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Estimating Human Comfort Levels in Autonomous Vehicles Based on Vehicular Behaviors and Physiological Signals

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Abstract— **In this study, we proposed a dynamic model that could quantify human comfort in autonomous vehicles (AVs) based on vehicular behaviors and a Kalman filter (KF) based approach to further refine comfort level estimation by leveraging physiological signals. The dynamic model could capture the dynamics in human comfort when the passenger was exposed to a continuous sequence of vehicular behaviors during an AV journey. The KF-based comfort estimation approach could fuse comfort level estimations based on physiological signals and the dynamic model. A simulator-based user study was conducted to evaluate the comfort estimation approaches in which the participants experienced a set of virtual AV journeys on a high-fidelity driving simulator with 6-degree-of-freedom motions. Experimental results show that the proposed approaches could quantify human comfort levels and the KF-based approach outperforms the others.**

I. Introduction

Despite the efforts devoted to improving the technical competence of autonomous vehicles (AVs), low user acceptance could potentially be a significant obstacle to the promotion of AVs [1]. According to J. D. Power [2], the consumers expressed low confidence toward AVs, and the concern over the comfort of AVs was a significant factor. Therefore, comfort needs to be considered a fundamental research topic in AVs.

Comfort is a subjective feeling for each individual, and a wide variety of factors influence it. Traditionally, the factors related to human comfort in vehicles could be divided into three aspects, the dynamic aspect, the ambient aspect, and the ergonomic aspect [3]. For AVs, some researchers [4] suggested that the influential factors of comfort could differ from those in traditional human-driven vehicles. While factors in traditional human-driven vehicles should retain their influence, the deprivation of controllability over the vehicle could expose the passengers in AVs to new influential factors of comfort.

Several studies used qualitative methods to analyze human comfort in AVs. Bellem [5] carried out a simulator study to explore the AV driving style that would be perceived as comfortable. Results of the study suggested that keeping acceleration and jerk as small as possible and taking early perceivable actions in a maneuver would improve the comfort of AVs. Hartwich [6] led a study that focused on the influences of the driver's age and the familiarity of the driving style on the perceived comfort in AVs. Both younger and older drivers confirmed perceiving more comfort in AVs than manual driving vehicles. While younger drivers felt more comfortable when the AV was driving in a style similar to their manual driving style, the older drivers showed higher comfort with the unfamiliar AV driving style. Schockenhoff [7] used qualitative methods to explore relationships between passenger subjective discomfort and vehicular maneuvers.

Some quantitative studies have shown the relationship between different factors and passenger comfort. Brizon [8] proposed a computational model for evaluating acoustic comfort. The model could combine the subjective ratings from the participant and the objective measurements of acoustical features to evaluate a journey's overall acoustical comfort level. In [9], a computational model of human comfort in AVs influenced by vehicular maneuvers was proposed and evaluated. The model describes the human comfort level in an AV journey as the combination of comfort levels perceived in individual vehicular maneuvers.

Real-time human comfort estimation can be applied to adaptive AV controllers [10], [11] to improve comfort in AVs. However, there is a lack of studies on real-time comfort level estimation approaches. Comfort in AVs can be assessed with self-reported comfort levels through Likert scales or hand-held devices [12]. However, self-reporting comfort levels require continuous engagement from the passengers, which is impractical in real human-AV interactions. Indirect estimation of comfort through physiological signals [13] is an alternative to the self-reporting method. However, the accuracy is limited in some situations due to noises in physiological signals.

In this study, we proposed a dynamic model of human comfort that could capture dynamics in human comfort levels influenced by the vehicular behaviors of AVs based on the computational model proposed in [9]. In the dynamic model, human comfort in AVs was parameterized as a function of the current comfort level and the subsequent change in comfort level caused by vehicular behaviors. The physiological signal-based comfort level detection approach proposed in [13] was implemented in this study to detect the real-time human comfort level in AVs. Furthermore, we proposed a Kalman filter-based method to fuse the estimations from the dynamic model and physiological signal-based approach into the real-time estimation of human comfort level in AVs. To examine the performance of the proposed method, we conducted a simulator-based user study on a high-fidelity driving simulator that could generate 6-degree-of-freedom (6-DOF) motions. Participants were required to imagine themselves in an SAE Level 5 AV [14] and report their per-

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ceived comfort levels influenced by vehicular behaviors. Data analysis results indicated that the proposed Kalman filter-based approach could successfully quantify human comfort in AV journeys.

