A Marker-free Head Tracker Using Vision-based Head Pose Estimation with Adaptive Kalman Filter

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Abstract—The immersion and the interaction are the important features of the driving simulator. To improve these characteristics, this paper proposes a low-cost and mark-less driver head tracking framework based on the head pose estimation model, which makes the view of the simulator can automatically align with the driver’s head pose. The proposed method only uses the RGB camera without the other hardware or marker. To handle the error of the head pose estimation model, this paper proposes an adaptive Kalman Filter. By analyzing the error distribution of the estimation model and user experience, the proposed Kalman Filter includes the adaptive observation noise coefficient and loop closure module, which can adaptive moderate the smoothness of the curve and keep the curve stable near the initial position. The experiments show that the proposed method is feasible, and it can be used with different head pose estimation models.

I. INTRODUCTION

The intelligent driving is a currently hot research and trend, which requires a combination of multiple disciplines and multiple algorithms. Developing and testing algorithm in the real intelligent vehicles is an expensive and time consuming process[1]. The development of simulation technology provides a alternative way, the simulator can offer physically and visually realistic simulation for many research goals, it can also collect a large amount of annotated samples to leverage the deep learning and machine learning[2][3].

The driving simulator cockpit is a widely used experimental platform. The one of the key features is the immersion. To improve the visual realism, a multi-screen mode is often used. But this will cause the distortion of the graphic ratio, and the field of the virtual view is limited and fixed. The cost of the multiple screens is also higher. Another way is to use virtual reality (VR) devices, this will bring two problems: 1. The dizziness caused by the serious mismatch between the fixed seat and the dynamic virtual graphic; 2. The VR glasses will cover the driver’s face, which makes it impossible to carry out the research on the driver’s state[4][5]. Therefore, this paper aims to propose a low-cost adaptive view simulator solution through head tracking, as shown as Fig.1.

The head pose as an important cue has been used in many human machine interaction fields. Nigel Sim et.al. proposed a wearable head-tracking device with inertial sensors as indicator of human movement intentions for Brain-Machine Interface application[6]. Chang Ho Kang et.al. presented a sensor fusion method which integrate the IMU, IR LED, CCD camera and other sensors[7]. Adrian et.al. developed a low-cost head tracking device based on the SteamVR Tracking technology for virtual reality system[8]. These methods usually adopt different types of sensors to build the system. There are also several similar products in the flight simulators, such as TrackIR and Opentrack. They usually need some special device or optical marker, like IR Camera. Although the newer FaceTrackNoIR only needs the RGB camera, they all require the user to manually adjust the relative parameters, and they usually use some traditional head estimation methods. This paper aims to adopt the state-of-the-art estimation model based on the deep learning which can improve the accuracy of the system.

To achieve the low-cost and mark-less solution, only the RGB sensor is used as the input device, and the head pose estimation model based on deep learning is adopted to improve the basic accuracy of the solution [9]. Due to the error of the model, the estimation curve of consecutive frames fluctuate sharply. The Kalman Filter is used to handle this problem [10]. By analyzing the error distribution of the estimation model, an adaptive Kalman Filter is proposed to improve the performance of the solution, which includes an adaptive observation noise coefficient and a loop closure module, it can adaptive moderate the smoothness and keep the curve stable near the initial position. Finally, the proposed framework is verified by the designed experimental platform.

The main contribution of this paper as follows: 1. A simple, low-cost and effective framework of head tracking is proposed, which only uses the normal RGB camera; 2. According to the characteristics of the head pose estimation model, the adaptive Kalman Filter is proposed to improve the performance of the method.

The paper is organized as follows. Section 2 describes the
proposed head pose tracking method. Section 3 illustrates the designed experiment platform and multiple experiment results. The conclusion and future work are in the Section 4.

II. METHODOLOGY

A. Overview

The purpose of this paper is to build a simulator whose view can be automatically adjusted with the driver’s head pose based on frontal camera. The benefits are as follows: 1. It can improve the immersion and interaction of the simulator. The driver’s view will be unconstrained and non-fixed, and the virtual camera will be synchronized with the driver’s head pose; 2. The extracted head pose can also be used to monitor the state of driver; 3. It is a low-cost solution through a non-invasive camera sensor.

The development of deep learning and computer vision technology provides the basis for the proposed method. The state-of-the-art head pose estimation methods can achieve an error of $4 - 5^\circ$ on some public datasets. Although these methods work well, they cannot be directly applied to the simulator due to the inconsistency and volatility of the estimation. To solve this problem, this paper proposes a framework combining adaptive Kalman Filter (KF) and head pose estimation as shown as in Fig.2.

