Extrinsic Parameter Self-Calibration and Nonlinear Filtering for in-Vehicle Stereo Vision Systems at Urban Environments

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Abstract: Present work analyses the continuous self-calibration of extrinsic parameters of a stereo vision system for safe visual odometry applications in vehicles at urban environments. The calibration method determines the extrinsic parameters of a stereo vision system based on knowing the geometry of the ground in front of the cameras. The slight changes of the road profile cause variations in the extrinsic parameters of stereo rig that are necessary to filter and maintain between tolerance values. Then, height, pitch and roll parameters are filtered, to eliminate pose outliers of the stereo rig that appear when a vehicle is maneuvering. The reliable approach at urban environment is firstly composed of the calculation of the road profile slope, the theoretical horizon, and the slope of the straight line in the free map. Secondly, the nonlinear filtering is applied using Unscented Kalman Filter to improve the estimation of height, pitch and roll parameters.

1 INTRODUCTION

The advanced driver assistance systems (ADAS) and autonomous vehicles require safe applications to be integrated progressively in vehicles towards the burgeoning driverless vehicle industry. These safe applications are mainly based on stereo vision systems (Musleh et al., 2012b; Llorca et al., 2012). In-vehicle stereo vision systems are fostering the development of new applications for Intelligent Vehicles, allowing these vehicles to aid the driver in maneuvers such as pedestrian safety in urban environments. The advancements in these mentioned technologies are being extended nowadays to solve complex tasks in the forthcoming Intelligent Transportation Systems, which require normally the combination of sensors and computation to accomplish a reliable solution. Then vision-based sensors have to cope with the correspondence between the position of the objects in the world and its projection in the image plane, and it is possible by means of the intrinsic and extrinsic parameters of the camera. The intrinsic parameters are those related to the camera-optic set and are normally determined by stereo rig maker.

The extrinsic parameters are formed by height and orientation related to the ground in front of the cameras to compose the pose of the stereo vision system. The utilization of in-vehicle stereo rig implies changes of these extrinsic parameters according to the road profile, the trajectory of the vehicle and vehicle dynamics (Dornaika and Sappa, 2009; Turnip et al., 2009). The estimation of the pose of the in-vehicle stereo vision system can be calculated by the use of a calibration pattern that is positioned on the ground (Marita et al., 2006; Hold et al., 2009a), or painted in the hood of the vehicle (Broggi et al., 2001). There are authors that prefer to use the landmarks of the road (Hold et al., 2009b), (Li and Hai, 2011), such as traffic lines (Collado et al., 2006), making easier the calibration process and updating continuously the extrinsic parameters. However, the landmarks cannot be detected caused by degraded landmarks or occluded by other elements, such as parked vehicles. The method that is utilized in this work is based on the geometry estimation of the ground in front of the vehicle (Labayrade and Aubert, 2003; Wang et al., 2010). So, road geometry makes possible to calculate the extrinsic parameters avoiding the use of a calibration pattern or landmarks on the road.

The nonlinear filtering used in this work is based on Unscented Kalman Filter (UKF) that improves the estimation of height, pitch and roll parameters. The typical approach with respect to estimation algorithms has traditionally involved Extended Kalman Filters (EKF) to linearize the process and measurement models, usually involving highly

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nonlinear equations to relate coordinate frame transformations in the measurement model. However, this model relies on linear approximation of a nonlinear system, a complicated mathematical task that sometimes leading to bad performance (Wagner, 2005). Nowadays, with the availability of more computation power, recent works have employed more advanced techniques, like the Unscented Kalman Filter to avoid linearization while providing estimates that capture the statistics of the target distribution more accurately (Crassidis and Markley, 2003; Zhou et al., 2010). An integrated approach to simultaneous attitudinal and positional estimation is described by Van der Merwe (Van der Merwe et al., 2004), who apply a UKF to estimate a joint Gaussian distribution over orientation and position for an unmanned aerial vehicle (UAV). The resulting filter is found to be more accurate than an EKF used for the same purpose. A constrained unscented Kalman filter algorithm has been proposed in (Li and Leung, 2003) to fuse differential GPS, INS (gyro and accelerometer) and digital map to localize vehicles for ITS applications. The state vector includes accelerometer and gyro biases, and the UKF nonlinear character is employed to include some state constraints from the surface geometry. Other advanced nonlinear filtering has been applied recently in navigation, e.g., the context-aided sensor fusion for enhanced urban navigation (Martí et al., 2012), where the main contribution is the proposal of a robust and adaptable solution, exploiting the good trade-off between nonlinear estimation and efficiency of UKF, and including explicit domain knowledge.

