# Letter

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## Letter

### Driver-Centric Velocity Prediction with Multidimensional Fuzzy Granulation

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Dear editor,

This letter deals with a real-world problem regarding chaotic time series prediction, where a driver-centric velocity prediction model is presented for vehicle intelligent control and advanced driver assistance, i.e., multi-dimension fuzzy predictor. Inspired by fuzzy granulation technology, a finite-state Markov chain (MC) is reinforced to capture probabilities of the transitions between velocity and acceleration and present signals that vary in a continuous range. The predictability of the multi-dimensional fuzzy predictor is examined by comparing two existing MC-based predictors over the two laboratory cycles and one virtual driving cycle, both of which have high accuracy.

There are idiosyncrasies in the driving behavior of drivers. Different drivers differ in using the accelerator, brake pedal, and steering wheel [1]. Given these differences, energy management based on individual driving habits can be more efficient [2]. In order to successfully implement this differential energy management, one approach is to control the vehicle by analyzing a representative driver model to help each driver [3]. Individual driver models or models under a subset of driving behavior categories can be trained offline or online. For supporting the target driver efficiently, a vehicle controller chooses a suitable driver model by differentiating drivers or assigning a model appropriate to their driving behavior.

Unlike previously, Augustynowicz divided the driver behavior into the region (-1,1); within 1, 0, and -1 mean offensive, moderate, and mild separately [4]. This is usually calculated based on fuel consumption, and the operating efficiency of vehicles reflected the aggressiveness level of driver behavior. Manzoni et al. [5] calculated the percentage of excessive consumption reflected the additional cost by comparing the estimated fuel consumption during the trip and a benchmarked consumption. Neubauer and Wood [6] calculated the vehicle efficiency to represent the driving behavior by using fuel consumption. Corti et al. [7] introduced a cost function faced to energy to assess the driving behavior and predict fuel overconsumption. However, the feasibility of implementing this continuous index or discrete class-based classification approach for HEV energy management needs to be further analyzed and validated.

**Related work**: Considering the related algorithms for driver recognition, the driver torque demand is assumed to be exponentially varying over the predictive horizon based on the empirical formula [8]. In contrast, the RB algorithm limits the number of managed parameters. The RB algorithm can produce redundant and complex rules when dealing with larger data sets of variables. Fuzzy logic (FL) graphs are used instead of RB algorithms to address this situation. Syed et al. introduced an FL algorithm to optimize the application of pedals in hybrid vehicles [3]. Li et al. introduce type-2 fuzzy sets to describe the driving style used for driver-oriented energy management [9]. Based on these two algorithms, the results are simplistic and uniform in an acceptable way, but the classification quality is closely related to the threshold value.

The RB algorithm threshold defines the resulting robustness and needs a huge number of data to be analyzed. Unsupervised algorithms can work efficiently without a clear understanding of the underlying process. Miyajima et al. implemented a Gaussian mixture model by analyzing the vehicle-following behavior and the signal spectrum of pedal operation [10]. In the work of Li et al., the spectrum-informed long short-term memory networks have been developed that achieve the real-time recognition of drivers under the same driving scenario

[11]. The Markov model has also proven to be suitable for driving behavior recognition. Therefore, the driving behavior representation can be generated from the random patterns of previous data.

**Fuzzy Granulation for Markov Chains**: Firstly, the velocity and acceleration of vehicles are expressed as a finite state MC [12]. The state spaces of these two parameters are represented as $V = \{v_i \mid i = 1, \ldots, M\} \subset X \subset R$ and $W = \{a_j \mid j = 1, \ldots, N\} \subset Y \subset R$. $V$ and $W$ denote the state space of velocity and acceleration, separately; $M$ and $N$ denote the sample numbers of velocity and acceleration, separately. Meanwhile, $X$ and $Y$ denote the finite set of variables, and $R$ denotes the set of real numbers. Considering the balance of accuracy and computational efficiency, the collected samples of vehicle speed with the range of 0-135km/h are uniformly discretized as 135 elements. The collected samples of vehicle acceleration with the range of -6-3m/s$^2$ are uniformly discretized as 90 elements. The frequencies of its transition could be evaluated based on the possibilities of transition observation as follow.