II. Estimation of Human Comfort in AVs

A. Definition of Human Comfort in AVs

In this study, the definition of human comfort from the authors' previous study [13] was inherited. According to the definition, human comfort in AVs is defined as a feeling of not being unsafe or unnatural resulting from the behaviors of the AV itself and the way the AV interacts with the environment.

According to the definition, human comfort is defined as a unidimensional construct, and being comfortable is a state of not being affected by factors related to uncomfortable feelings. The influence of discomfort is emphasized in this definition, where being comfortable can be interpreted as not being uncomfortable. Such emphasis on discomfort originated from the finding that discomfort feeling has a dominant influence on overall human comfort [15] and was employed in multiple studies [6], [7]. Identifying and understanding how discomfort-related factors influence human comfort in AVs is crucial. Based on these understandings, such a definition of human comfort was employed in this study.

B. Dynamic Model of Human Comfort in AVs

Suppose an AV journey where the behaviors of the vehicle can be described by a set of m vehicular behaviors $\boldsymbol{u} \in \mathbb{R}^{m\times 1}$, we define an event as a period of time in the journey when no change of vehicular behaviors occurs. Consequently, the journey can be decomposed into a continuous series of events. The dynamics in comfort levels during the journey can be studied with each event as the fundamental unit. Suppose the journey consists of n continuous events, the dynamic human comfort model can be expressed by

$$L_{k+1} = AL_k + \boldsymbol{B}\boldsymbol{u}_{k+1} \tag{1}$$

where the previous event and the current event are indexed by k and $k+1$, L_{k+1} and $L_k \in \mathbb{R}^{1\times 1}$ denote the comfort levels in events $k+1$ and k, $A \in \mathbb{R}^{1\times 1}$ is the state transition matrix, $\boldsymbol{B} \in \mathbb{R}^{1\times m}$ is the input matrix, and $\boldsymbol{u}_{k+1}$ describes the vehicular behaviors in event $k+1$.

Besides, we can monitor the comfort levels of the passenger through particular methods. The relationship between the observed variable $\boldsymbol{y}_k$ and the comfort level L_k at event k can be expressed by

$$\boldsymbol{y}_k = \boldsymbol{C}L_k \tag{2}$$

where $\boldsymbol{C}$ is the observation matrix.

Considering that comfort is a subjective feeling, noises exist when people perceive and express comfort levels. For simplicity, we assume such noises are Gaussian noises. Based on Equations (1) and (2), a linear time-invariant system state-space model of human comfort in AVs can be formulated as

$$\begin{cases} L_{k+1} = AL_k + \boldsymbol{B}\boldsymbol{u}_{k+1} + w_{k+1} \\ \boldsymbol{y}_k = \boldsymbol{C}L_k + v_k \end{cases} \tag{3}$$

where $w \sim \mathcal{N}(0, Q)$ denotes the noise from the estimation of human comfort level with the dynamic model, $v \sim \mathcal{N}(0, R)$ denotes the noise from the observation of comfort levels.

C. Detecting Human Comfort in AVs with Physiological Signals

The authors proposed a comfort level detection approach based on wearable sensors in [13]. The approach employed a support vector machine (SVM) to detect human comfort levels in AVs with physiological signals collected from multiple wearable sensors. Selected physiological signals included electroencephalogram (EEG), electrodermal activities (EDA), blood volume pulse (BVP), and skin temperature (SKT). For each participant, four SVM classifiers were trained to perform different binary classification tasks: being comfortable vs. uncomfortable, being in low/medium/high uncomfortable level vs. other uncomfortable levels.

