INTEGATION OF INERTIAL SENSORS AND GPS SYSTEM DATA FOR UNDERWATER NAVIGATION

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The Inertial Navigation System (INS) is usually employed to determine the position of an underwater vehicles, like Remotely Operated Vehicles (ROV) and, more recently, Autonomous Underwater Vehicle (AUV). The accuracy of the position provided by the INS, which uses accelerometers and gyroscopes, deteriorates with time. An external aiding sources such as the Global Positioning System (GPS) can be employed to reduce the error growth in the INS. The GPS aided INS system provides enhance positioning accuracy of the underwater vehicles compared to that of a stand-alone INS technique.

In the paper integration algorithm of inertial sensors (accelerometers and gyroscopes) and GPS system data for underwater navigation is presented. For data integration algorithm External Kalman Filter (EKF) is proposed.

INTRODUCTION

The GPS is widely used in navigation. The GPS receiver can offer long-term stable absolute positioning information with output rate at around 1 to 10 Hz. However, the system performance depends largely on the signal environments. In an INS system, the angular rate and specific force measurements from the Inertial Measurement Unit (IMU) are processed to yield the position, velocity and attitude solution. Such systems can navigate autonomously and provide measurements at a higher data rate (e.g., 100 Hz). However, the system has to be initialized and calibrated carefully before application. Moreover, the sensor errors are growing unboundedly over time. Due to the complimentary characteristics of GPS and INS, they are often integrated to obtain a complete and continuous navigation solution [1, 2].

The inertial sensors used in IMU are made in MEMS (Micro Electro-Mechanical Systems) technology. MEMS technology enables miniaturization, mass production, and cost reduction of many sensors. In particular, MEMS inertial sensors that include an acceleration sensor and an angular velocity sensor (gyroscope, or simply “gyro”) are the most popular devices. Almost all MEMS acceleration sensors have a seismic mass and support spring made of silicon. The structure of MEMS gyros is somewhat similar to that of acceleration sensors –

a mass supported by a spring is continuously vibrated in the device, and the Coriolis force generated by the applied angular velocity affects the movement of the mass (vibrating gyroscope). The mass in a MEMS device is very small, and therefore, the inertial forces acting on the mass, especially the Coriolis force, are also extremely small. Thus, the design of the circuit that measures the movement in mass due to the force is important in addition to the design of the mechanical structure. Recently MEMS inertial sensors have been built with an integrated circuit, with sensor structure on a single device chip [3].

A typical structure of a MEMS acceleration sensor is shown in figure 1 [3], where a silicon mass is supported by silicon springs and the displacement of the mass due to acceleration is measured by capacitance change between the mass and fixed electrodes. Since the mass is very small and the displacement is also small, the resolution of the device is generally limited to around 0.1 mg $Hz^{-1/2}$.

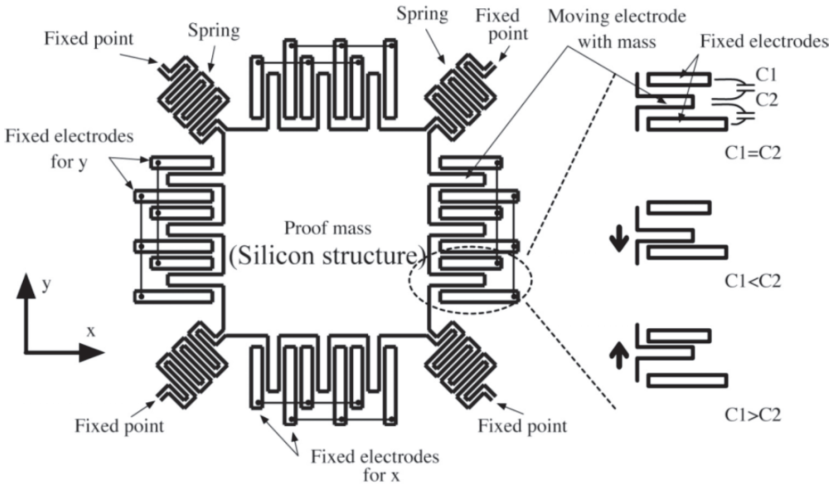

Fig.1. Structure of MEMS acceleration sensor (2-axis).

The basic structure of MEMS gyroscopes is similar to acceleration sensors, i.e., a mass is supported by springs. The main difference in operation is that the angular velocity is obtained by measuring the Coriolis force on the vibrating mass. Thus, the movement of the mass should have at least two degrees of freedom. The device is shown in figure 2.