$$\begin{cases} p_{ij} = P\left(a^+ = a_j \middle| v = v_i\right) = \dfrac{H_{ij}}{H_i} \\ H_i = \sum_{j=1}^{N} H_{ij} \end{cases} \quad (1)$$

where $v$ means the velocity; $a^+$ means the acceleration of the next time step; $p_{ij}$ means the transition probability between $v_i$ to $a_j$; $H_{ij}$ denotes the number of transitions from $v_i$ to $a_j$; $H_i$ means the number of total transitions from $v_i$; the matrix $\prod$ represents the transition probability matrix which is occupied with $p_{ij}$. Followed by (2), the probability vector of the next step is obtained as

$$\left(\lambda^+(a)\right)^T = \left(\lambda(v)\right)^T \prod = \prod_j^T \quad (2)$$

where, $\lambda^T(v) = [0 \ldots 1 \ldots 0]$ means a multi-dimensional probability vector with the $j$th element to denote a discontinuous state $a_j$ in disjoint zones $I_j, j = 1, \ldots, N$; $\prod_j^T$ means the $j$th row of the matrix $\prod$. $X$ and $Y$ are subdivided into finite groups, respectively, with fuzzy subsets $\Phi_i, i = 1, \ldots, M$ and $\Phi_j j = 1, \ldots, N$ when using fuzzy granulation technology. The fuzzy subset $\Phi_i$ and $\Phi_j$ are pairs of $(X, \mu_i(\cdot))$ and $(Y, \mu_j(\cdot))$, wherein $\mu_i(\cdot), \mu_j(\cdot)$ are Lebesgue member functions which can be measured to satisfy the following equation:

$$\begin{cases} \mu_i : X \to [0,1] \; s.t. \forall v \in X, \exists i, 1 \le i \le M, \mu_i(v) > 0 \\ \mu_j : Y \to [0,1] \; s.t. \forall a \in Y, \exists j, 1 \le j \le N, \mu_j(a) > 0 \end{cases} \quad (3)$$

where, $\mu_i(v)$ displays the membership degree of $v \in X$ in $\mu_i$; $\mu_j(a)$ denotes the membership degree of $a \in Y$ in $\mu_j$. Followed by the theory of approximate reasoning [13], the transformation assigned a multi-dimensional probability vector for each $v \in X$ as:

$$\left(O(v)\right)^T = \left[\frac{\mu_1(v)}{\sum_{i=1}^{M} \mu_i(v)}, \frac{\mu_2(v)}{\sum_{i=1}^{M} \mu_i(v)}, \ldots, \frac{\mu_M(v)}{\sum_{i=1}^{M} \mu_i(v)}\right] \quad (4)$$

This transformation is applied to develop the fuzzy norms and map velocity in the $X$ to vector in multi-dimensional probability vector space $\bar{X}$. Furthermore, the elements in the probability vector $\sim O(v)$ are summed as 1. The next step's probability distribution in $\bar{Y}$ is calculated from Eq. (5) and gathered with member function $\mu(a)$ to decode the vectors in $\bar{Y}$ back to the space $Y$ as:

$$z^+(a) = \left(O^+(v)\right)^T \mu(a) = \left(O(v)\right)^T \prod \mu(a) \quad (5)$$

where, in the transition probability matrix, $p_{ij}$ is explained as a transition probability between $\Phi_i$ and $\Phi_j$. The member function $\mu(a)$ is applied to encode the probability vector of the next step in space $Y$.

The centroid and volume of the membership function $\mu(a)$ are expressed as:

$$\begin{cases} \bar{c}_i = \int y \mu_j(y) dy \\ V_j = \int \mu_j(y) dy \end{cases} \quad (6)$$

where, $\bar{c}_i$ and $V_j$ are the centroid and volume of the membership function $\mu_j(v)$.