The theoretical feasibility of the approach was validated in [13], and this paper employs the approach in practice. Four SVM classifiers with the same functionality as the ones introduced above were trained for each participant in this study. A hierarchical one-vs-all multi-class classifier based on the four SVM classifiers was constructed. The top layer of the hierarchical structure consists of the SVM classifier that discriminates between being comfortable and uncomfortable. Data is passed down to the bottom layer consisting of three one-vs-all SVM classifiers if the classification result from the top layer is uncomfortable. The three one-vs-all SVM classifiers process the data and vote on the final classification of the comfort level. The structure and working process of the hierarchical classifier are demonstrated in Figure 1.

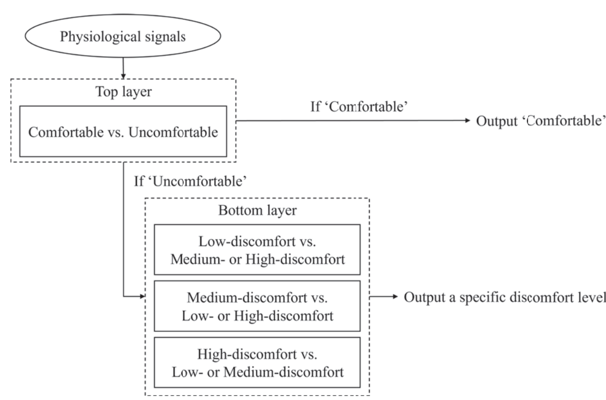


Fig. 1: The structure and working process of the hierarchical one-vs-all multi-class classifier based on SVM.

D. Human Comfort Level Estimation by Fusion

Kalman filter (KF) is an optimal estimator of the system state in a linear system with Gaussian noises [16]. KF has been effectively applied to the continuous estimation of subjective feelings, e.g., trust [17] and comfort [18].

Based on the dynamic comfort model described by Equation (3) and the comfort level detection approach with physiological signals, a KF-based human comfort level estimation procedure was proposed. The comfort level estimation based on physiological signals was considered the observed variable $y_k \in \mathbb{R}^{1\times 1}$ in the state-space model. And thus the observation matrix $C \in \mathbb{R}^{1\times 1}$ should be a scalar value. The procedure is explained with Algorithm 1.

Algorithm 1 Comfort Estimator Based on Kalman Filter

$k \leftarrow 1.$
$L_k \leftarrow C^{-1} y_k$ ▷ Initialize system state
$\Sigma_k \leftarrow 1$ ▷ Initialize covariance
while $k < n+1$ **do**
  $\hat{L}_{k+1} \leftarrow AL_k + \boldsymbol{Bu}_{k+1}$ ▷ Predict system state
  $\hat{\Sigma}_{k+1} \leftarrow A\Sigma_k A + Q$ ▷ Predict covariance
  $\hat{y}_{k+1} \leftarrow C\hat{L}_{k+1}$
  $v \leftarrow y_{k+1} - \hat{y}_{k+1}$ ▷ Innovation
  $K \leftarrow \hat{\Sigma}_{k+1} C (C\hat{\Sigma}_{k+1} C + R)^{-1}$ ▷ Kalman gain
  $L_{k+1} \leftarrow \hat{L}_{k+1} + Kv$ ▷ System state correction
  $\Sigma_{k+1} \leftarrow (I - KC)\hat{\Sigma}_{k+1}$ ▷ Covariance correction
  $k \leftarrow k+1$
  return L_{K+1}
end while

