training sample, then lane change trajectory were created by using maximum likelihood criterion method [1]. Smart CVIS was used as object in some research work, trajectory reconstruction algorithm according to data collection protocol and the characteristics of the data was proposed [2]. The main idea is to repair the trajectory which is missing or unknown by using interpolation algorithm, thus recovering the whole trace sensitivity. To solve the disadvantage that GPS and GIS cann't ascertain vehicle path, vehicle trajectory deduction algorithm in vehicle ad Hoc Network was proposed to taking full advantage of the information of telematics base station [3]. According to the certain longitude and latitude of every sensor, vehicle path can be deduced [4]. Sensors of vehicle lateral acceleration, longitudinal speed and suspension displacement was used to get the vehicle status information of current and the next time, where the vehicle model included six degrees of freedom and was described by 20 state differential equations [5], this model considered road spectrum as well as the non-linear characteristics of the suspension system, and it can avoided complex mathematic derivation. So, this method could not only be relatively accurate to estimate the state of vehicle, but predict the vehicle's rollover of sharp turn on the slopes as well [6]. Adaptive Kalman filtering algorithm was used to estimate vehicle's sideslip angle and yawrate on the two-degree-of-freedom vehicle model [7]. As the input of steering wheel angle was sinusoidal signal, the simulation results of the adaptive Kalman filter algorithm was very close to real results [8].

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Aiming at the problem that vehicle's state parameters is not easy to obtain or high costs to get accurate measurement, some researchers proposed using easily measured parameter to estimate the important parameters in the process of vehicle motion [9]. They established non-linear vehicle model, used the extended Kalman filter theory to establish information fusion algorithm and gave the fusion results of vehicle state parameters in minimum variance sense.The algorithms above have the same feature which is reconstitution the path of this car, auxiliary information of telematics base station is also needed, no doubt it will restrict the applications. By take full consideration of the retardance of changes in vehicle operating parameters and the hierarchy of parameter changes, then using Colored Petri nets to forecast vehicle path, establishing vehicular mobility model according to vehicle kinematic characteristics, and manufacturing the forecasting model of vehicle trajectory based on Petri nets. By using control hierarchy modeling software to simulate and analyze real vehicle test data, the result was similar with real results [10].

2. Analysis of Vehicle Characteristics

External environment and the driver's driving habits have an effect on vehicle path. The driver could change the vehicle motion state by operating pedal and steering wheel when the motion of the vehicle is different with the driver's demand, and it's similarly to changing the vehicle path. If the operation order of pedal and steering wheel is different, so does the timing of the status change in the process of change of vehicle trajectory. This process relates to the time stamp, taking accelerator pedal, brake pedal, steering wheel angle, turn signal and stalls operating rod as resources, the difference that driver's operation order on these resources is reflected in the frequency and time of access to resources. In fact, certain operating sequences are fixed according to driver knowledge. For example, the first step is to release the accelerator pedal and then to operate the braking pedal. The time interval between the drivers releases the accelerator pedal and apply braking pedal is varying with different drivers. Therefore, there is time difference between the vehicle's lateral and longitudinal acceleration change and the actual movement state of the vehicle, while the hierarchy and time sequence of Petri nets can precisely reflect the time sequence of lane change process, which was under the operation of drivers and the forming process of vehicle trajectory.

Petri nets is a kind of network information flow model, it contains two types of nodes which are conditions and events. Adding token distribution indicates information status on the base of directed bipartite graph which conditions and events compose the node. According to the firing rule, the e event-driven state can be evolved, and this will reflect the dynamic process of the system [11]. Under normal circumstances, event node (called change) was represented by a small rectangle and condition (called position) was represented by a small round. Direct arcs can't be existed between change nodes and location nodes, but direct arcs can be existed between change nodes and location nodes, the graph formed above called directed bipartite graph. Some nodes of the network mark on a number of black spots (token), and thus constitute a Petri net.