This paper presents a self-calibration method based on nonlinear filtering to determine continuously the extrinsic parameters of a stereo vision system using the geometry of the road ground in front of the in-vehicle stereo rig. The disparity map (Scharstein and Szeliski, 2002) and the u-v disparity (Labayrade et al., 2002; Hu et al., 2005) are used in order to distinguish between image points belonging to the ground and the ones which belong to the obstacles (Musleh et al., 2012a). Moreover, two methods have been selected for comparison, the first one uses Hough Transform (HT) and the second one the Random Sample Consensus (RANSAC) (Fischler and Bolles, 1981). These methods allow both calculations of the road profile slope (C_r), the theoretical horizon ($v_{\Delta 0}$), and the slope of the straight line in the free map (C), that lead to both estimations of the height (h), pitch (θ) and roll (ρ) using Unscented Kalman Filter for each frame of stereo rig and considering constant in-vehicle yaw deviation.

This paper is organized as follows: Section 2 describes data set and vehicle parameters. The section 3 explains the self-calibration method to obtain continuously the extrinsic parameters. Section 4 describes the nonlinear method based on Unscented Kalman Filter for filtering extrinsic parameters. Finally, Section 5 provides results to demonstrate the proposed method, and conclusions are presented in Section 6.

2 DATA SET AND VEHICLE PARAMETERS

In-vehicle stereo rig images have been extracted from the visual odometry benchmark of Karlsruhe Institute of Technology that consists of 22 stereo sequences (Geiger et al., 2012), where we have selected the sequence 7 to test our self-calibration method. The sequence 7 is captured by 2 Grayscale cameras, 1.4 Megapixels, Point Grey Flea 2 (FL2-14S3M-C), and is composed with 1100 stereo rig images, that have been acquired when a Volkswagen Passat B6 performs a trajectory of approximately 0.7 km in Karlsruhe residential environment. Cameras are mounted approximately level with the ground plane and are triggered at 10 frames per second. Stereo rig images have a size of 1226 x 370 pixels after rectification. Moreover, we can compare the result of our continuous self-calibration of extrinsic parameters with additional information of this dataset, which contains height, pitch and roll measurements of the vehicle provided by Inertial Navigation System (GPS/IMU OXTS RT 3003).

3 SELF-CALIBRATION OF EXTRINSIC PARAMETERS

The extrinsic parameters are continuously calculated using geometry of the road ground for self-calibration. So we present here the equations that allow us obtain height (h), pitch (θ) and roll (ρ) based on geometry of the road ground. The equations consider constant in-vehicle yaw deviation to simplify demonstration, so we establish constant angle estimation in this work.

The in-vehicle stereo rig has two cameras, where image planes are coplanar and epipolar lines are parallel. Then, the aim is to obtain the homogeneous image coordinates ($u_i{\cdot}S,\ v{\cdot}S,\ S,\ 1$) of a world point P = ($X,\ Y,\ Z,\ 1$), equations (1– 6), following Labayrade nomenclature (Labayrade and Aubert, 2003).

$$\begin{bmatrix} u_i S \\ vS \\ S \\ 1 \end{bmatrix} = M_{proj} \cdot M_{Translx} \cdot M_{Rotx} \cdot M_{Rotz} \cdot M_{Transly} \cdot \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{1}$$

$$M_{proj}(\alpha, u_0, v_0) = \begin{bmatrix} \alpha & 0 & u_0 & 0 \\ 0 & \alpha & v_0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

$$M_{Translx}(\varepsilon_i b) = \begin{bmatrix} 1 & 0 & 0 & -\varepsilon_i b \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$M_{Rotx}(\theta) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta & 0 \\ 0 & \sin\theta & \cos\theta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$M_{Rotz}(\rho) = \begin{bmatrix} \cos\rho & -\sin\rho & 0 & 0 \\ \sin\rho & \cos\rho & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{5}$$

$$M_{Transly}(-h) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & h \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

The subindex i can be selected for both cameras (r = right camera and l = left camera) and we consider $\varepsilon_r = 1$ and $\varepsilon_l = 0$, therefore the projection of the world point P over the left image plane is (u_l, v_l) and the right image projection is (u_r, v_r). The baseline between both cameras is b, the coordinates of the optical center are (u_0, v_0), and the focal length in pixels is indicated by letter α (see Fig. 1). The movement of the vehicle implies angle variations of the in-vehicle stereo rig related to ground reference, so pitch angle rotates around axis X (perpendicular direction to moving forward of vehicle) and roll angle rotates around axis Z (direction of vehicle moving forward). The third extrinsic parameter is height, which has a constant value from ground when vehicle is stopped, but height oscillates around its constant value when vehicle is driving.