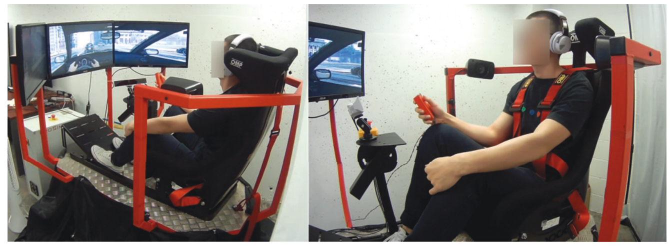
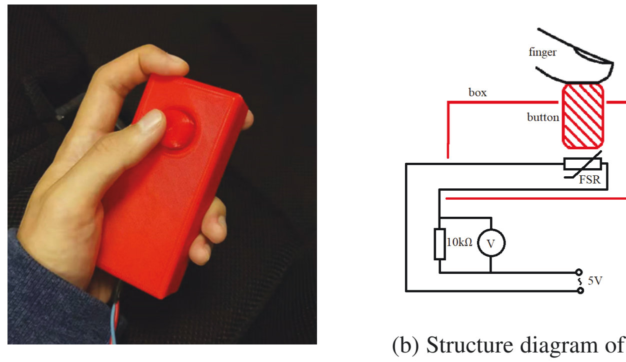


Fig. 2: The high-fidelity driving simulator used in this study.



(a) Picture of the button box.

(b) Structure diagram of the button box.

Fig. 3: Button box for comfort level collection.

III. User Study and Data Processing

This study employed the stimuli, study protocols, and part of the data in the authors' previous study on predicting human comfort levels in AVs based on wearable sensors [13]. Partially based on [13], this study had an independent sample of 10 participants and explored an entirely new topic. For the brevity and clarity of reading, the stimuli and study protocol were selectively reintroduced in this section. One figure from [13] was reused in this section with permission.

A. Participants

A total of 10 participants (eight male, two female) participated in the study. Ages of participants ranged from 26 to 41 years (M = 30.1 years, SD = 4.2). All participants held valid U.S. driver's licenses. After completing the experiment, all participants received equal monetary incentive compensation.

B. Stimuli

A total of 27 video AV journeys with synchronized 6-DOF motions were created as the stimuli for our study. Each video lasted around three to five minutes. The journeys take place on three types of roads: highway, city, and mountain/rural roads. Three driving styles were designed for the AV, including gentle, normal, and aggressive styles.

Figure 2 shows the high-fidelity driving simulator was used to present the stimuli to the participant. The driving simulator could generate 6-DOF motions of the vehicle in the stimuli. A three-screen display system was equipped to provide a wide field-of-view (FOV). Combining the motion simulation and wide display FOV, the simulator could generate an immersive experience for the participant.

C. Data Acquisition

1) Human Comfort Levels Acquisition: A button box shown in Figure 3a was employed to collect the real-time comfort level of the participant. The button was pressed when the participant perceived discomfort due to the vehicle's behavior. A harder pressing on the button represented a higher level of discomfort. Not pressing the button represented perceiving no discomfort. The Z-score standardization [19] was applied to mitigate individual differences in pressing forces. Standardized pressing forces were calculated as self-reported comfort levels and were regarded as the ground truth comfort levels.

2) Physiological Signals Acquisition: Two types of wearable sensing devices were used in this study, including the Empatica E4 wristband and Emotiv EPOC X headsets. The wristband provided measurements of EDA, BVP, and SKT. The headsets measured EEG of the participant. The preprocessing and feature extraction of these signals followed the processes in [13]. Data collected from all journeys was processed for the training and implementation of the physiological signal-based comfort estimation method. A total of 3,032 samples with 96 features per sample were generated for each participant.

3) Vehicular Behaviors Identification: Highway presents a challenging scenario for AVs [20], and thus a great volume of studies have contributed to the realization of highway automated driving [21]. To further supplement the existing studies from the comfort perspective, highway journeys were selected to examine the effectiveness of the comfort estimation method. Six maneuvers were identified within highway journeys: lane switching to the left/right lane, free driving, following, overtaking, and emergency braking. Headway distance was a critical influential factor of comfort in highway automated driving [22]. Three levels of headway distance was defined within the journeys: close, medium, and far. The maneuvers and different levels of headway distance were dummy coded to generate nine binary indicators in the vehicular behavior vector $\boldsymbol{u} \in \mathbb{R}^{9\times 1}$. Each journey was sliced into 0.5s segments to extract the $\boldsymbol{u}$ in each segment. A continuous sequence of segments with the same $\boldsymbol{u}$ values was marked as an event in the journey. A total of 317 events were generated within highway journeys. Vehicular behaviors $\boldsymbol{u_k}$ in event k would be used as the dynamic model input in Eq. (3).