It is supposed that member functions show the same volume to follow that $\sum_{j=1}^{N} p_{ij} = 1$ and $\sum_{i=1}^{M} O_i(v) = 1$. The next step ahead velocity is obtained and simplified as:

$$\begin{cases} a^+ = \dfrac{\sum_{i=1}^{M} O_i(v) \sum_{j=1}^{N} p_{ij} V_j \, \bar{c}_i}{\sum_{i=1}^{M} O_i(v) \sum_{j=1}^{N} p_{ij} V_j} = \left(O(v)\right)^T \prod \bar{c} \\ v^+ = v + a^+ \end{cases} \quad (7)$$

**Multi-dimensional Fuzzy Granulation:** The multi-dimension fuzzy predictor (MDFP) with multi-dimensional fuzzy granulation is introduced to enhance the prediction performance of vehicle velocity by considering the driver behaviors for look-ahead steps. By using cluster algorithms, the original samples are classified into the personalized Markov chain models and then aggregate their outputs to improve sensitivity of the prediction model to sudden change of driving behaviors. Here, two types of clustering algorithms are explored, i.e., fuzzy C-mean (FCM) with soft margin and support vector machine (SVM) with hard margin.

The auto-regression (AR) model is an efficient tool for generalizing the signal's mean-time regressive pattern and predicting by the following dynamically. The applied AR model follows the structure displayed as [14]:

$$v(k) = \sum_{r=1}^{K} \vartheta_r v(k-r) + \varepsilon_k \quad (8)$$

where, $\vartheta_r$ are the AR model coefficients; $K$ is the order of the AR model; $\varepsilon_k$ reflects the ith noise; $v(k)$ means the vehicle speed at step $k$. In this research, the sample period $\tau$ is 0.1s.

As real-world driving involves frequent transitions of the driving behavior, the AR models are applied to obtain driver speed information in moving horizontal lines, where parameters measure the length of these lines and the order R of the models. According to the Corrected Akaike Information Criterion [15], the second-order AR models with a 200-second horizontal line showed a consistent advantage. The results are related to the data vector $\gamma_r$ of speed interval samples, which includes four information sets as:

$$\gamma_r = [\vartheta_{r1} \quad \vartheta_{r2} \quad a_{r\_avg} \quad a_{r\_maxR}] \quad (9)$$

where the AR coefficient set $\vartheta$ displays the tendency of sample speed change; mean acceleration ratio $a_{r\_avg}$ measures the mean state and the maximum acceleration rate $a_{r\_maxR}$ measures the range of acceleration changes.

Markov chain models with five layers show efficient computational efficiency and high predictive performance through training [14]. The AR model coefficient sets are divided into five groups reflecting different acceleration statuses to represent specific driver states in this research. The five groups are fuzzified to display the acceleration range relationship for different driver behaviors. These behaviors are marked as Over Mild; Mild; Moderate; Offensive and Over Offensive. Given the unknowability of a priori information about vehicle performance and driving behavior preferences, two clustering

matrix $\prod$ in Eq. (2) is detailed to be five specific transition probability matrixes as follows:

$$|\prod_1 \quad \prod_2 \quad \prod_3 \quad \prod_4 \quad \prod_5| \quad (10)$$

The acceleration probability distribution with different driving behaviors can be obtained more exactly by these detailed transition probability matrixes. Based on these matrixes, the next one-step-ahead accelerations by driver groups can be displayed as:

$$a_n^+ = \left(O_n(v)\right)^T \prod_n \bar{c}_n \quad (11)$$

Here, the weighted sum coefficient is the member criterion aggregating acceleration prediction from five driver MC models. Eq. (12) shows the next one-step-ahead velocity calculated as:

$$\begin{cases} a^+ = \displaystyle\sum_{n=1}^{B} \left(O_n(v)\right)^T \prod_n \bar{c}_n \cdot \omega_n(v) \\ v^+ = v + a^+ \end{cases} \quad (12)$$

where, the member criterion vector $\omega_n(v)$ reflects the data vector $\gamma_r$ of the speed zone sample obtained by FCM; but the weights obtained by SVM, which only has 0 or 1 due to its binary classification, are introduced to replace $\omega_n(v)$.