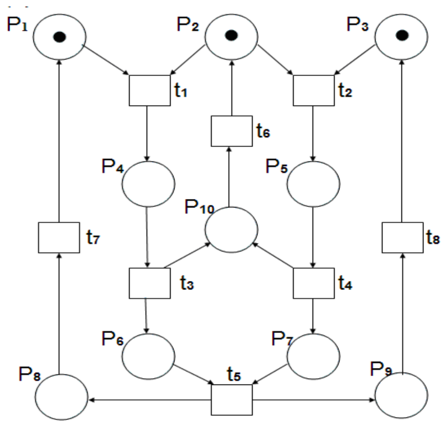

Figure 1. Petri net

Fuzzy Petri Nets is used to fuzzy the inputs, and it will build a limited number of fuzzy rules based on the characteristics of input data. After defuzzification step, final result will be outputted. A simple Petri nets is a triple, $\mathrm{N}=(\mathrm{P},\mathrm{T},\mathrm{F})$,where $\mathrm{P}=\{\mathrm{p}_1,\mathrm{p}_2,...,\mathrm{p}_\mathrm{m}\}$ is a place aggregate; $\mathrm{T}=\{\mathrm{t}_1,\mathrm{t}_2,...,\mathrm{t}_\mathrm{n}\}$ is a transition aggregate; $\mathrm{F}=(\mathrm{P}\times\mathrm{T})\cup(\mathrm{T}\times\mathrm{P})$ is the input and output functions aggregate, called flow relation. Triple $\mathrm{N}=(\mathrm{P},\mathrm{T},\mathrm{F})$ is the necessary and sufficient condition to constitute net. The distribution of token in place decides transition's enabled and fire, transition's fire will change the distribution of the token. Petri nets can be used to simulate the system's dynamic process, and reflect the system dynamic characteristics by fire change to lead flow between the token in the place. Net $\mathrm{N}=(\mathrm{P},\mathrm{T},\mathrm{F})$ constitute the system's static structure framework, but it can't describe the static structure of the whole system. Net theory respects the fact of limited resources. In fact, the desired resources of transition are limited and the capacity of place should also be limited. Complete net system should be specified the initial distribution of resources, regulate the principles governing the activities of the transition, and determine the capacity of place and the relationship between transition and the number of resources .

Comparing to other modeling methods, Petri nets had advantages in modeling ability and in the analysis ability. Petri nets have some specialized analysis methods, such as analysis the liveness and deadlock of several system, analysis the system complex event relations as order, concurrency and conflict, and system boundness and safety can be analysed by using reachability tree theoretical.

3. Vehicle Trajectory Model

Tire sideslip is very small during real vehicle operation process. Vehicle motion model can be simplified into a linear 2-DOF model in case of not considering the tire sideslip. The vehicle position in ground coordinate system can be determined as following.

$$X=\int V_X \cdot dt=\int(u\cos\psi - v\sin\psi)dt \tag{1}$$

$$Y=\int V_Y \cdot dt=\int(u\sin\psi - v\cos\psi)dt \tag{2}$$

where X, *Y* represent the vehicle longitudinal and the transverse displacement in the ground coordinate system respectively, V_x, V_y represent the vehicle longitudinal and transverse velocity respectively; u, v represent the vehicle longitudinal and transverse velocity in the vehicle coordinate system respectively; ψ represents the vehicle yaw angle. Expression of vehicle motion parameters in the ground coordinate system and in the vehicle coordinate system is shown in Figure 2. OXY is the fixed coordinate system and oxy is the vehicle coordinate system [12].

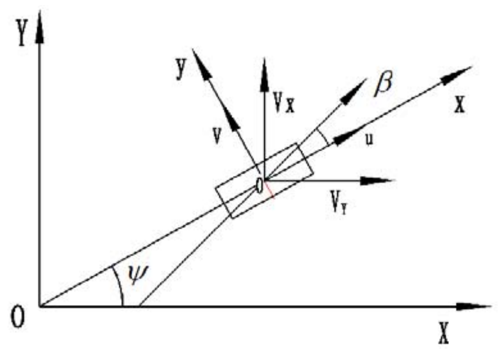

Figure 2. Vehicle movement parameters expression

The relationship among of vehicle yaw angle, roll angle $\dot{\phi}$, pitch angle θ and pitch rate $\dot{\theta}$ were showed as following:

$$q = \frac{\dot{\theta} + w_r \times \sin\phi}{\cos\phi} \tag{3}$$

$$\dot{\psi} = \left(q \cdot \sin\phi + w_r \cdot \cos\phi\right) \cdot \sec\theta \tag{4}$$

$$\psi = \int \dot{\psi} dt \tag{5}$$

The relationship betweem transverse and longitudinal acceleration can be obtained according to the geometric relationship between the ground coordinate system and the vehicle coordinate system, as following:

$$\begin{bmatrix} a_x \\ a_y \end{bmatrix} = \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \cdot \begin{bmatrix} a_X \\ a_Y \end{bmatrix} \tag{6}$$