The disparity (Δ) is the difference between the horizontal image coordinates of the world point in both image planes. The value of $u_r \cdot S$ for the right camera and $u_l \cdot S$ for the left one is calculated through (1) to (6).

Then, we can easily obtain the disparity expression (Δ) for each world point P = (X, Y, Z, 1)

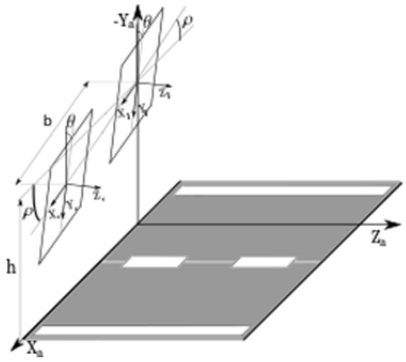

Figure 1: Schema of the in-vehicle stereo rig configuration.

by (7). Following, we calculate the inverse relationship between world points and left image coordinates obtaining inverse expressions (8). It can be observed also that road ground in front of the in-vehicle stereo rig corresponds to every world point which world coordinate Y is equal to zero. Thus, we would find the expression of world coordinate Y as a function of the coordinates of the image, the extrinsic and intrinsic parameters of the stereo system {α, b, u_0, v_0, h, θ, ρ}, and the disparity (Δ) (8). However, the value of S is a function of the world coordinates (X, Y, Z) (1). So, in order to avoid the use of the world coordinates, S can be expressed as S = -α·b/Δ by means of (7).

$$\Delta = u_l - u_r = \frac{u_l S - u_r S}{S} = \\ = \frac{\alpha \cdot b}{Z\cos\theta + (Y+h)\cos\rho\sin\theta + X\sin\rho\sin\theta} \tag{7}$$

$$\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = M_{Transly}^{-1} \cdot M_{Rotz}^{-1} \cdot M_{Rotx}^{-1} \cdot M_{Translx}^{-1} \cdot M_{proj}^{-1} \cdot \begin{bmatrix} u\frac{\alpha b}{\Delta} \\ v\frac{\alpha b}{\Delta} \\ \frac{\alpha b}{\Delta} \\ 1 \end{bmatrix} \tag{8}$$

So, equation (9) shows the relationship between the image coordinates (u, v) for the world points of the road ground. This equation (9) is a straight line whose expression is $v = C \cdot u + d$ for the different values of disparity Δ. The roll angle is normally low in urban environments, so $\cos\rho \approx 1$ and $\sin\rho \approx 0$, which simplifies expression (9) to obtain (10). Moreover, equation (10) is another straight line, which is achieved from the v-disparity and named road profile (Labayrade et al., 2002), which describes the relationship between image vertical coordinate (v) and disparity (Δ), being $v = C_r \cdot \Delta + v_{\Delta 0}$, where C_r is the slope and $v_{\Delta 0}$ is the value of v when the disparity is Δ = 0 (theoretical horizon).

$$Y = -h + \frac{(v - v_0) b \cos\rho \cos\theta}{\Delta} - \\ - \frac{(u - u_0) b \sin\rho}{\Delta} + \frac{\alpha b \cos\rho \sin\theta}{\Delta} = 0 \Rightarrow \\ \Rightarrow (v - v_0) = \frac{\tan\rho}{\cos\theta}(u - u_0) - \\ - \alpha \tan\theta + \left(\frac{h}{b \cos\rho \cos\theta} \right) \Delta \tag{9}$$

$$v = \frac{h}{b \cos\theta} \Delta + v_0 - \alpha \tan\theta \tag{10}$$

Finally, we calculate the pitch angle (θ) with expression (11) and height (h) by (12) using obtained road profile. The roll angle (ρ) is estimated by means of the free map, which is only the road ground part (without obstacles) of the disparity map. Equation (9) is used again, but here is applied to the free map to detect another straight line $v = Cu + d_\Delta$, utilizing a constant value of disparity Δ, extracted from a close area of the vehicle. Then, the roll angle is estimated knowing the slope C of the free map straight line by means of equation (13).

$$\theta = \arctan\left(\frac{v_0 - v_{\Delta 0}}{\alpha} \right) \tag{11}$$

$$h = C_r \cdot b \cdot \cos\theta \tag{12}$$

$$C = \frac{\tan\rho}{\cos\theta} \Rightarrow \rho = \arctan\left(C \cdot \cos\theta \right) \tag{13}$$

Then, the estimation of the road profile slope (C_r), the theoretical horizon ($v_{\Delta 0}$), and the slope of the straight line in the free map (C) using Hough Transform or RANSAC in equations (11), (12) and (13), allow the continuous estimation of height (Fig. 2(a)), pitch angle (Fig. 2(b)), and roll angle (Fig. 2(c)) of the vehicle through whole trajectory.

