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• **Supplementary File** •

Reliable attitude estimation algorithm considering atypical observation

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Appendix A Related works

In the past decades, vision measurement technique has been successfully applied in this kind of tracking task. And two typical measurement configurations have been developed which are outside-in and inside-out. But they are limited by small acceleration and range of motion. Besides, for vision measurement, there is supposed to be clear line of sight between the camera and feature information. Otherwise, the vision signals may easily be blocked or lost. The mismatching of feature points including out of range can be collectively referred to as atypical cases. Based on the above analysis, the vision technique needs to be strengthened especially in rapid target tracking. Known as its strong autonomy, inertial measurement technique is suitable for rapid motion tracking. But its integral calculation errors will accumulate and eventually diverge with time. For attitude estimation task, common single measurement technologies [1] based on inertial technique or monocular vision, have defects to meet multiple measurement requirements owing to its own inherent feature. Considering their respective imperfections, the fusion technologies have gained extensive applications, providing complementary characteristics of different techniques. A multi-sensor fusion system based on inertial gyroscope and vision sensor camera is employed for attitude measurement in this paper to enhance reliability and robust [2] especially in complex environments.

The fusion systems have been extensively studied and it is easy to find many contributions dealing with modeling, analysis, control and design of the systems [3]. As to the issues of vision and inertial integrated system, optimal parameters are expected to obtain from inertial and visual sensor data which include noises. Based on the recursive optimal estimation theory and mathematical model established in time domain, KF (Kalman filter) method is convenient for real-time implementation. Thus, the filter-based algorithms also known as model-driven methods are commonly used in vision and inertial integrated system. Due to the nonlinearity of the integrated system, the nonlinear filters[4] are actually used such as EKF (Extended Kalman filter), which is based on first-order Taylor-series approximation of state transition and observation equations about the estimated state trajectory and will provide a suboptimal estimation. However, when the nonlinearity is severe or the linearisation errors are large, its performance becomes poor. UKF (Unscented Kalman filter) [5] employs a series of sigma points to approximate the nonlinear distribution other than the nonlinear equations and can obtain higher order statistic of a system. Thus, it can achieve better estimation and convergence performance. For CKF (Cubature Kalman filter)[6,7], a series of cubature points with equal weight values is used to calculate the posterior probability density. And among the existing Gaussian filters domain,CKF has superior nonlinear approximation performance and numerical accuracy.

Appendix B Atypical observation cases

In normal visual attitude measurement, the light path between the camera and the stereo target is unobstructed as displayed in Figure B1(a). So the camera can directly capture the information of the four target feature points. However, in the measurement process due to some unknown objects between the camera and stereo target, some feature points may be occluded as shown in Figure B1(b) and Figure B1(c). This will make the matching of feature points impossible and leads to the inability of visual attitude measurement to output correct data.

Appendix C NARX training process and predicting process

The specific configurations of the NARX training process and predicting process are respectively given in C1(a) and Figure C1(b). From Figure C1(a), it clearly shows that with both inertial data and vision data, the attitudes are given by integration of CKF algorithm. And $e(k)$ represent angle errors, which are used to correct the output of gyroscope when visual system works well. $G(k)$ and $C(k)$ are respectively gyroscope and camera data. At the same time, the difference $\delta(k)$ between inertial and visual data is input to the NARX model as training data.

Once the NARX model is well trained and well validation, when there is no visual data, the NARX algorithm can provide prediction data. These moments without vision may result from sampling frequency discrepancy, occlusion or stray light. The NARX model will predict angles difference continuously and is employed as the input of optimal estimation to correct inertial data.

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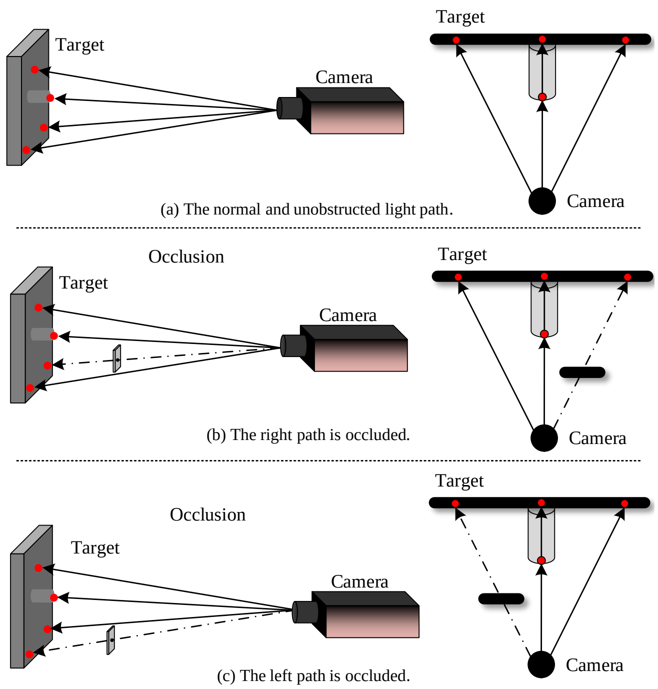