The transverse and longitudinal acceleration in the vehicle coordinate:

$$\begin{cases} \dot{u} = v \cdot w_r + a_x \\ \dot{v} = -u \cdot w_r + a_y \end{cases} \tag{7}$$

The longitudinal speed and transverse speed in the vehicle coordinate can be obtained by using the equations above.

$$\begin{cases} u = \int \left(v \cdot w_r + a_x\right) dt \\ v = \int \left(-u \cdot w_r + a_y\right) dt \end{cases} \tag{8}$$

Then, combining (1), (2) to calculate the vehicle centroid trajectory. In terms of three degrees of freedom nonlinear vehicle model, the degrees are yaw rate, sideslip angle and vertical speed. The model structure diagram is shown below.

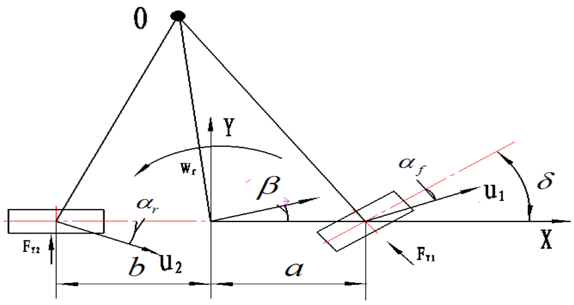

Figure 3. Model of 3-degrees freedom vehicle

where F_{Y1}, F_{Y2} is lateral reaction of front and rear wheels respectively; α_f, α_r are slip angle of front and rear wheels; a, b are the distance from centroid to the front and rear axles; w_r is the yaw angular velocity; β is the sideslip angle; δ is the front wheel angle. u_1, u_2 are front wheel velocity and rear wheel velocity. Based on the vehicle model the vehicle's differential equation of motion is:

$$\left(ak_1 - bk_2\right)\beta + \frac{1}{u}\left(a^2 k_1 + b^2 k_2\right) w_r - ak_1\delta = I_z \dot{w}_r \tag{9}$$

$$\left(\frac{1}{u}\left(ak_1 - bk_2\right) - 1\right) w_r + \left(k_1 + k_2\right)\beta - k_1\delta = mu\dot{\beta} \tag{10}$$

$$m w_r u \beta + m a_x = m\dot{u} \tag{11}$$

where k_1, k_2 are cornering stiffness of front and rear wheel, $k_1 = -1.1 \times 10^5 N/rad$, $k_2 = -1.2 \times 10^5 N/rad$; $a = 1.25m, b = 1.428m$, $m = 1570kg$.

4. Vehicle Trajectory Prediction Model

From analysis above in can known that vehicle trajectory was influenced by vehicle yaw angle, transverse and longitudinal velocity in the vehicle coordinate system and other factors mainly. These parameters were estimated in the prediction model. In CPNtool, using difference quotient to instead of derivative quotient to building the vehicle trajectory prediction model. Model input includes four parameters including vehicle lateral acceleration, longitudinal acceleration, body roll angular velocity and pitch rate, which is shown as following.

