Highway Lane-Changing Behavior Prediction Using a Hierarchical Software Architecture based on Continuous Hidden Markov Model

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Introduction

- A novel hierarchical software architecture for prediction of lane changing behavior on highways has been developed and evaluated.
- The two-layer hierarchical structure of the proposed model is based on continuous Hidden Markov Model (HMM) incorporated with a Gaussian Mixture Model (GMM)
- The trajectory classification predicted in the first layer is binary, i.e., Lane Change(LC) and Lane Keep (LK) behaviors. The second layer of the software architecture further classifies the LC behavior output of the first layer to left-lane change (LLC) and right-lane change (RLC) behaviors.
- The Environmental parameters (positions, speed and time based) are taken as input parameters in the model execution.
- This model can be effectively used as a lane changing suggestion system in the advanced driver assistance systems (ADAS).

Vehicle Trajectory dataset

- The developed model has been evaluated using the real-world Next Generation Simulation (NGSIM) data set of U.S. Highway 101 and Interstate 80.
- The lane changing behavior is also divided into two categories as named discretionary lane change (DLC) and mandatory lane changing (MLC).
- The relationship or influence between these vehicles can be represented by three types of variables: (1) Gap or distance, (2) Speed and (3) Time (Time to the collision (TTC) and Time Gap (TAG)).

These parameters are:

- Distance between surrounding vehicles with target vehicle (D_i)
- Gaps between surrounding vehicles with target vehicle in x axis $(\Delta X_i = X_S - X_i)$
- Gaps between surrounding vehicles with target vehicle in y axis $(\Delta Y_i = Y_S - Y_i)$
- Relative velocity between surrounding vehicles with target vehicle $(\Delta V_i = V_S - V_i)$
- Time to collision $(TTC_i = D_i / |\Delta V|)$
- Time to Gap $(TG_i = D_i / V_S)$ with forward vehicles on current, left and right lane.
- Acceleration of the target vehicle (α_S).
- Velocity of the target vehicle (V_S).

Here $i \in \{PCL, FCL, PLL, FLL, PRL, FRL\}$

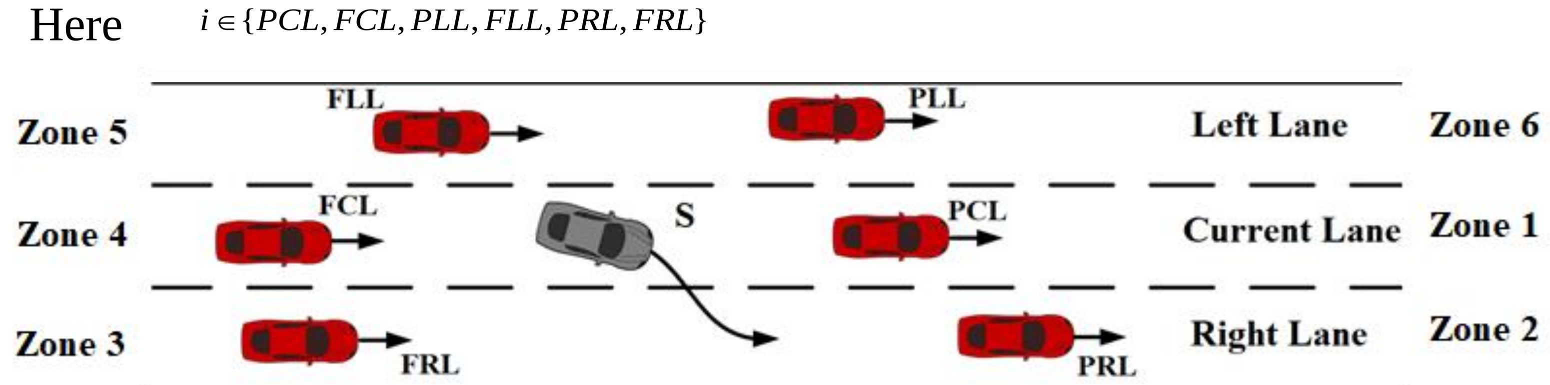

Fig. 1. Subject vehicle and surrounding vehicles in lane changing scenario

Proposed Framework

- First layer classify the lane keep (LK) and lane changing (LC) by using three GMM-HMM units and voting.
- Second layer further classify the lane change decision into Lane change to left (LCL) and lane change to right (LCR) by using three GMM-HMM units and voting.
- The decision making flow and require input sequence in different stage of proposed model are shown in Fig. 2.

- The combined GMM-HMM can be represented by five components $\lambda(A, \pi, C, u, \Sigma)$
- Learning of HMM parameter is achieved by using the forward-backward (Baum-Welch) algorithm to maximizing the probability of occurring observation.
- The GMM parameters are learned by Expectation maximization (EM) algorithm.