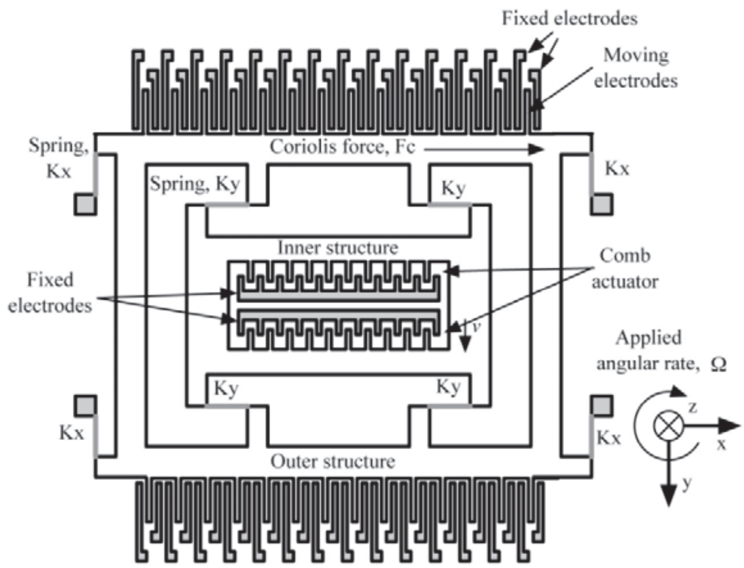

Fig.2. Conceptual structure of an MEM gyroscope.

Inertial sensors have numerous applications. An Inertial Navigation System (INS) is a self-contained system that integrates three acceleration and three angular velocity components with respect to time and transforms them into the navigation frame to deliver position, velocity, and attitude components. The three orthogonal linear accelerations are continuously measured through three-axis accelerometers while three gyroscopes monitor the three orthogonal angular rates in an inertial frame of reference. In general, inertial measuring unit (IMU), which incorporates three-axis accelerometers and three-axis gyroscopes, can be used as positioning and attitude monitoring devices. However, INS cannot operate appropriately as a stand-alone navigation system.

The presence of residual bias errors in both the accelerometers and the gyroscopes, which can only be modeled as stochastic processes, may deteriorate the long-term positioning accuracy. Hence, the INS/GPS data integration is the desirable solution to provide navigation system that has better performance in comparison with either a GPS or an INS stand-alone system.

1. ALGORITHM FOR INS AND GPS DATA INTEGRATION

The INS/GPS data integration algorithm consists in Extended Kalman Filter (EKF) usage. EKF uses Taylor series where the idea of a linear approximation to describe a function in the neighborhood of some point by a linear function is applied. The algorithm works in a two-step prediction/correction process. In the prediction step, the Kalman filter produces estimates of the current state variables. Because of the recursive nature of the algorithm, it can be run in real time. The present input measurements and the previously calculated state is used; no additional past information is required [4]. The very idea is presented in the figure 3 where:

- $\hat{x}_k^-$, $\hat{x}_k$ are á priori and á posteriori system state,
- P_k^-, P_k are á priori and á posteriori covariance matrix,
- H is measurement matrix,
- K_k is Kalman gain,
- R, Q are process and state variance of the system,
- z_k is measurement matrix,
- A is process model.

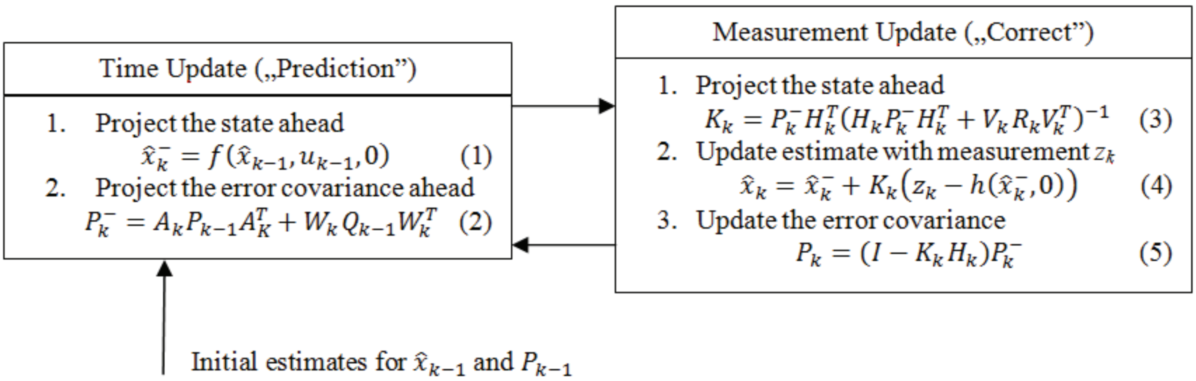

Fig.3. EKF sensor data integration algorithm diagram [4].