4 NONLINEAR METHOD FOR FILTERING EXTRINSIC PARAMETERS

The UKF is an algorithm that belongs to Kalman family. So, following the basic Kalman filter theory, it is a recursive algorithm that estimates the state $\hat{x}_k$ of discrete-time dynamic system (Julier and Uhlmann, 2004), which is composed by observable variables (the road profile slope (C_r), the theoretical horizon ($v_{\Delta 0}$), and the slope of the straight line in the free map (C)), and hidden variables (the height (h), pitch (θ) and roll (ρ)). Fig. 3 displays the block diagram of the estimation process of extrinsic parameters of in-vehicle stereo rig.

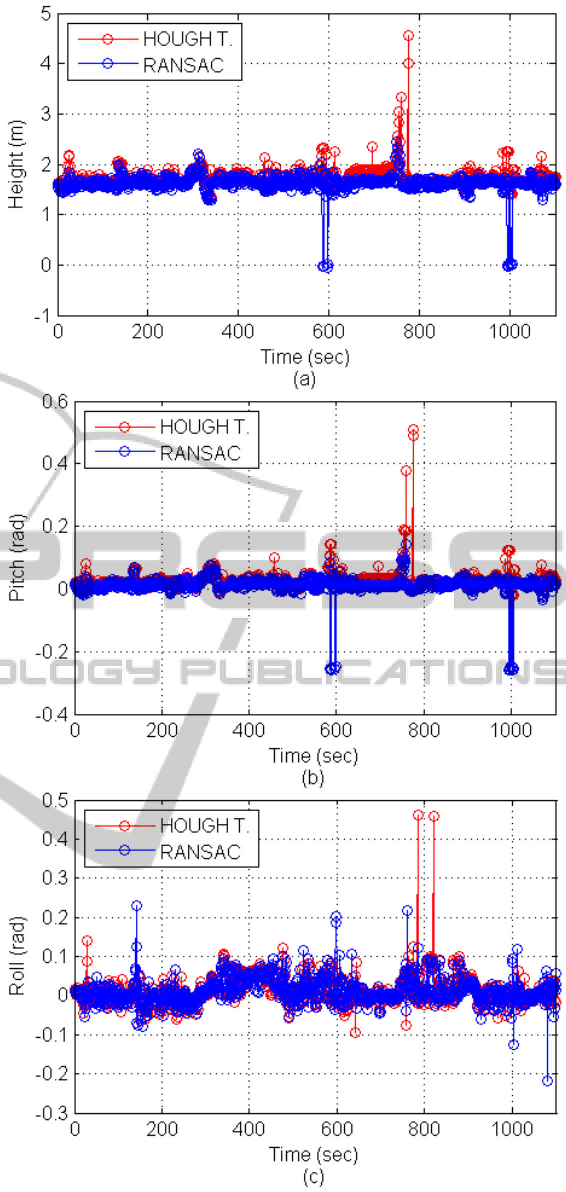

Figure 2: Height (h), pitch angle (θ) and roll angle (ρ) estimation.

The state vector for UKF filtering of height, pitch and roll is expressed as follows (14):

$$x_k = \left(h_k \quad \theta_k \quad \rho_k \right)^T \tag{14}$$

where h_k is the height on time step k, θ_k is the pitch angle on time step k, and ρ_k is the roll angle on time step k.

The estimation is described like a multivariate Gaussian distribution with mean x_k and covariance P_k. The filter uses a mathematical description of the

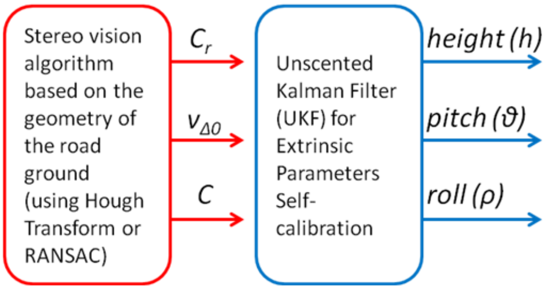

Figure 3: Block diagram with UKF measurement model.

system evolution over time, that is the prediction process (15),

$$\hat{x}_{k+1} = f\left(\hat{x}_k, v_k\right) \tag{15}$$

but we unknown the complex dynamic model of vehicle that has been used in experiments, so we simplify the prediction process considering previous state estimation and $v_k \sim N(0,\ R_v)$ represents a process noise distributed as a Gaussian with mean zero and covariance matrix R_v (16):

$$R_v = \begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 1\cdot 10^{-8} & 0 \\ 0 & 0 & 0.01 \end{bmatrix} \tag{16}$$

where covariance values are small due to urban environment, since we don't expect large changes in process update. So, slightly changes are considered around former estimated state in process update.

