Driver Posture Prediction Using Pressure Measurement and Deep Learning

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I. INTRODUCTION

Driving automation technologies are expected to substantially reduce the 94% of road traffic accidents that are attributed to human errors, but also yield new types of safety concerns [1]. One critical issue is related to the transition between the human driver manoeuvres and automated operations [2]. Monitoring driver behaviour to evaluate the driver's intention and the readiness to take over could facilitate a safe transition. Another consistently mentioned topic is the occupant protection in case of automated vehicles (AVs) [3]. Drivers may be in a seated posture far from the current standard driving posture and existing safety protection systems may not be adapted to this new situation. In case of an accident, real-time postural monitoring is needed to develop a more personalised and efficient protection system.

A large amount of studies has been initiated to develop driver posture monitoring systems using various types of sensors, such as cameras and pressure sensors, among many others [4-5]. As opposed to cameras, pressure sensors do not suffer from the varying lighting conditions in the cabin and can be invisibly integrated into the driver seat. Reference [6] used the Support Vector Machine (SVM) and the pressure values at both backrest and seat pan surfaces to estimate eight postures (pressing accelerator, looking right/left, looking right/left rear, holding phone right/left and pressing brake). Training data was collected from seven participants and the total estimation error of the test data from the same participants was 20%. Reference [7] also used the SVM technique. Based on the pressure centres in addition to the pressure values, in-vehicle activities including cell phone use, looking ahead and sleeping performed by 14 drivers were classified. An accuracy of 76.8% in the cross evaluation for new drivers was achieved. However, only three driver activities were involved. The results of these two studies also showed that the postural information only related to driver' head or hands cannot be reliably retrieved from pressure measurement. In reference [8], the authors revealed the potential of detecting four different driver seated positions (normal, forward, left and right inclined trunk) by analysing pressure centre trajectories, but quantitative results were not given. Although this area is covered, only a limited number of driver activities were investigated and few studies performed cross validation to test the system performance on new driver's data.

This study aims to apply a deep learning method to predict driver postures using pressure measurement. A wide range of in-vehicle driver activities is included to extract typical postures for classification. Both the overall validation on new postures of the familiar drivers and the Leave-One-Out (LOO) cross validation on unknown drivers are performed. We will discuss our findings, encountered problems and future research directions.

II. METHODS

Experiment

Twenty-three male and female volunteers with at least three years of driving experience, aged from 22 to 65 years (M=40, SD=11.5), were selected according to stature and weight. They varied from 153 to 195 cm (mean=171, SD=13) in height and from 18.2 to 43.4 kg/m2 (mean=27.8, SD=6.7) in Body Mass Index (BMI). Université Gustave Eiffel (formerly French Institute of Science and Technology for Transport, Development and Networks, IFSTTAR) ethics committee approved the experimental protocol. Informed consent was obtained prior to experiment from all participants.

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Participants were instructed to perform 42 activities in a random order on a mock-up (Fig. 1) to cover a large range of in-vehicle postures. The activities included both primary driving operations such as standard driving, braking, switching gear, etc., and non-driving activities such as drinking, texting and picking up an object in a car, etc., as well as possible new actions that may occur in an AV such as relaxing with the feet on the floor, reading a book, etc. Two Xsensor pressure mats (Model: PX 100: 48.48.02) were used to measure the pressure distributions on the seat pan and backrest with a sampling frequency of 25 Hz. In addition, driver movements were recorded by a marker-based optical motion capture system VICON with a frequency of 50 Hz. An electronic trigger was used to synchronise the two measurement systems.

Fig. 1. Experiment configuration

Motion Reconstruction

Motions recorded by VICON were reconstructed using RPx [9], a customized human model based motion analysis and simulation tool. After reconstruction, the body was simplified as a skeleton with 28 articulated joints from head to feet and its posture was described by an array of joint angles as well as joint centre positions. Reconstructed postures were considered as the ground truth. A motion thus consists of a succession of postures varying in time. Driver postures in this study were mainly determined by trunk and feet positions.