Prediction can be describe as follows (1) and (2) where $f(x, u, w)$ is nonlinear function, which uses a previous filter state as well as control impact and the process noise. A_k (or A^J) is a Jacobian, f with respect to x, W_k (or W^J) is a Jacobian, f with respect to w function. Where A and W are follows:

$$A^J_{[i,j]} = \frac{\delta f_{[i]}}{\delta x_{[j]}}(\hat{x}_{k-1}, u_{k-1}, 0) \tag{6}$$

$$W^J_{[i,j]} = \frac{\delta f_{[i]}}{\delta x_{[j]}}(\hat{x}_{k-1}, u_{k-1}, 0) \tag{7}$$

And correction is applied as follows (3), (4) and (5) where H_k (or H^J) is Jacobian, derivative of the function h with respect to x, V_k (or V^J) is Jacobian, function h derivative of with respect to v and $h(x,v)$ is nonlinear function of the state and measurement relation. Jacobians H and V can be expressed as follows:

$$H^J_{[i,j]} = \frac{\delta h_{[i]}}{\delta x_{[j]}}(\tilde{x}_k, 0) \tag{8}$$

$$V^J_{[i,j]} = \frac{\delta h_{[i]}}{\delta x_{[j]}}(x_k, 0) \tag{9}$$

where:

$$\tilde{x}_k - f(x_{k-1}, u_{k-1}, 0) \tag{10}$$

All Jacobians Ought to be recalculated In every iteration step.

2. RESULTS

The figures 4, 5 and 6 show a comparison between the INS position and the EKF filter position estimation following the three axes x, y and z. As can be seen from figures 4 and 5, the performances of the EKF and theoretical state are quite similar especially when the process and observation noises are uncorrelated zero mean Gaussian with known covariance. The figures 5 and 6 show that the EKF estimator is more accurate than the INS position, the latter diverge exponentially with time. We also observe, from figure 6, that the EKF have a poor performance facing the heavy system nonlinearity since there are large deviations of the estimated state trajectory from the nominal trajectory. Thus, the nonlinear signal model is less accurately approximated by the Taylor series expansion, neglecting the higher order terms, about the conditional mean.

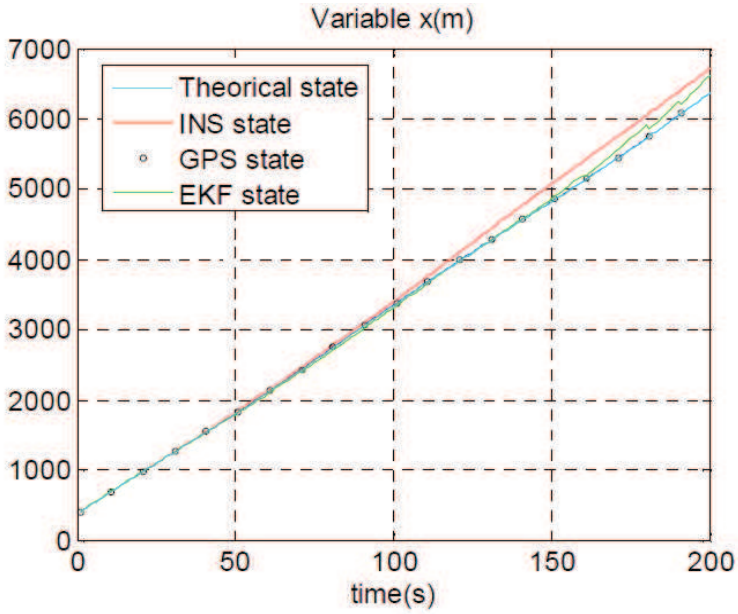

Fig.4. Estimation of the position x.