However, we know observable variables, which are continuously calculated from stereo images. These observations of the true state are transformed by a known measurement model (17), and perturbed by a random sample of the observation noise $w_k \sim N(0,\ R_w)$ (18). Observation noise matrix is similar to that has been applied to process noise, but here covariance values are higher to eliminate the outliers of the measurements. Following, this information due to such observations is integrated into state estimation during UKF process update.

$$\hat{y}_k = h\left(\hat{x}_k, w_k\right) \tag{17}$$

$$R_w = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{18}$$

UKF algorithm allows continuously the utilization of a nonlinear measurement model to filter outliers of extrinsic parameters. So, the purpose of nonlinear UKF is reliable estimation of height, pitch and roll extrinsic parameters to improve the performance of in-vehicle stereo vision systems, using former expressions (11), (12), (13) and road geometry: (i) the road profile slope (C_r), (ii) the theoretical horizon ($v_{\Delta 0}$), and (iii) the slope of the straight line in the free map (C). The constants of equations, that have been utilized in this work, are: $b = 0.54$ m, $v_0 = 183.1104$ pixels, and $\alpha = 707.0912$ pixels. Therefore, we use the UKF filter to estimate height, pitch and roll nonlinear signals, which are perturbed by outliers that come from road geometry estimation of the ground in front of the vehicle. The nonlinearity of the extrinsic parameters is expressed by the measurement model, which is composed of inverse former expressions (19), (20), (21). This approach simplifies UKF prediction process, while dynamic suspension model of the vehicle is unknown. So, it is possible to propagate the current state through nonlinear measurement functions to obtain the actual measurement.

$$C_r = \frac{h}{0.54\cos\theta} \tag{19}$$

$$v_{\Delta 0} = 183.1104 - \left(707.0912 \cdot \tan\theta\right) \tag{20}$$

$$C = \frac{\tan\rho}{\cos\theta} \tag{21}$$

5 RESULTS

The results of extrinsic parameter self-calibration method and their nonlinear filtering are shown in this section. The stereo sequence captured by in-vehicle stereo rig has been processed using two methods to obtain the estimation of the geometry of the ground in front of the cameras, that is, using Hough Transform or RANSAC to obtain C_r, $v_{\Delta 0}$, C parameters. So, results are separated, Fig. 4 displays extrinsic parameter self-calibration and nonlinear filtering using C_r, $v_{\Delta 0}$, C parameters from Hough Transform, and Fig. 5 shows extrinsic parameter self-calibration and nonlinear filtering using C_r, $v_{\Delta 0}$, C parameters by means of RANSAC.

Height (Fig. 4(a)), pitch angle (Fig. 4(b)) and roll angle (Fig. 4(c)) extrinsic parameters present enormous outliers (red color), where it can be observed the overall performance of the proposed UKF filter (blue color) through whole sequence of 1100 frames. It is difficult to appreciate local performance of the UKF filter in these three graphs, so detail of the trajectory are in (Fig. 4(d)), (Fig. 4(e)), and (Fig. 4(f)) graphs.

Detail graphs belong to 100 frames of the trajectory [640 - 740] that include stopped vehicle from sequence frame 665 to 715. Detail graphs when vehicle is stopped, allow to establish comparison between Hough Transform and RANSAC methods, and comparison with high-accuracy measurements (black color) of Inertial Navigation System (GPS/IMU OXTS RT 3003). The roll/pitch accuracy of OXTS system is $5.236 \cdot 10^{-4}$ rad 1σ. The altitude measurements of OXTS device are used to calculate the height changes of the vehicle, by simple subtraction of consecutive altitude measurements. The maximum accuracy of OXTS altitude is 2 cm 1σ L1/L2.

Figs. 4(d-f)) display outliers when vehicle is stopped and the good performance of UKF filter to eliminate wrong estimations of extrinsic parameters. In comparison with INS OXTS reference, height estimation (Fig. 4(d)) presents a deviation of 0.2 m from 1.65 m (height of the in-vehicle stereo rig over ground), pitch angle estimation (Fig. 4(e)) has again deviation, and roll angle estimation (Fig. 4(f)) shows good performance around 0 rad, where it can be observed an INS small bias of 0.02 rad caused by road slope for water drainage.