**Experiments:** In this study, the experiments are based on a cockpit package where five drivers are invited as observation subjects for 8000 seconds of virtual driving [18]. The entire route consisted of a mix of highways and local roads with multiple stop signs, traffic lights and speed limit changes provided by IPG CarMaker. A Thrustmaster T500RS cockpit package and a host PC with I5-6500 3.2GHz processor and 8 GB RAM are connected by a 3.0 USB cable to provide a static system experience platform driving simulators to human drivers.
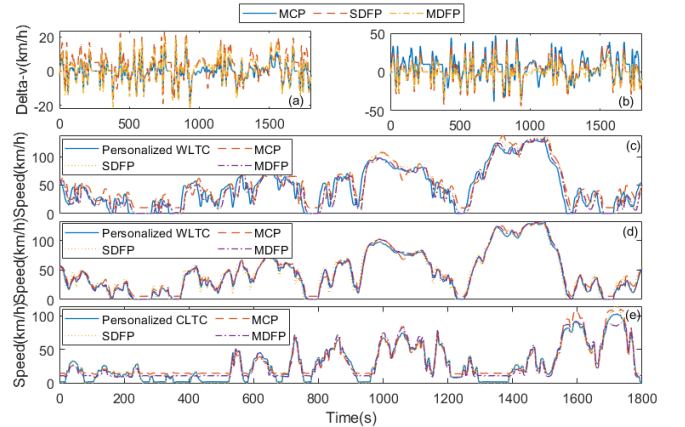


**Fig. 1.** Speed prediction results of three MC-based predictors: the speed prediction errors by (a) using SVM; and (b) by using FCM; the speed prediction results under WLTC by (c) using FCM; and (d) using SVM; (e) the speed prediction results by using SVM under CLTC

In this paper, existing MC-based predictors are introduced for analysis, including the Markov chain predictor (MCP) [19] and the single-dimension fuzzy predictor (SDFP) [20]. Fig. 1 shows the

Table 1. Velocity prediction comparison of three MC-based predictors in the WLTC

| Predictor | Behavior recognition | | Maximum error | | ITAE ($10^5$) | | Reduction (%) | |
|---|---|---|---|---|---|---|---|---|
| | FCM | SVM | FCM | SVM | FCM | SVM | FCM | SVM |
| MCP | NA | | 46.9517 | 326.376 | 3.3412 | 0.0805 | - | - |
| SDFP | NA | | 44.0925 | 15.192 | 2.7074 | 0.0689 | 18.97% | 14.41% |
| MDFP | Yes | | 47.9171 | 11.343 | 2.4237 | 0.0370 | 27.46% | 54.04% |

algorithms of FCM and SVM in the unsupervised learning process are used to classify information with inaccurate internal boundaries as well as unknowable external boundaries [16][17].

The results show the data member distributions for all of the groups. Based on the driving behavior classification, the transition probability

prediction speeds obtained by three predictors based on the personalized Worldwide harmonized Light vehicles Test Cycles (WLTC) and personalized China Light-Duty Vehicle Test Cycle (CLTC) by using FCM and SVM. MCP is proven with weak prediction performance in the low-speed zone because of the minute

transition probability calculated by using one discrete MC model in this zone. The fuzzy granulation helps the SDFP fix the problem above in the low-speed zone. However, maintaining uniformity in the handling of different driving habits makes the predictability unsatisfied in the medium-high-speed zone. Due to the training dataset of the predictive model is continuously updating during virtual driving, MDFP displays a better prediction performance compared to the other two predictors mentioned above. More details about the comparison are shown in Table 1. Compared to FCM, SVM helps MDFP to reduce 98.4% of ITAE and 76.3% of maximum error.