D. Study Procedures and Protocols

Before the experiment, the participant would be introduced to the experimental protocols and sign the consent form. After providing consent to participate in the study, the participant would be introduced to the tasks to complete during the experiment. Because the vehicle was fully autonomous, no driving-related task was required and the only task was to experience the journey and report the real-time comfort level with the button box.

The experimental journeys were evenly spread across three separate days to avoid fatigue. Nine journeys experienced each day came from one specific type of road. A questionnaire [23] was conducted to monitor any sign of motion sickness after each journey. No sign of motion sickness was recorded during the study, thus no further information would be reported. The experiment for each day typically lasted for an hour. The experiment procedure and the study protocol were approved by the Institutional Review Board of Clemson University.

E. Data Processing

Among the 317 events identified from the nine journeys, five test trials were selected where changes in self-reported comfort levels were found along vehicular maneuver transitions. Trial 1 consists of 29 events covering lane switching, free driving, and overtaking maneuvers. Trial 2 consists of 21 events covering lane switching, free driving, following, and emergency braking maneuvers. The vehicle was driving in the aggressive style in Trials 1 and 2. Trial 3 consists of 17 events covering lane switching, free driving, and following maneuvers. Trial 4 consists of 12 events covering lane switching and free driving maneuvers. The vehicle was driving in the gentle style in Trials 3 and 4. Trial 5 consists of 13 events covering lane switching, free driving, and overtaking maneuvers. The vehicle was driving in the normal style in Trial 5. The test trials covered 92 events, and the rest 225 events were used as training data for fitting dynamic models and calculating KF parameters.

A multi-class comfort level classifier based on physiological signals was trained for each participant. The classifier was trained based on the 2,703 samples for each participant, excluding the samples within the test trials. The classifier's output would be used as the observed variable y in the KF estimator. The original output was categorical in four levels: low-, mid-, hi-discomfort, and comfortable. Categorical labels were further processed into numerical labels. For discomfort labels, the average self-reported comfort level for each type of discomfort label was calculated and assigned to the corresponding label. The numerical label for comfortable samples was assigned as zero.

Within each event, the average self-reported comfort level and physiological signal-based comfort level estimation were calculated for each participant. These values were further used to obtain the parameters of the KF. The state transition model in Equation (1) was fitted for each participant based on the event-based self-reported comfort levels in the training data. The variance of residuals from the state transition model fitting was calculated as the process noise covariance Q value in the KF for each participant. The variance of the errors between physiological signal-based comfort estimations and self-reported comfort levels in the training data was calculated as the measurement noise covariance R value in the KF for each participant.

To evaluate the performance of different comfort estimation methods, a series of performance metrics were calculated across the test trials for all participants, i.e., mean absolute error (MAE), root mean squared error (RMSE), and R squared value (R^2). Both MAE and RMSE are widely used metrics in model evaluation and are negatively oriented, which means that a lower value indicates a better performance. While MAE is more intuitive and easier to interpret, RMSE penalizes larger errors [24]. R^2 is another commonly used model evaluation metric that demonstrates the proportion of the total variance in the dependent variable explained by the independent variables [25].

IV. Results and Analysis

The three methods of comfort estimation were applied to the test trials to obtain the dynamic model estimation, physiological signal-based estimation, and KF estimation of human comfort levels. The performance metrics mentioned above were calculated for each method.

