Dual Optic-flow Integrated Inertial Navigation

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Abstract
This paper addresses the recent development of real-time visual odometry system based on dual optical-flow systems and its integration to aided inertial navigation aiming for small-scale flying robots. To overcome the unknown depth information in optic-flows, a dual optic-flow system is developed. The flow measurements are then fused with a low-cost inertial sensor using an extended Kalman filter. The experimental results in indoor environment will be presented showing improved navigational performances constraining errors in height, velocity and attitude.

1 Introduction
Optic flow is the apparent visual motion seen by an observer when moving relative to a textured surface. This motion can be used to infer information about the state of the observer relative to that surface. This principle is used heavily by insects, where optic flow is used to calculate odometry [Si et al., 2003] and regulate ground speed [Barron and Srinivasan, 2006].

The advantages in using optic flow for motion measurement has made it attractive for implementation in robotic vehicles. Recent advances in digital signal processors and charge-coupled device (CCD) cameras have provided a means of embedding the devices on the same chip. This technology has been utilised by several manufacturers in developing a chip that is dedicated to measuring displacement through optic flow. The devices have facilitated the implementation of optic flow sensors into robotic aerial vehicles [Jufferey and Floreano, 2006] and in ground vehicles as displacement measuring devices [Brenner and Smeets, 2003], [Pratt and Turk-Browne, 2003] and odometry estimation [Palacin et al., 2006]. They have also been adapted to visual-servoing obstacle avoidance applications [Green et al., 2003].

The optical chips operate by analysing successive frames of the surface over which they are travelling. The frames are acquired at a rate of around 1500 frames-per-second or greater, each of which is analysed by an in-built image-processing algorithm. This algorithm identifies specific features on the image plane and tracks their position with each successive frame, then assigns two displacement values describing the overall motion of these features. The displacement values are given in terms of pixel counts. These numbers are either stored in specific registers for reading by an external source. If these registers have not been read before an additional set of values have been acquired, then the values are added to the values already in the register. Assuming that there is no overflow, two integrated values of motion are returned after a motion request. When used in optical mice, they are part of a larger assembly that also includes a lens and a light emitting diode of a specific frequency range. In this setup the mouse is accurate to many hundreds of counts-per-inch, but is especially sensitive to changes in height above the surface [Ng, 2003].

In the application presented in this paper, two opti-
cal mouse chips have been used (as shown in Figure 1) with different optical and lighting conditions, with the expectation that they can be used for assisting with the navigation of Unmanned Aerial Vehicles (UAVs). This is an environment not originally intended for optical mouse chips, because the conditions are vastly different from those considered ideal. First, the terrain beneath the vehicle is not guaranteed to be flat, nor comprise of homogeneous textures. Furthermore, the level of light enveloping the surface is not guaranteed to be of any specific wavelength or intensity. In addition, the attitude and angular rate of the vehicle manifest as errors in the optic flow values. These motion and attitude induced errors must be removed before any assistance to the vehicle navigation can be made.

While a considerable amount of research has been put into their implementation with robotic vehicles, the problem of fusing two-dimensional (2D) optic flow into the full 6 degrees-of-freedom (DoF) state estimation problem has not yet been fully addressed. This paper will present the fusion of 2D optic flow data with that of the inertial measurement unit into the full 6DoF platform state using an extended Kalman filter (EKF). Moreover, the algorithms use the inertial navigation system equations as opposed to platform specific state models. Thus, the algorithms presented here are general and can be used for any 6DoF platform.

This paper is structured as follows: Section 2 describes the properties of strap-downed optic-flow with a method to compensation the body-induced motion. Section 3 presents the Bayesian data-fusion model and its implementation using extended Kalman filter. Section 4 will provide experimental results on an indoor robot-arm with conclusions in Section 5.

2 Strap-downed Optic-Flows

The optic-flow sensors were designed for use inside a standard desktop mouse. In this environment the lighting is precisely controlled and the reference surface has specific textural properties. When fitted to a moving 6DoF vehicle however, the environmental conditions are no longer ideal. A qualitative assessment of the fundamental differences in the working environments is necessary to ensure the proper integration into a mobile platform. Several key differences in the working environments are:

- In most instances, the optical axis of the camera will not be perpendicular to the terrain beneath the vehicle. This is due to the attitude of the vehicle and the gradient of surrounding terrain.
- The platform will normally have a resultant velocity vector that is not parallel to the surface.
- The intensity and wavelength of the light will not be controllable.
- There will be a rotation rate about some axis that manifests as optic flow.

If the optic flow data are not compensated for the effects of platform motion, large discrepancies between the actual and estimated platform states will arise. It is therefore necessary to calculate and eliminate the effects of platform motion on the optic flow.

2.1 Optic-flow Measurement

The optic-flows measured in sensor are accumulated pixel counts \( (n_x, n_y) \) over sampling time \( \Delta t \). The optic-flow \( (\theta_x, \theta_y) \) in radians is thus equivalent to angular displacement and be computed using camera parameters:

\[
\theta_x = \alpha \left( \frac{n_x}{n_p} \right), \quad \theta_y = \alpha \left( \frac{n_y}{n_p} \right)
\]

with \( \alpha \) and \( n_p \) are the field-of-view (in radians) and the principle pixel dimension (in pixels) within the camera, respectively.

The total optic-flow in radians is also related to the vehicle motion as a ratio of the linear distance travelled \( (v_x \Delta t) \) and height-above-ground \( (h_{ag}) \). That is,

\[
\theta = \frac{v_x \Delta t}{h_{ag}}.
\]

This relationship will be used in the following section to compute the height-above-ground from the dual optic-flow measurements.