Assume that the true vector the driver’s head pose at $k$ time is $\bar{x}_k = (\bar{p}, \bar{y}, \bar{r}, \bar{v}_p, \bar{v}_y, \bar{v}_r)$. The proposed method takes the estimation of the head pose estimation method based on deep learning as the observation vector $z_k = (\tilde{p}, \tilde{y}, \tilde{r})$. The posterior state estimation $\hat{x}_{k|k} = (\hat{p}, \hat{y}, \hat{r}, \hat{v}_p, \hat{v}_y, \hat{v}_r)$ is used as the coordinates of the virtual camera. To optimize the filter algorithm, this paper adopts an adaptive observation noise $R_k$ based on the different performance of the estimation model in different pose intervals. In addition, the proposed method also uses loop closure to make the virtual camera return to the initial position more effectively.

B. Head pose estimation

Estimating the head pose is a crucial problem that has a large amount of applications, which is a task that needs to infer the 3D pose ($\text{Pitch, Yaw, Roll}$) of the head from the input image. There are several different methods which use different input data, including depth image, RGB image and video clips. Considering the cost of hardware and computing, this paper will focus on the model based on a single RGB image.

With the development of the deep learning, the research on the head pose estimation has also achieved good results. In this paper, the different state-of-the-art head pose estimation models will be used to observe the driver’s head. These methods have different performance and accuracy on different datasets, like BIWI[11], AFLW2000[12] and AFLW[13] etc.
The error range is about 3 – 5°. Using the different models are also to test the robustness of the proposed method.

C. Adaptive Kalman filter

The error range is about 3 – 5°. Using the different models are also to test the robustness of the proposed method.

$K_k = \frac{P_k|k-1H_k^T}{H_kP_k|k-1H_k^T + R_k}$ (4)

$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H_k\hat{x}_{k|k-1})$ (5)

$P_{k|k} = (I - K_kH_k)P_{k|k-1}$ (6)

$H_k = [I_{3\times3} \ 0]$ (7)

The $K_k$ is the Kalman gain factor, $H_k$ means the measurement matrix which converts the state variable into the corresponding observation variable. The $\hat{x}_{k|k}$ is the posterior state estimation, which is also the pose of the virtual camera of the simulator. The $z_k$ is the output of the head pose estimation model, which as the observation value. The $P_{k|k}$ is the posterior estimation covariance at $k$ time. The $R_k$ is the observation noise covariance, which is related to the estimation model and will also affect the performance of the filter.

To determine the $R_k$, the several head pose estimation models are analyzed. Through statistics, it is found that these models have different performances in different intervals of the head pose. Usually, the accuracy is higher when the pose angle is small, otherwise the error is higher, especially $Y_{aw}$ and $Roll$. For example, the AFLW2000 dataset, a widely used benchmark, is used to test the head pose estimation model, and the result is as shown as in the Fig.4. The $Y_{aw}$ and $Roll$ of the samples are taken as the $X$ and $Y$ axis, and the Error is taken as the $Z$ axis. The blue 3D points represent the different samples. A 2D Gaussian function is used to fit the points as shown as the curved surface in the Fig.4.

Therefore, the adaptive $R_k$ is proposed by this paper as follows:

$$R_k(x) = \tau - \lambda \cdot \frac{1}{\sqrt{2\pi}\sigma} \exp(-\frac{(x - \mu)^2}{2\sigma^2})$$ (8)

Where the $\tau$ means the offset, the $\lambda$ represents the amplitude factor, the $\sigma$ and $\mu$ are the mean and variance respectively. So the $R_k$ can be adaptively adjusted in the iterative process. It can make the filtered value close to the observed value when the rotation angle is small, while the filtered value changes smoother when the rotation angle is large.

D. Loop closure

There are two important points for the experience of use: First, the rotation of the simulator virtual camera is smooth. The smoothness of the filter can be changed by adjusting the $Q_k$. Based on this, the adaptive $R_k$ makes the filter close to the real value. Another point is whether the virtual camera can accurately return to its initial position in time. The driver spends more time in a relatively position, such as looking ahead. Moreover, the driver is more sensitive to whether the virtual camera is back-aligned than whether it is rotated to the correct angle. To handle this situation, the loop closure is added into the proposed pipeline.
Fig. 5. The error distributions of different model in the AFLW2000 dataset. The X axis means the angle intervals, the Y axis represents the corresponding error.

The loop closure is widely used in the Simultaneous localization and mapping (SLAM) algorithm. Usually, the purpose is to reduce the accumulative error by detecting whether the agent has return to a previously visited position. In this paper, the loop closure can be used to maintain the virtual camera close to the initial position by fusing the observed value with the initial value when they are close.

\[ z_k = \begin{cases} 
\xi \cdot z_k + (1 - \xi) \cdot \kappa, & s.t. \|z_k - \kappa\| \leq \theta \\
\kappa, & s.t. \|z_k - \kappa\| > \theta 
\end{cases} \]  

(9)

where the \(\kappa\) is the initial value, the \(\xi\) is the fusion factor and the \(\theta\) means the threshold. When the driver moves in a small range near the initial position, the simulator will keep the initial scene as soon as possible. This is more in line with actual experience.