Figure 4 displays the metrics of each comfort evaluation approach for all participants. Table I contains the mean values of the performance metrics across participants for each comfort evaluation approach. From Figure 4, we found that the KF estimator had the lowest MAE among the three approaches with seven participants, the lowest RMSE among the three approaches with nine participants, and the highest R^2 among the three approaches with eight participants. On average, KF achieved MAE value of .231, RMSE value of .314, and R^2 value of .444, suggesting that the KF

TABLE I: Comfort Level Estimation Performance

Method	MAE	RMSE	R^2
Kalman filter fusion	.231	.314	.444
Physiological signal	.283	.405	.402
Dynamic model	.267	.373	.253

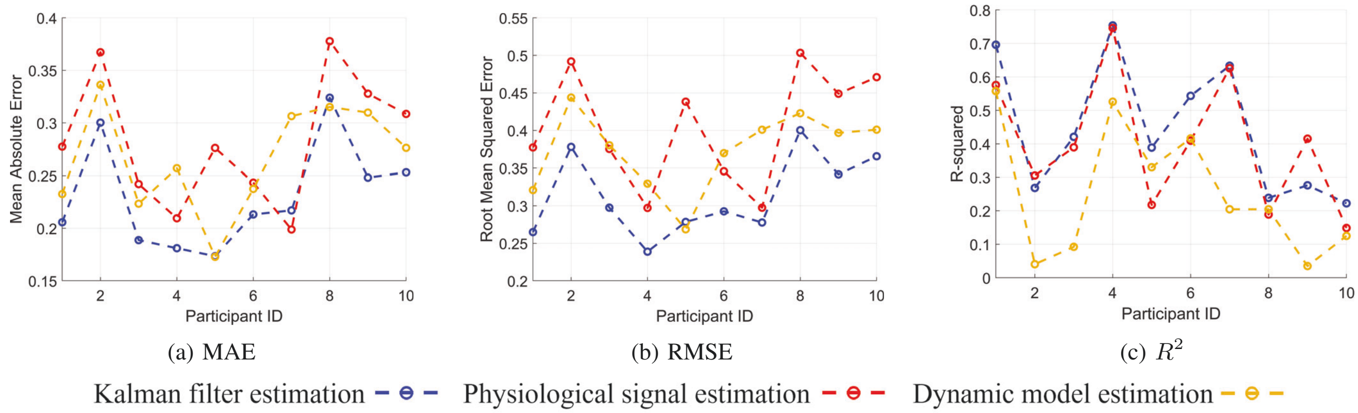


Fig. 4: Comfort estimation performances with different approaches across participants.