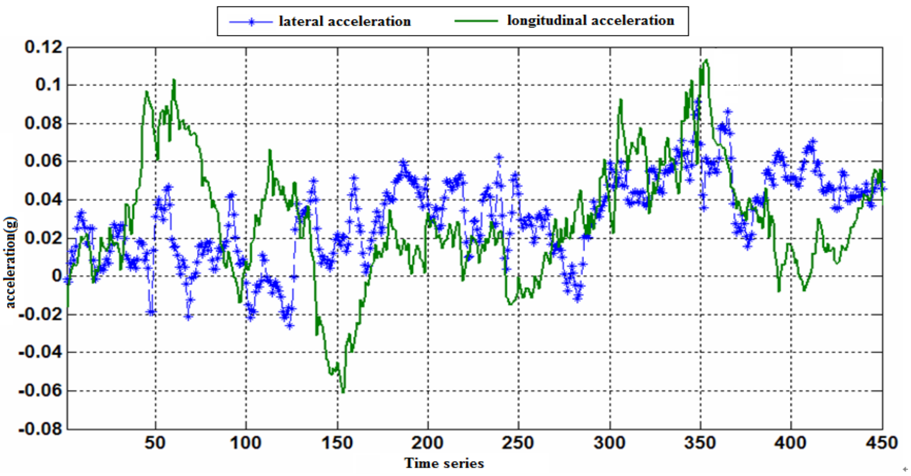

Figure 4. Longitudinal and lateral acceleration

The data in the Figure 4 above was collected during process of lane change in real vehicle test. In Figure 4, the vehicle longitudinal acceleration variation range is small which declare that drivers operate accelerator pedal more cautious in the process of lane changing. However, lateral acceleration variation range is bigger, showing a sine-line-sine change trend, which is consistent with the actual lane change process. Figure 5 is the vehicle body pitch and roll angular rate curves.

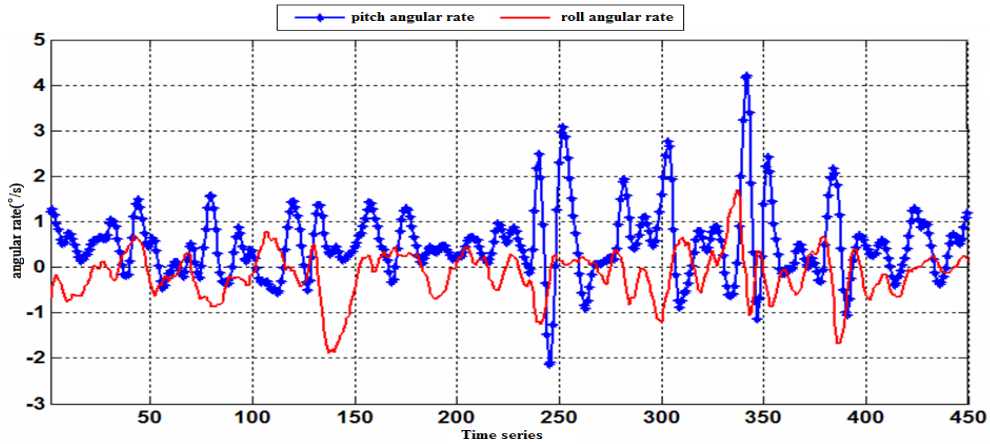

Figure 5. Roll and pitch angular rate

Pitch rate reflects the roughness of the road surface. About 250 sampling data of road roughness is aggravated which lead to severe oscillations of the vehicle pitch rate, but roll angular rate fluctuation is less. Input fuzzy membership function and select the triangular membership function, the domain of parameters depend on the parameters range. According to different percentile to divide the input parameters, the results shown in table 1. Figure 6 is the membership function of longitudinal acceleration.

Table 1. Domain of Input Parameters

Domain	Lower	Low	Medium	High	Higher
longitudinal acceleration	-0.0136	0.0064	0.0327	0.0495	0.0726
lateral acceleration	-0.0307	0.0000	0.0277	0.0523	0.0951
pitch angular rate	-1.9800	-0.6380	0.0350	1.2900	3.3040
roll angular rate	-1.9460	-0.9140	-0.1000	0.5200	1.4020

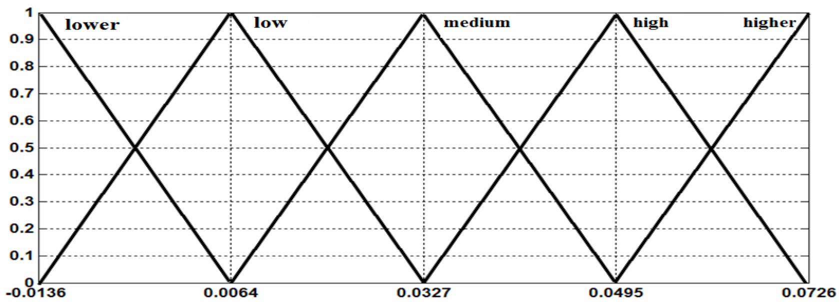

Figure 6. Membership Function of Longitudinal Acceleration

Membership functions of several other parameters similar with longitudinal acceleration are not discussed here. The trajectory prediction model which is established by CPNtool. The input variables are multiplied by 10,000 converted an integer, the change type of input library is INTLIST and fuzzes the input variables by FUZZIF ICATION change, then establish the appropriate prediction model based on (1) to (8). Finally, defuzzification was carried out for output data according to its features.