Figure B1 The light path in different conditions from different directions.

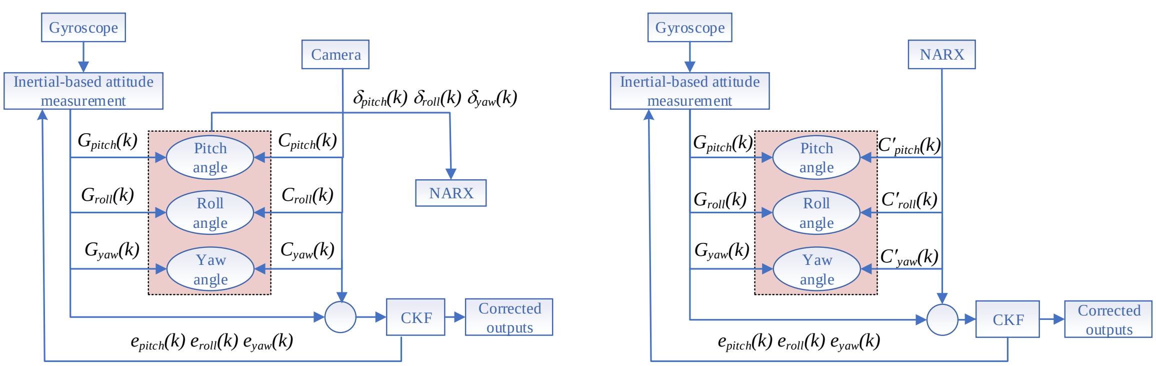

Figure C1 (a) The configuration of training process;(b) the configuration of predicting process.

Table D1 The RMSE of different filtering algorithms (angle[degree])

Methods	EKF		UKF		GHKF		PF		CKF	
	Pitch	*Yaw*	*Pitch*	*Yaw*	*Pitch*	*Yaw*	*Pitch*	*Yaw*	*Pitch*	*Yaw*
RMSE	0.2951	0.2414	0.1572	0.2336	0.1466	0.2437	0.1353	0.1781	0.1260	0.1991

Appendix D Experimental results and comparison

As optimal state estimators, filter methods are suitable to handle the effects of measurement noise and process noise. The state dynamic equation used in this paper is defined by quaternion

$$q_{k+1} = [cos(\frac{|w|\,\Delta t}{2})I + 2sin(\frac{\frac{|w|\,\Delta t}{2}}{|w|})\Omega(w)]q_k, \tag{D1}$$

We use the above state functions, and five bayes-based nonlinear filtering methods including EKF, UKF, PF (Particle filter), GHKF (Gauss-Hermite Kalman filter) and CKF to conduct attitude estimate. The RMSE of different filtering algorithms is given in Table D1.

The fusion error results of BP model, NARX model, and CKF itself are compared. To provide intuitive and convincing results, the RMSE of the repeat experiments are listed in Table D2 to show quantitative results. It indicates the effectiveness of combining the nonlinare filtering method CKF with the data-driven model, which reflects by the comparison between CKF and CKF-based method as shown in Table D2. The estimation accuarcy of the two CKF-based method is superior to the CKF-only method. In

Table D2 The RMSE of different data model (angle[degree])

Groups	CKF		CKF-BP		CKF-NARX	
	Pitch	*Yaw*	*Pitch*	*Yaw*	*Pitch*	*Yaw*
1	0.1371	0.2194	0.1211	0.1953	0.1097	0.1690
2	0.1260	0.1991	0.1120	0.1770	0.1080	0.1602
3	0.1444	0.2148	0.1415	0.1835	0.1527	0.1515

addition, it can be also easily seen that the NARX model has optimal performance, which reflects by the comparison between RMSE results and the error curves. It signifies that the NARX model is more suitable for the attitude estimation system to provide pseudo data for drift suppression.

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