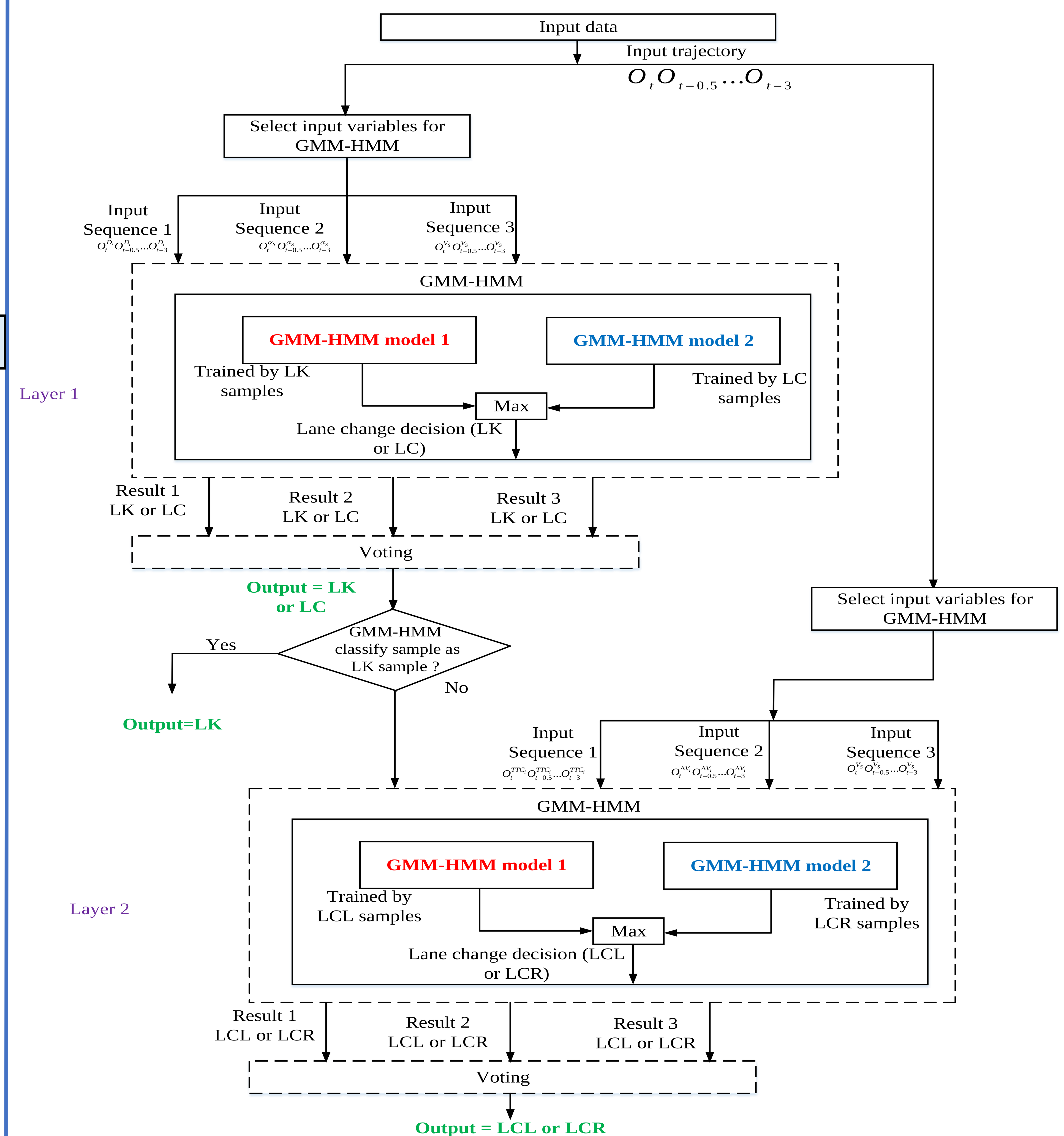

Fig. 2. Flow diagram of the proposed lane-changing behavior prediction using GMM-HMM and Voting

Results and Discussions

- Testing dataset (remaining 30% of extracted data) includes 223 left lane-changing samples, 1099 lane keep samples, and 79 right lane changing samples.
- Behavior prediction accuracy is maximum by taking three GMM-HMM units in 1st stage and three GMM-HMM units in 2nd stage of proposed model, as listed in Table 1.
- Distance, host vehicle speed and acceleration are used to get higher prediction accuracy in the 1st stage of model.
- TCC, relative speed and host vehicle speed are used to get higher prediction accuracy in the 2nd stage of model.
- Comparison results of 1st stage of model are shown in Table 2 for two class.
- Comparison results of proposed model are shown in Table 3 for three class.

Table 1: Effect of number of GMM-HMM units in 1st and 2nd layer.

S. No	No of GMM-HMM units in 1st layer	No of GMM-HMM units in 2nd layer	Testing accuracy (%) LK	LCL	LCR	Total
1	3	3	**98.8**	**90.5**	**88.6**	**96.9**
2	3	5	98.8	83.8	86.1	95.7
3	3	7	98.8	79.3	69.6	94.1
4	5	3	85.9	31.4	30.4	74.1
5	5	5	85.9	29.1	29.1	73.7
6	5	7	85.9	27.7	25	66.6

Table 2. Comparative performance of 1st layer of proposed model.

Method	Testing accuracy: Lane keep (LK)	Lane change (LC)
Fuzzy Logic [1]	97.0%	82.5 %
GM-HMM [2]	98.0 %	94.0 %
Proposed Hierarchical multi GMM-HMM	98.8%	96.3%

Table 3. Comparative performance of proposed hierarchical multi GMM-HMM for LK, LCL and LCR behavior

Method	Testing accuracy: Lane keep (LK)	Lane change to left (LCL)	Lane change to right (LCR)
Neural network model [3]	94.17 %	73.54 %	46.43 %
Rule based model [4]	96.91 %	89.34 %	81.28 %
Proposed Hierarchical Multi GMM-HMM	98.8 %	90.5 %	88.4 %

Conclusions

- The results show that the accuracy of proposed hierarchical model is up to 98.8% for LK, 90.5% for LCL and 88.6% for LCR behavior. The overall accuracy of the model is 96.9% which illustrates the feasibility and effectiveness of the proposed hierarchical model for lane-changing behavior decision making.
- Proposed model is more accurate compared to neural network and rule based model.
- Only environment parameters are used for behavior prediction, thus model can be used in absence of vehicle communication.
- The proposed model has the potential to be programmed into lane changing advisory system for human-driven vehicles, autonomous vehicles and also microscopic traffic simulation models.

References

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