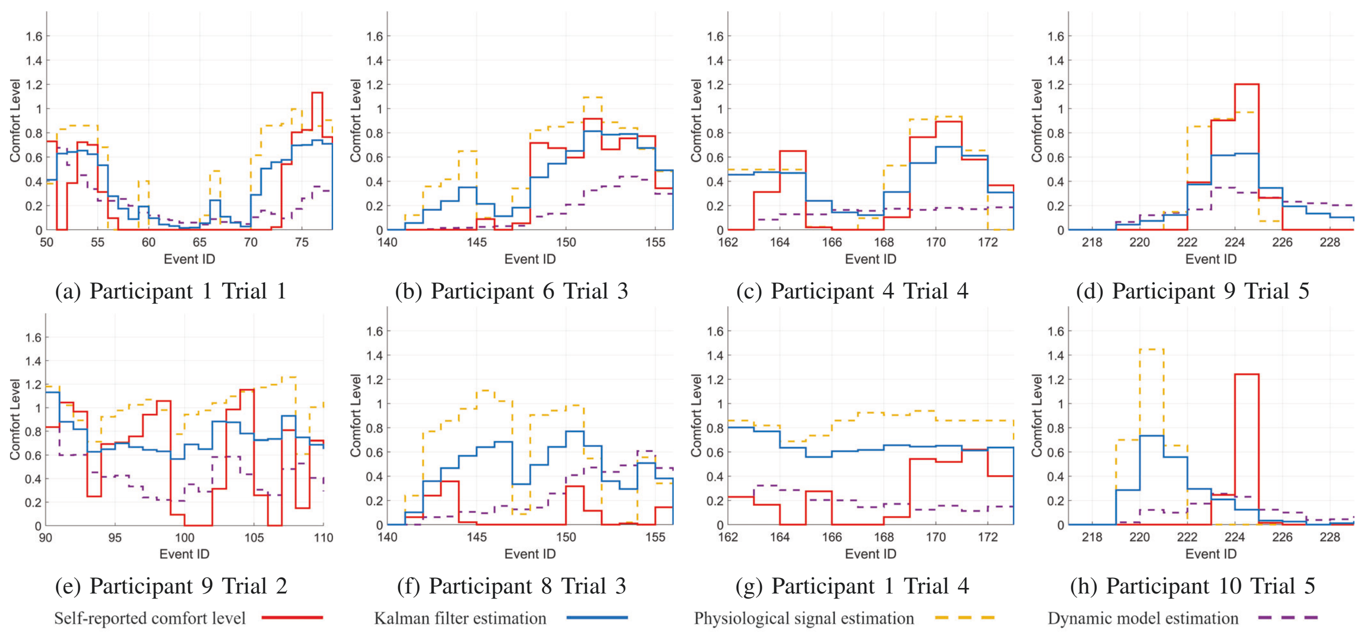


Fig. 5: Examples of comfort estimation results for some participants during various test trials.

had the overall best performance of comfort estimation among the three approaches. The physiological signal-based approach had higher MAE, RMSE, and R^2 values than the dynamic model, indicating that the physiological signal-based approach might generate large estimation errors more frequently than the dynamic model but estimate variations in comfort levels better.

Overall, the KF estimator could generate a more accurate estimation of comfort level than the other two approaches. Furthermore, good performances from the dynamic model and physiological signal-based approach could further enhance the good performance of the KF estimator. Performance metrics were evaluated for each participant in different test trials. The evaluation baseline was established referring to another comfort modeling study using similar metrics [26]. In test trials with good estimation accuracy from the KF ($R^2 \geq .40$, $MAE \leq .25$, $RMSE \leq .30$), both the physiological signal-based approach and the dynamic model achieved acceptable accuracy ($R^2 \geq .20$, $MAE \leq .30$, $RMSE \leq .40$), e.g., in Figures 5a, 5b, 5c, 5d. Whereas in test trials where both the physiological signal-based approach and the dynamic model failed to provide an acceptably accurate estimation ($R^2 < .20$, $MAE > .30$, $RMSE > .40$), the KF could not yield accurate estimation either ($R^2 < .20$, $MAE > .30$, $RMSE > .40$), e.g., in Figures 5e, 5f, 5g, 5h. The KF estimator overcame the weaknesses of the physiological signal-based approach and the dynamic model through model fusion. However, model fusion could not handle the situation when both individual models in the fusion failed to work. Therefore, it is critical to have accurate models before applying the KF, and a significant way to improve the performance of the KF estimator is to improve the individual models in the KF.

In summary, the proposed KF-based comfort estimation approach was implemented and tested in this study. The KF estimator successfully estimated the human comfort levels of different participants in multiple test trials. The performance metrics of different comfort estimation approaches were calculated. The KF-based approach outperformed the physiological signal-based approach and the dynamic model in all metrics. The physiological signal-based approach showed a stronger ability to explain variations in comfort levels than the dynamic model but tended to generate large errors more frequently. Although the KF-based approach outperformed the other two approaches in comfort estimation, the performance of the KF-based approach was dependent on the performances of the other two approaches. This suggested that it is critical to have accurate models before applying model fusion techniques, e.g., KF, to achieve good performance and that improving the the individual models is a significant way of improving the performance of the model fusion.

V. Conclusions

We proposed a dynamic human comfort model and a KF-based approach to estimating human comfort in AV journeys. The dynamic model incorporates vehicular behavioral factors and has a state-space model formulation that makes it useful for future designs of AV controllers or decision-making algorithms. A KF-based comfort level estimation approach was proposed in this paper that could fuse comfort level estimations from the dynamic model and the physiological signal-based estimation method. An empirical study with 10 participants was conducted to evaluate the effectiveness of the proposed comfort estimation method. Results indicated that the proposed KF-based comfort level estimation approach successfully measured the comfort levels of the participants and outperformed both the dynamic model and the physiological signal-based approach. This study shows the potential of estimating human comfort levels by fusing the model-based approach and physiological approach.

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