The change code segment is used for output defuzzification. Finally, predicting 200 samples, wherein, 194 samples' prediction error is less than 0.5m. The prediction results consistent with the actual results. Comparison analysis between the vehicle real trajectory and trajectory simulation result are performed within a certain period of time. The vehicle trajectory in prediction model is shown as following.

Figure 7 shows that the prediction of lateral displacement changes in conformity with the real vehicle experiment, and it also shows that the prediction model can accurately predict the vehicle trajectory within a certain length of time. It can provide accurate and reliable basic data for vehicle tracking and vehicle collision point prediction and a necessary prerequisite for the reliable operation of the vehicle auxiliary systems.

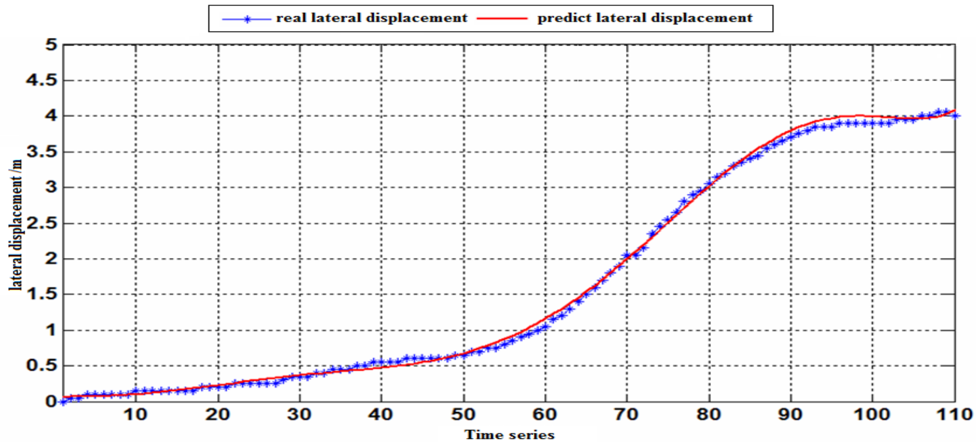

Figure 7. Prediction result of lateral displacement

Figure 8 shows the speed changing during the lane change process. It can be seen that the estimated value of the model coincides with the real value. The speed is significantly reduced in lane change process, which is the driver in the decision around the vehicle's movement in order to sent accurate lane change signal to other vehicles. The high speed easily induces traffic accidents in a lane change process. So, during lane changing, the driver will be appropriate to reduce the speed to meet the safety requirements of lane changing.

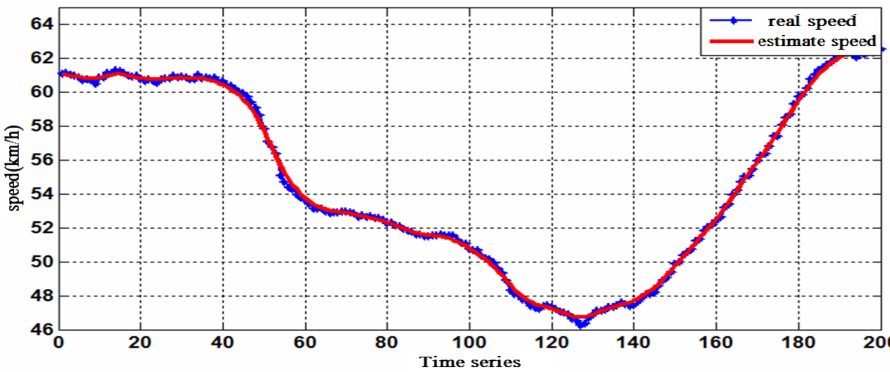

Figure 8. Estimation result of speed

Yawrate is a inportant represention papameter during the lane change process. In Figure 9, yawrate volatility increases significantly. Between 150 to 300 samples, data shows a sinusoidal variation, and the vehicle's lateral movement is more obviously. After 300 samples the data becomes greater volatility, which is mainly because the driver was making proper adjustment in the target lane. On the whole, the estimated value is close with the real value. Figure 10 shows the estimated results of vehicle slip angle of the center of mass.