Fig. 2 shows the driving simulation results of the DiL experiment with human drivers operating in a simulated driving scenario, where the absolute errors between prediction and reference speed are displayed. After 600 seconds of initialization, the MDFP begins to generate a 10s look-ahead horizon, and its prediction model is updated in real-time every 5 seconds. The MDFP relies on the last driving step independent of the driver change while predicting speed, which helps the model to adaptively adjust speed based on the new pedal action if

the individual driver's driving behavior changes dramatically. It needs to be emphasized that the data recorded by the MDFP will be completely overwritten within 600 seconds. Therefore, the required cool downtime after a new driver replaced is 10 minutes.
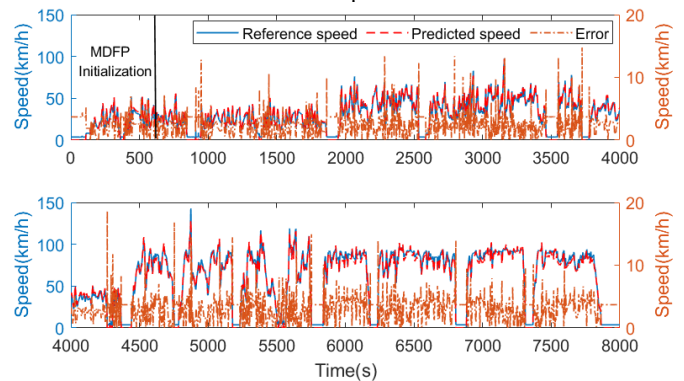


**Fig. 2.** Online prediction results over virtual driving by SVM

**Conclusions:** This letter presents a driver-centric velocity prediction model for vehicle intelligent control and advanced driver assistance, i.e., multi-dimension fuzzy predictor. Its predictability is proven and examined with existing MC-based predictors. Two laboratory cycles and one virtual driving cycle are implemented for vehicle performance validation. The proposed multi-dimension fuzzy predictor has an ability to distinguish driving behaviors in real time.

The contributions of this study are: 1) A novel method of online predictors is imported. and its performance is compared with the MC-based predictors. 2) The performance of imported energy management strategy and its online calculation efficiency are demonstrated by a DiL experiment.

**References**

[1]     J. Huang, Y. Chen, X. Peng, L. Hu, and D. Cao, "Study on the driving style adaptive vehicle longitudinal control strategy," IEEE/CAA Journal of Automatica Sinica, vol. 7, no. 4, pp. 1107–1115, Jul. 2020, doi: 10.1109/JAS.2020.1003261.

[2]     J. Li, Y. Gu, C. Wang, M. Liu, Q. Zhou, G. Lu, D. T. Pham and H. Xu, "Pedestrian-Aware Supervisory Control System Interactive Optimization of Connected Hybrid Electric Vehicles via Fuzzy Adaptive Cost Map and Bees Algorithm," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 2, pp. 2959-2970, 2021, doi: 10.1109/NAFIPS.2007.383833.

[3]     F. U. Syed, D. Filev, and H. Ying, "Fuzzy rule-based driver advisory system for fuel economy improvement in a hybrid electric vehicle," *Annual Conference of the North American Fuzzy Information Processing Society - NAFIPS*, pp. 178–183, 2007, doi: 10.1109/NAFIPS.2007.383833.

[4]     A. Augustynowicz, "Preliminary classification of driving style with objective rank method," *International Journal of Automotive Technology*, vol. 10, pp. 607–610, 2009, doi: https://doi.org/10.1007/s12239-009-0071-8.

[5]     V. Manzoni, A. Corti, P. De Luca, and S. M. Savaresi, "Driving style estimation via inertial measurements," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, pp. 777–782, 2010, doi: 10.1109/ITSC.2010.5625113.

[6]     J. S. Neubauer and E. Wood, "Accounting for the variation of driver aggression in the simulation of conventional and advanced vehicles," *SAE Technical Papers*, vol. 2, 2013, doi: 10.4271/2013-01-1453.