Height (Fig. 5(a)), pitch angle (Fig. 5(b)) and roll angle (Fig. 5(c)) extrinsic parameters calculated by RANSAC present again outliers, as can be observed are different outliers from Hough method, but outliers are eliminated again by UKF filter through whole sequence. Moreover, the detail graphs show better performance than former Hough results. Fig. 5(d) presents height UKF filtering around 1.65 m with minimal error when vehicle is stopped. Pitch angle filtering (Fig. 5(e)) shows good result in comparison with INS OXTS reference (bias of 0.015 rad), and roll angle filtering (Fig. 5(f)) presents again minimal deviation around 0 rad, as constant INS OXTS reference is 0.02 rad.

6 CONCLUSIONS

In this article, extrinsic parameters have been estimated continuously for the self-calibration of in-vehicle stereo rig, as an essential task for Intelligent Transportation Systems in urban environments. Extrinsic parameter results have demonstrated the feasibility of the geometry estimation of the ground in front of the vehicle using RANSAC method. Moreover, the accuracy improvement of the height, pitch angle and roll angle measurements, by means of the elimination of outliers, have been accomplished using nonlinear UKF filtering based on nonlinear measurement model. These results have

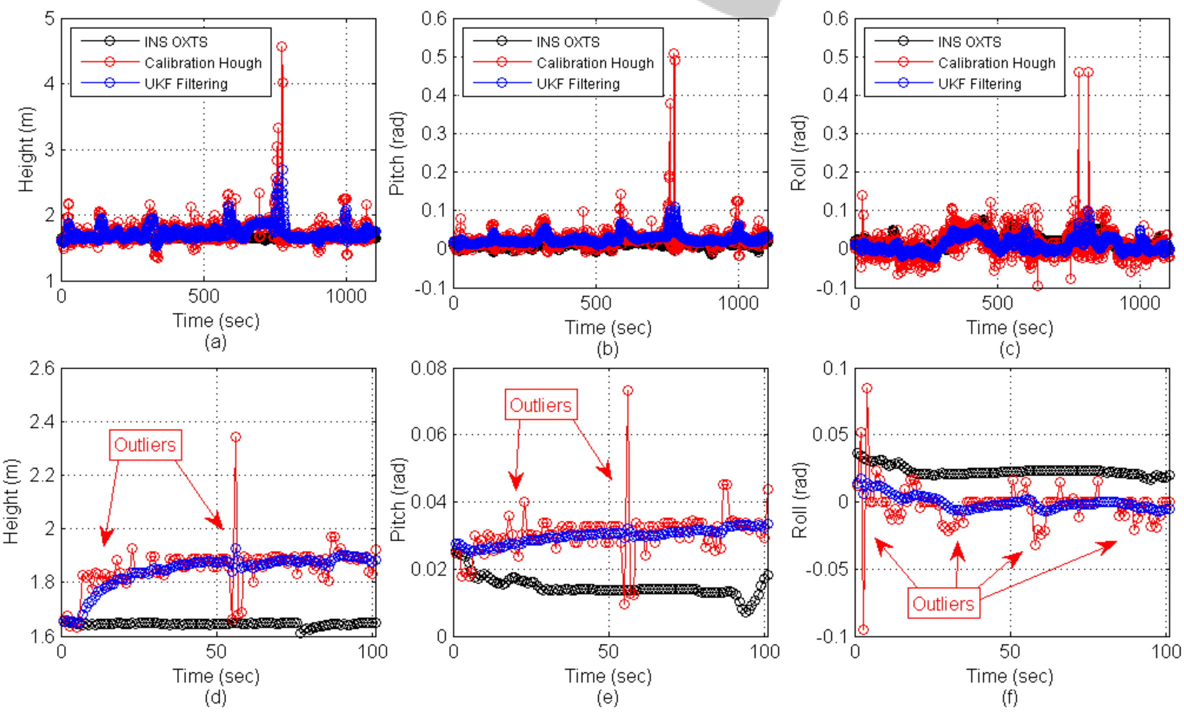

Figure 4: (a) Height, (b) pitch angle, (c) roll angle extrinsic parameters through whole sequence of 1100 frames using continuous estimation of C_r, $v_{\Delta 0}$, C parameters by Hough Transform method, and (d) height, (e) pitch, (f) roll details from 100 frames of sequence with stopped vehicle during 50 frames.