Definitions of Typical Postures

Three angles were first calculated for each frame to represent global trunk rotation, inclination and lateral tilt relative to the Standard Driving Posture (SDP). To avoid label ambiguity, special attention was paid to small and large trunk movements with respect to the SDP. The intermediate transitional trunk positions were thus excluded. A cluster analysis using mean shift [10] was performed to group the remaining trunk postures into different classes. Among the trunk positions with large deviations from SDP, five trunk posture classes (P1, P2, P3, P4 and P5) were identified. Among the trunk positions with small deviations, driver postures were further subdivided into four additional classes (P0, P6, P7 and P8) according to the feet positions, corresponding to accelerating (SDP), braking, pressing the clutch and resting both feet on the floor, respectively. The definitions of nine posture classes was illustrated in Fig. 2. Apart from the nine discrete posture classes, the intermediate transitional postures were labelled *Pm* to *Pn* (*m*≠*n*) for evaluating the generalisation ability of the classifier in a motion.

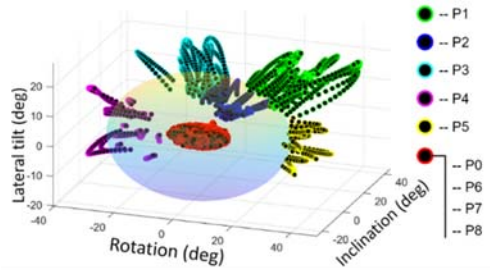

Fig. 2. Definitions of posture classes. The positive direction of each dimension denotes right rotation, forward inclination and lateral right tilt, respectively.

Deep Learning Classifier

We adapted a pre-trained deep learning neural network ResNet-50 [11] using the transfer learning technique [12] to classify the nine postures. For the overall evaluation on new postures from known drivers, labelled samples from all participants were randomly combined into two data sets for training (85% of all data) and testing (15%) the classifier. For assessing the prediction capacity for a new person, a leave-one-out (LOO) cross-validation was performed for each participant. For evaluating the results of classification, the *Precision* (the number of true positive predictions divided by the total number of true positives and false positives), *Recall* (the number of true

positive predictions divided by the total number of true positives and false negatives), and *F_1 Score* (a harmonic mean of Precision and Recall) of each class were computed.

Using a deep learning classifier, the final predicted class is the one which has the maximum probability. The postures in a motion thus can be continuously predicted by decoding the change of the scores over time. To improve the consistency and reliability of these scores, a Gaussian weight was applied for adjacent frames with the largest value for the most recent one.

Pressure Image Processing

According to the effective contact area, each mat was tailored to 42 by 44 sensor elements for both seat pan and backrest (Fig. 3). Raw measurements were filtered by an averaging window filter of size 3 by 3. Then, pressure data from the backrest and seat pan were normalised by their respective peak pressures to reduce data variability due to weight. Finally, we horizontally concatenated the backrest and seat pan pressure distribution maps to a single image (44×84) as shown in Fig. 3. Each image was further resized and converted to a colour image of size 224×224×3 as required by the deep learning model. With the help of reconstructed motion data, the correspondence between pressure images and the nine pre-defined posture classes was established.

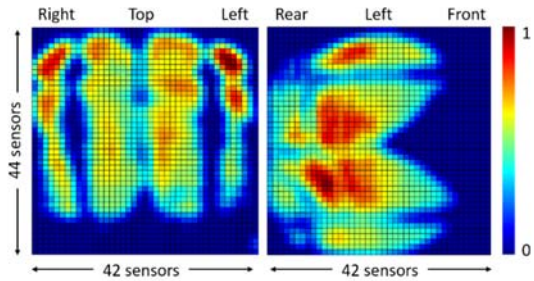

Fig. 3. Normalised pressure distributions from backrest (left) and seat pan

III. RESULTS

The results of classification by the overall test with 15% of total datasets (N=1860) and LOO 23-fold cross-validation (N=12412) are summarised in Table I. The overall test demonstrated an average F_1 Score of 94% (SD=2%) for all classes. The average Recall was 97% with a range between 89% and 100%, and the average Precision was 93% varying between 83% and 98%. In contrast, the LOO cross validation showed an average F_1 Score of 51% (SD=19%). The Recall ranged from 22% to 85% (Avg=50%, SD=20%) and the *Precision* varied between 28% and 90% (Avg=54%, SD=21%).