[7]     A. Corti, C. Ongini, M. Tanelli, and S. M. Savaresi, "Quantitative driving style estimation for energy-oriented applications in road vehicles," *Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013*, pp. 3710–3715, 2013, doi: 10.1109/SMC.2013.632.

[8]     Q. Zhou, Y. Zhang, Z. Li, J. Li, H. Xu and O. Olatunbosun, "Cyber-Physical Energy-Saving Control for Hybrid Aircraft-Towing Tractor Based on Online Swarm Intelligent Programming," *in IEEE*

*Transactions on Industrial Informatics*, vol. 14, no. 9, pp. 4149-4158, 2018, doi: 10.1109/TII.2017.2781230.

[9]     J. Li, Q. Zhou, Y. He, H. Williams, H. Xu, and G. Lu, "Distributed Cooperative Energy Management System of Connected Hybrid Electric Vehicles with Personalized Non-Stationary Inference," *IEEE Transactions on Transportation Electrification*, 2021, doi: 10.1109/TTE.2021.3127142.

[10]    B. C. Miyajima *et al.*, "Driver Modeling Based on Driving Behavior and Its Evaluation in Driver Identification," 2007.

[11]    J. Li, Q. Zhou, Y. He, H. Williams, and H. Xu, "Driver-Identified Supervisory Control System of Hybrid Electric Vehicles Based on Spectrum-Guided Fuzzy Feature Extraction," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 11, pp. 2691–2701, Nov. 2020, doi: 10.1109/TFUZZ.2020.2972843.

[12]    D. P. Filev and I. Kolmanovsky, "Generalized Markov Models for Real-Time Modeling of Continuous Systems," *IEEE TRANSACTIONS ON FUZZY SYSTEMS*, vol. 22, no. 4, pp. 983–998, 2014.

[13]    L. Johannesson, M. Åsbogård, and B. Egardt, "Assessing the Potential of Predictive Control for Hybrid Vehicle Powertrains Using Stochastic Dynamic Programming," *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, vol. 8, no. 1, pp. 71–83, 2007.

[14]    J. Jing, D. Filev, A. Kurt, E. Özatay, J. Michelini, and Ü. Özgüner, "Vehicle Speed Prediction using a Cooperative Method of Fuzzy Markov Model and Auto-regressive Model," in *Intelligent Vehicles Symposium (IV), 2017 IEEE*, no. Iv, pp. 881–886, 2017.

[15]    Hirotogu. Akaike, "Information theory and an extension of the maximum likelihood principle," in *Selected papers of hirotugu akaike*, Springer, pp. 199–213, 1998,.

[16]    Li Liu, Aolei Yang, Wenju Zhou, Xiaofeng Zhang, Minrui Fei and Xiaowei Tu, "Robust Dataset Classification Approach Based on Neighbor Searching and Kernel Fuzzy C-Means," *IEEE/CAA J. of Autom. Sinica*, vol. 2, no. 3, pp. 235-247, 2015.

[17]    Zhang, Y. Support vector machine classification algorithm and its application. In International conference on information computing and applications, pp. 179-186, 2012, Springer, Berlin, Heidelberg.

[18]    J. Li *et al.*, "Dual-loop online intelligent programming for driver-oriented predict energy management of plug-in hybrid electric vehicles," *Applied Energy*, vol. 253, Nov. 2019, doi: 10.1016/j.apenergy.2019.113617.

[19]    C. Lin, H. Pengl, and J. W. Grizzle, "A Stochastic Control Strategy for Hybrid Electric Vehicles," in *American Control Conference*, pp. 4710–4715, 2004.

[20]    T. Liu, X. Hu, S. E. Li, and D. Cao, "Reinforcement Learning Optimized Look-Ahead Energy Management of a Parallel Hybrid Electric Vehicle," *IEEE/ASME TRANSACTIONS ON MECHATRONICS*, vol. 22, no. 4, pp. 1497–1507, 2017.