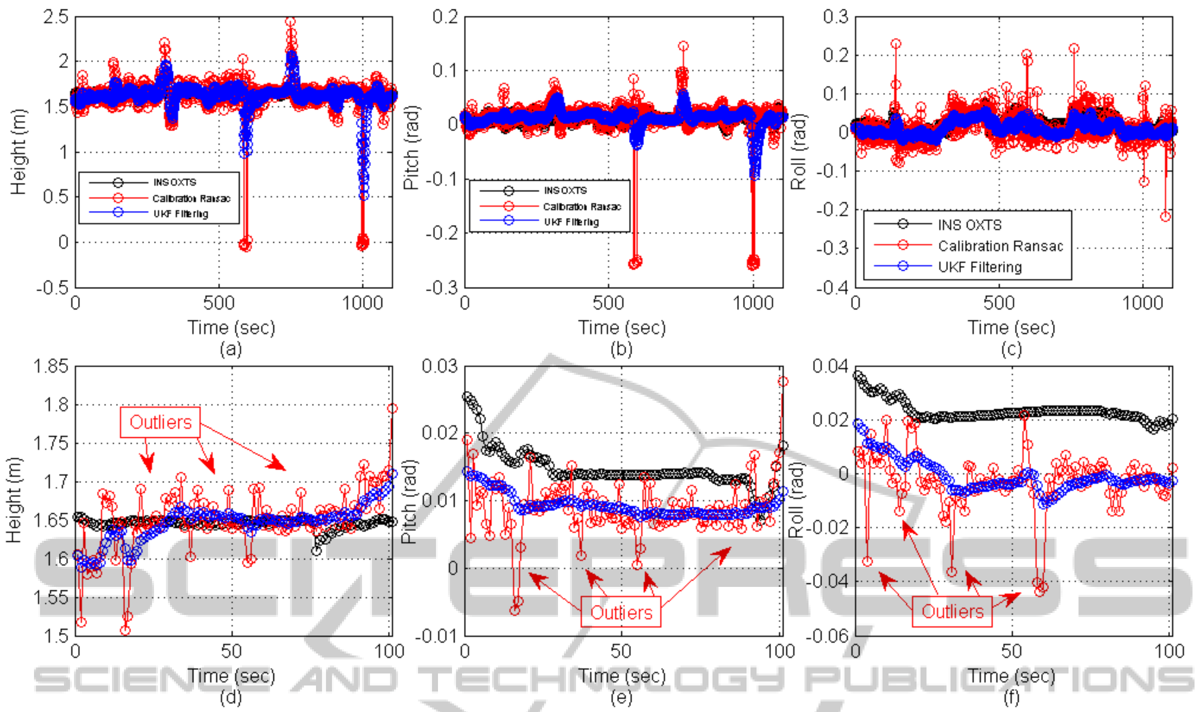

Figure 5: (a) h, (b) θ, (c) ρ UKF filtering using estimations of C_r, v_{A0}, C by RANSAC, and (d) h, (e) θ, (f) ρ details from 100 frames.

been validated through time-domain comparison with high-accuracy measurements, which have been provided by an in-vehicle INS device.

This approach is composed of continuous parameter estimation and UKF filter that will lead to use safe applications based on in-vehicle stereo vision systems. Such as visual odometry for local vehicle positioning that can be used in forthcoming urban navigation.

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REFERENCES

Broggi, A., Bertozzi, M., Fascioli, A., 2001. Self-calibration of a stereo vision system for automotive applications. In *Proc. IEEE International Conference on Robotics and Automation*, vol. 4, pp. 3698–3703.

Collado, J. M., Hilario, C., de la Escalera, A., Armingol, J.M., 2006. Self-calibration of an on-board stereo-vision system for driver assistance systems. In *Proc. IEEE Intell. Veh. Symposium*, pp. 156–162.

Crassidis, J. L., Markley, F. L., 2003. Unscented Filtering for Spacecraft Attitude Estimation. *AIAA J. Guid. Control. Dyn.*, vol. 26, pp. 536–542.

Dornaika, F., Sappa, A. D., 2009. A featureless and stochastic approach to on-board stereo vision system pose. *Image and Vision Computing*, vol. 27, pp. 1382–1393.

Fischler, M. A., Bolles, R. C., 1981. Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Com. of the ACM*, no. 6, 381–395.

Geiger, A., Lenz, P., Urtasun, R., 2012. Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite. In *Proc. Computer Vision and Pattern Recognition (CVPR)*, USA, pp. 3354–3361.