TABLE I

TYPICAL POSTURE CLASSIFICATION RESULTS

Class	Recall		Precision		F_1 Score	
	Overall	LOO	Overall	LOO	Overall	LOO
P0	89%	85%	98%	68%	94%	76%
P1	98%	62%	97%	90%	97%	73%
P2	93%	62%	95%	51%	94%	56%
P3	98%	40%	88%	45%	92%	42%
P4	100%	56%	93%	72%	96%	63%
P5	94%	33%	92%	28%	93%	30%
P6	100%	30%	83%	29%	91%	29%
P7	97%	57%	93%	61%	95%	59%
P8	100%	22%	95%	40%	97%	28%
Avg	97%	50%	93%	54%	94%	51%
Std	4%	20%	5%	21%	2%	19%

When it comes to continuous posture prediction in a motion, two examples are illustrated in Fig. 4. In the first example on the left, the participant rotated the trunk 45° to right (P5) and then 45° to left (P4), consecutively. In the second situation on the right, the participant moved the right foot to press the brake pedal (P6). For both cases, the standard driving posture (P0) was resumed as the starting posture as well as the ending posture. The probability of each class was visualised as a function of time when the motion proceeded forward. In addition, the postures that contributed to the training process and the pedal engagement moments were marked on the

plots. The ground truth of motion labels was displayed below each example as reference. For both examples, the predicted class with the highest score could correctly identify the transitional postures, even though those postures were not included in the training process.

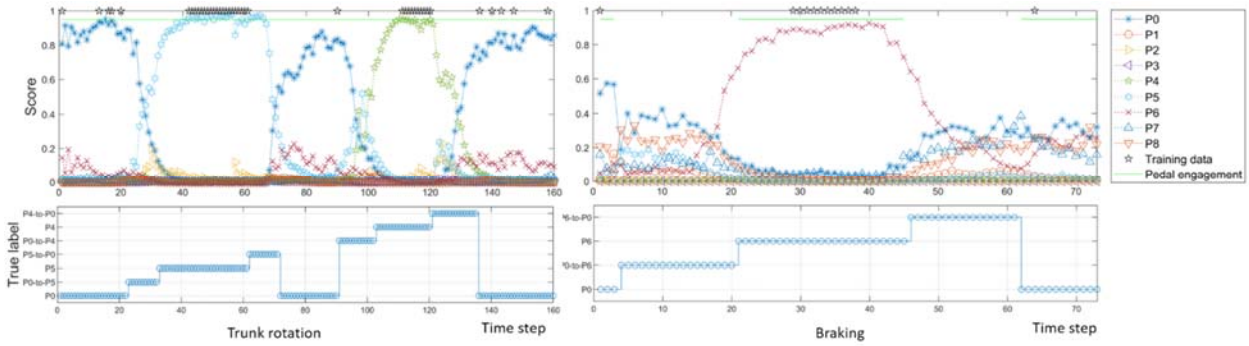

Fig. 4. Two examples showing the detection of the transitional postures between different postural classes. Left: a participant rotated the trunk 45° to right (P5) from the standard driving posture (P0) and then 45° to left (P4), consecutively. Right: a participant moved the right foot from the standard driving position (P0) to press the brake pedal (P6).

IV. DISCUSSION

This study was aimed to predict driver trunk and feet positions using pressure measurement. A deep learning classifier was trained to recognise nine typical driver postures and meanwhile to continuously predict posture change in a motion. Our preliminary results show that the classifier trained on overall data set was promising. Typical postures from the test set were recognised with an average F_1 Score of 94%. For a driver known by the classifier, the posture class as well as posture change in a motion could be reliably predicted as shown in the examples above, thus providing necessary inputs for interpreting driver behaviours. In addition, foot position could be identified before the real contact with the brake pedal. The system achieved real-time performance and was capable of handling over 100 frames per second (fps). However, for LOO cross-validation, the average F_1 Score was only 51%, much lower than the overall evaluation when the data of all participants were used. This might be due to the pressure distribution diversities caused by individual body size variabilities and inter-participant difference in posture behaviours. In order to overcome this limitation, one solution could be to increase the database size to include a broader driver population and postures. Another alternative is to extract more relevant features from pressure distribution, which are more sensitive to postural variation while less affected by body size.

V. ACKNOLEDGEMENT

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