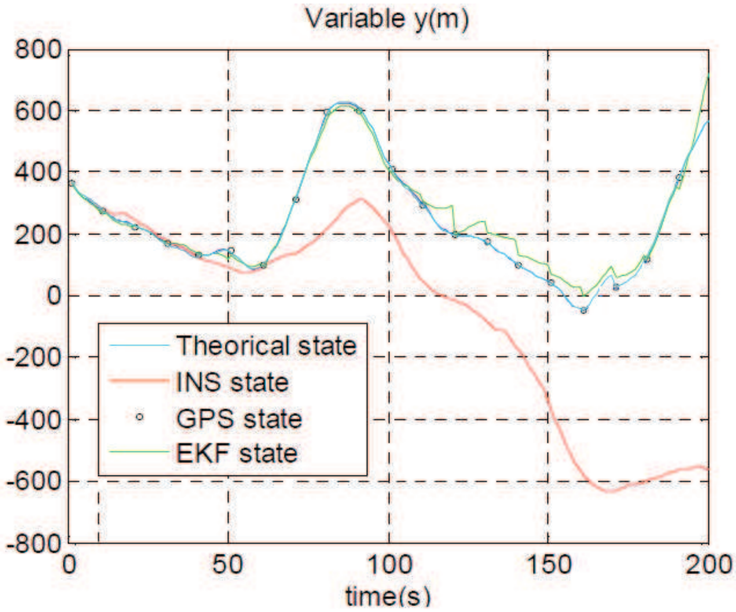

Fig.5. Estimation of the position y.

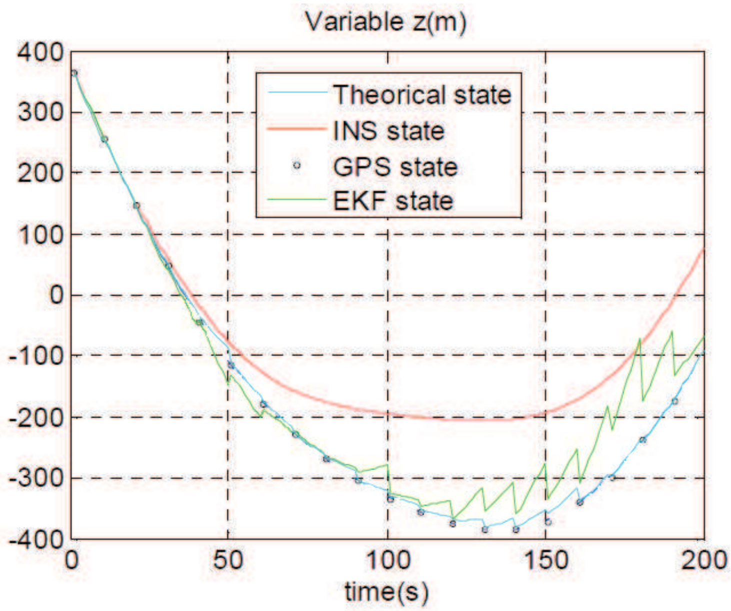

Fig.6. Estimation of the position z.

Figure 7 shows the UAV 3D trajectories given by the INS, EKF filter and GPS. These trajectories are compared with the theoretical one.

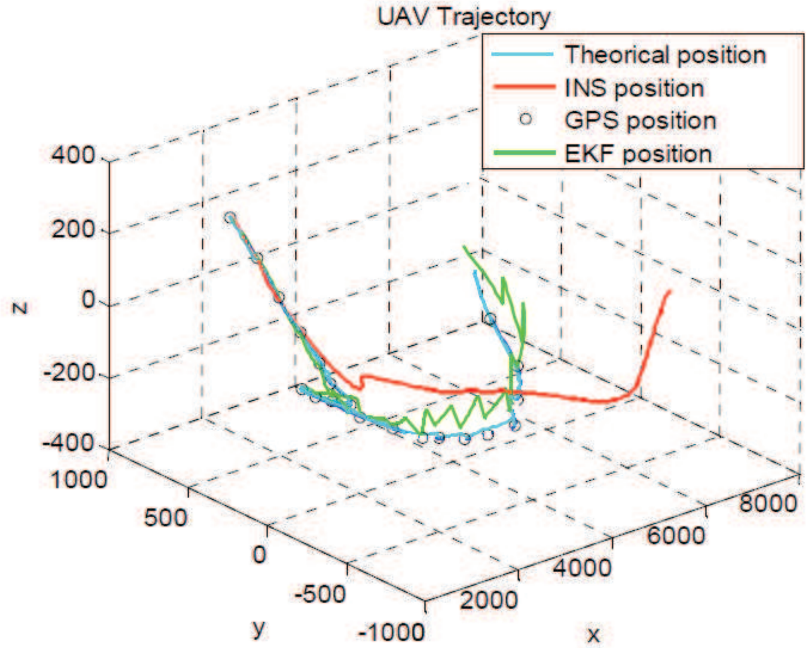

Fig.7. UAV localization.

3. CONCLUSIONS

In this paper, we proposed a External Kalman Filter to estimate the location of an underwater vehicles, using INS/GPS information. The proposed method solves issues related to linearization, which is linked mostly to classical filtering techniques. Different trajectories of the UAV are tested, and an accuracy UAV position was obtained by the EKF filter. We obtained quite good and promising results for future work.

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