III. EXPERIMENTS

A. Experimental platform

The purpose of this paper is to improve the driving simulation. So a driving simulator is used as the experiment platform as shown as the left of the Fig.2. The simulator includes a computing server (RAM 32GB, CPU i7, GPU 2080), a set of input devices (Logitech G29), a RGB Camera (Kinect V2). The camera does not need to be calibrated.

The software of the simulator is developed by the Unity3D and Airsim, which can simulate the several operations of the forklift in the warehouse scenario as shown as the Fig.1. So the virtual camera can be controlled easily. Finally, more than 10,000 driver frontal images have been collected like the Fig.3, and they are consecutive frames.

B. Head pose estimation models

To test the robustness of the proposed pipeline, two different head pose estimation models, the FSA-Net[14] and the Hopenet[15], are adopted in the next experiments, which have different performance in some open datasets. The FSA-Net is one of the state-of-the-art methods, which proposes a fine-grained structure mapping for spatially grouping features before aggregation. The Hopenet presents a robust way to determine pose by training a multi-loss model on a large synthetically expanded dataset to predict intrinsic angles (yaw, pitch and roll) directly from image intensities through joint binned pose classification and regression.

The AFLW2000 is a widely used benchmark, which contains 2000 different head pose images with different real-world backgrounds and light conditions. In this section, it is used to determine the error distribution of the head pose estimation model in different pose intervals. The results are as shown as the Tab.1 and Fig.5. Overall, the FSA-Net performs better, which has a lower error in different angles. But what they have in common is that the Gaussian distribution is more obvious on the Pitch and Roll. Then the Eq.8 can be used to fit these distributions.
TABLE I
EXPERIMENTS TO CALCULATE THE GAUSSIAN FITTING PARAMETERS OF DIFFERENT MODELS BASED ON THE AFLW2000 DATASET

| Methods  | Angles | \( \lambda \) | \( \mu \) | \( \sigma \) | \( \tau \) |
|----------|--------|----------------|----------|----------|----------|
| FSA-Net  | Yaw    | 4.11           | -0.35    | 30.87    | 7.64     |
|          | Pitch  | 312.07         | -5.19    | 132.41   | 315.43   |
|          | Roll   | 3.29e+05       | -5.62e-01| 4.44e+03 | 3.29e+05 |
| Hopenet  | Yaw    | 7.017          | -5.57    | 48.28    | 10.74    |
|          | Pitch  | 229.18         | -8.30    | 101.37   | 232.88   |
|          | Roll   | 9.35e+04       | 4.76e-02 | 2.219e+03| 9.35e+04 |

C. Comparison

To evaluate the performance of the loop closure, the standard KF is modified by the Eq.9, and the \( \xi \) is 0.618 and the \( \theta \) is 2. It can be seen that the loop closure can make the angle more stable and close to the initial value when the angle is near the initial value. In the remain angles, the curves of standard KF and the filter with loop closure are coincide.

The purpose of this paper is to propose a framework which takes the head pose estimation model as the input. The framework could handle different estimation models, which means that the proposed framework can be optimized as the head pose estimation technology improves. So the two different head pose estimation models are used to handle the same driver frames as shown in the Fig.8. It can be seen that the original outputs of the models have large differences and fluctuations. The proposed method can significantly reduce this kind of deviation, the trends of the curves are basically same. It shown that the different head pose estimation model with different accuracy can be used in the proposed framework.

IV. CONCLUSION

To improve the immersion and the interaction of the driving simulator, this paper proposes a framework which can make the view of the simulator automatically change with the driver’s head pose. The proposed method only uses the RGB camera without the other hardware or marker. The challenge is that the currently head pose estimation methods still have certain errors, which can not be directly adopted. To handle this problem, this paper proposes a framework which combines the head pose estimation and the Kalman Filter. By analyzing the error distribution of the estimation model and user experience, the adaptive Kalman Filter is proposed, which includes the adaptive observation noise coefficient \( R_k \) and loop closure module. The adaptive \( R_k \) makes the curve smoother in the area where the estimation model has large error, and the loop closure makes the curve stable near
Fig. 8. The comparison of the proposed Kalman Filter with different head estimation models.

the initial position. The experiments show that the proposed method is feasible, and it can be used with different head pose estimation models. The demo also can be found in the Youtube website.

This paper proposed a reasonable framework and solution for head tracking, it can be further optimized as algorithm of head pose estimation improves. It also can be used in the other human-in-the-loop applications, and the source code of this paper will be open sourced.

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