Hold, S., Nunn, C., Kummert, A., Muller-Schneiders, S., 2009. Efficient and robust extrinsic camera calibration procedure for lane departure warning. In *Proc. IEEE Intell. Veh. Symposium*, pp. 382–387.

Hold, S., Gormer, S., Kummert, A., Meuter, M., Muller-Schneiders, S., 2009. A novel approach for the online initial calibration of extrinsic parameters for a car-mounted camera. In *Proc. 12th International IEEE Conference on Intelligent Transportation Systems*, St. Louis, MO, USA, pp. 420–425.

Hu, Z., Lamosa, F., Uchimura, K., 2005. A complete uv-disparity study for stereovision based 3d driving environment analysis. In *Proc. Fifth Int. Conf. on 3-D Digital Imaging and Modeling*, pp. 204–211.

Julier, S. J., Uhlmann, J.K., 2004. Unscented Filtering and Nonlinear Estimation. *Proceedings of the IEEE*, vol.92, pp. 401 - 422.

Labayrade, R., Aubert, D., Tarel, J.P., 2002. Real time obstacle detection in stereovision on non flat road geometry through v-disparity representation. In *Proc. IEEE Intell. Veh. Sym.*, pp. 646–651.

Labayrade, R., Aubert, D., 2003. A single framework for vehicle roll, pitch, yaw estimation and obstacles detection by stereovision. In *Proc. IEEE Intelligent Vehicles Symposium*, pp. 31–36.

Li, S., Hai, Y., 2011. Easy calibration of a blind-spot-free fisheye camera system using a scene of a parking space. *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 1, pp. 232–242.

Li, W., Leung, H., 2003. Constrained Unscented Kalman Filter Based Fusion of GPS/INS/Digital Map for Vehicle Localization. In *Proc. IEEE 2003 International Conference on Intelligent Transportation Systems*, Shanghai, China, 12–15, vol. 2, pp. 1362–1367.

Llorca, D. F., Sotelo, M. A., Hellín, A. M., Orellana, A., Gavilán, M., Daza, I. G., Lorente, A. G., 2012. Stereo regions-of-interest selection for pedestrian protection: A survey. *Transportation Research Part C*, vol. 25, pp. 226–237.

Marita, T., Oniga, F., Nedevschi, S., Graf, T., Schmidt, R., 2006. Camera calibration method for far range stereovision sensors used in vehicles. In *Proc. IEEE Intelligent Vehicles Symposium*, pp. 356–363.

Martí, E. D., Martín, D., García, J., de la Escalera, A., Molina, J.M., Armingol, J. M., 2012. Context-aided Sensor Fusion for Enhanced Urban Navigation. *Sensors*, vol. 12, no. 12, pp. 16802-16837.

Musleh, B., de la Escalera, A., Armingol, J. M., 2012. U-v disparity analysis in urban environments. In *Proc. Computer Aided Systems Theory EUROCAST 2011*, vol. 6928 of LNCS, pp. 426–432.

Musleh, B., Martin, D., de la Escalera, A., Armingol, J. M., 2012. Visual Ego Motion Estimation in Urban Environments based on U-V Disparity. In *Proc. 2012 IEEE Intelligent Vehicles Symposium*, Alcalá de Henares, Spain, pp. 444–449.

Scharstein, D., Szeliski, R., 2002. A taxonomy and evaluation of dense two-frame stereo correspondence algorithms. *International journal of computer vision*, vol. 47, no. 1, pp. 7–42.

Turnip, A., Nguyen, L.H., Hong, K.-S., 2009. Detection of Critical Driving Situations Based on Wheel-Ground Contact Normal Forces. In *Proc. ICROS-SICE Inter. Joint Conf.*, Japan, pp. 2519–2524.

Van der Merwe, R., Wan, E.A., Julier, S.I., 2004. Sigma Point Kalman Filters for Nonlinear Estimation and Sensor Fusion: Applications to Integrated Navigation. In *Proc. AIAA Guidance, Navigation and Control Conf.*, Providence, RI, USA, pp. 1735-1764.

Wagner, J. F., 2005. GNSS/INS integration: still an attractive candidate for automatic landing systems?. *GPS Sol.*, vol. 9, pp. 179–193.

Wang, Q., Zhang, Q., Rovira-Mas, F., 2010. Auto-calibration method to determine camera pose for stereovision-based off-road vehicle navigation. *Environ. control in biol.*, vol. 48, no. 2, pp. 59–72.

Zhou, J., Knedlik, S., Loffeld, O., 2010. INS/GPS Tightly-coupled Integration using Adaptive Unscented Particle Filter. *J. Navig.*, vol. 63, 491–511.