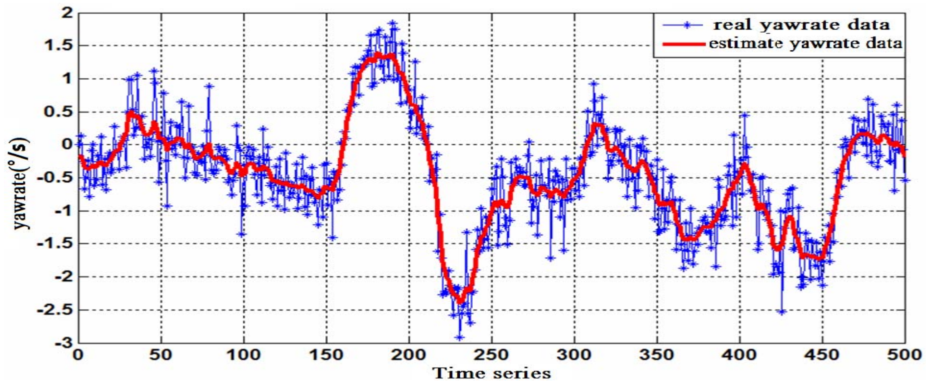

Figure 9. Estimation result of yawrate

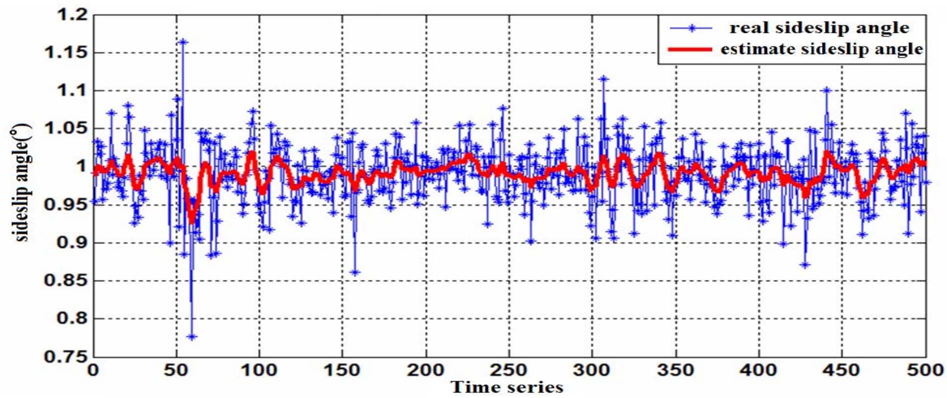

Figure 10. Estimation result of slip-angle

The volatility of the sideslip angle is also large, but the range is narrowly . In fact, the vehicle sideslip angle generally won't appear very big change, which is mainly because the sideslip angle is too large. This large slip angle shows that direction of the velocity of the center of vehicle mass and the direction of the real trajectory occurred significantly deviate, which will directly affect the safe operation of the vehicle. Therefore, the results also shows that the sideslip angle changed slightly, but the greater volatility, estimated result is consistent with real data. Through the above data analysis, the model has the best effect for speed estimation, which is associated with the characteristic of the original signal. Obviously, if the signal has greater volatility, model is difficult to accurately make a reasonable prediction for the parameter changes of the next time through the current estimated results. However, the model can be more accurate to estimate the vehicle’s state parameters of motion, meet requirements of some vehicle auxiliary equipments for data accuracy.

5. Conclusion

The effective predict of vehicle trajectory can not only provide credible data for prediction of the traffic conflict points and vehicle tracking, but also evaluate kinematic performance to vehicles that on different road conditions. In connection with hierarchy and time sequence, this article predicted vehicle trajectory by using of fuzzy Petri nets, then take full consideration of influencing factors during vehicle operation, taking linear 2-DOF vehicle model as research objects, establishing vehicle trajectory model, setting horizontal, vertical acceleration, pitch and roll angular velocity as input variables, using difference quotient instead of the derivative, then establish vehicle trajectory prediction model in the CPNtool software, Finally, validation the model by using real car test data. The result shows that, the model can accurately predict vehicle trajectory for a certain length of time and provide the necessary basic data to other on-vehicle auxiliary systems. Besides, predict results of vehicle speed, yawrate, and slip-angle are close with the measured data by using Petri net models.

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