2.2 Vehicle Motion Compensation

Vehicle rotation rates and optic flow are highly coupled since the cameras are rigidly mounted (or strap-downed) to the vehicle body. Any rotation about the \( x \) or \( y \) axes will manifest as optic flow. This is true even if the vehicle is not translating relative to the navigation frame. As the coordinate systems of the flow sensors are aligned with the body frame, a rotation about the \( x \) axis will appear as a change in the optic flow of the \( y \) axis, and vice versa.

The rotational motion can be described by the so-called rotation vector \( \phi \) and its differential equation [Bortz, 1971],

\[
\dot{\phi} = \omega_{ab}^b \phi + \frac{1}{2} \phi \times \omega_{ab}^b
\]

\[
+ \frac{1}{\phi_0^2} \left[ 1 - \frac{\phi_0 \sin \phi_0}{2(1 - \cos \phi_0)} \right] \phi \times (\phi \times \omega_{ab}^b),
\]

where \( \omega_{ab}^b \) is the angular rate of the body frame with respect to the navigation frame (measured from Gyroscopes), expressed in the body axes, and \( \phi_0 \) represents the magnitude of the rotation vector \( \phi = [\phi_x \phi_y \phi_z]^T \).

The optic-flow errors resulting from the vehicle rotation can thus be computed using Equations 1 and 2 by

\[
\delta n_x = \left( \frac{n_x}{\alpha} \right) \dot{\phi}_x \Delta t \quad \delta n_y = \left( \frac{n_y}{\alpha} \right) \dot{\phi}_y \Delta t,
\]
where \( n_p / \alpha \) is used as a conversion factor between radian and pixel.

The error terms are subtracted from the raw optic flow measurements. Note that the rotation motion along the \( z \)-axis of the body frame would not affect this correction. This is because that the optic flow around the centre of the image will be averaged out resulting in a zero-flow.

### 2.3 Ground-Speed and Height

From a single optic-flow measurement, the ground speed and height-above-ground are not computed separately, only the ratio of them. This can be overcome by placing a second source of optic flow with the same orientation, but displaced by a distance \( L \), along the \( z \)-axis of the body frame. A relationship analogous to the single sensor case exists for the dual sensor case:

\[
h_{ag,1} = \frac{v_y \Delta t}{\theta_1}, \quad h_{ag,2} = \frac{v_y \Delta t}{\theta_2}.
\]

(4)

Applying some algebraic manipulations and using relationship of \( h_{ag,2} = h_{ag,1} + L \), yielding

\[
h_{ag,1} = L \left( \frac{\theta_2}{\theta_1 - \theta_2} \right),
\]

(5)

and subsequently the ground speed being

\[
v_g = L \left( \frac{\theta_2}{\theta_1 - \theta_2} \right) \frac{\theta_1}{\Delta t}.
\]

(6)

### 3 Optic-Flow Integrated Navigation

In probability navigation, we are interested in the probability density function (pdf) of the vehicle state given observations, that is a posterior pdf:

\[
p(\mathbf{x}_k | \mathbf{z}_k)
\]

(7)

This density can be effectively maintained in prediction and update steps in Bayesian framework. The pdf of the predicted state of the system can be computed by Chapman-Kolmogorov equation:

\[
p(\mathbf{x}_k | \mathbf{z}_{k-1}) = \int p(\mathbf{x}_k | \mathbf{x}_{k-1})p(\mathbf{x}_{k-1} | \mathbf{z}_{k-1})d\mathbf{x}_{k-1}.
\]

(8)

Once observations are available, the predicted pdf is multiplied by the observational likelihood, and then scaled to give a posterior density:

\[
p(\mathbf{x}_k | \mathbf{z}_k) = c \cdot p(\mathbf{z}_k | \mathbf{x}_k)p(\mathbf{x}_k | \mathbf{z}_{k-1}),
\]

(9)

with \( c \) being a normalisation constant.

Direct implementation of this method is not feasible in most applications. With an assumption of Gaussian densities in a prior and a posterior pdfs, extended Kalman filter (EKF) can be used effectively. Figure 2 illustrates the structure of the integrated system using EKF where the optic-flow measurements are first compared with those predicted from INS and terrain map and then feed into the filter. The terrain map is required to predict the optic flow and a flat surface is used in this work.

### 3.1 Motion model

The probabilistic motion model is effectively a nonlinear inertial navigation model in this case, with a state vector of position, velocity, and attitude \( \mathbf{x}_k = [p \; v \; \psi]^T \):

\[
p(\mathbf{x}_{k+1} | \mathbf{x}_k) \Leftrightarrow \mathbf{x}_{k+1} = f(\mathbf{x}_k) + \mathbf{w}_k,
\]

(10)

with nonlinear state-transition function \( f(\cdot) \) (see details in [Kim and Sukkarieh, 2004]), \( \mathbf{w}_k \) being the process noise. The propagated uncertainty is approximated using Jacobian and the strength of the process noise.

### 3.2 Observation model

The probabilistic observation model relates the dual optic-flow observations \( \mathbf{z} = [n_{x1} \; n_{y1} \; n_{x2} \; n_{y2}]^T \) to the vehicle state:

\[
p(\mathbf{z}_k | \mathbf{x}_k) \Leftrightarrow \mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k,
\]

(11)

with \( \mathbf{v}_k \) being the observation noise. The nonlinear observation model can be obtained by combining Equations 1 and 4, yielding

\[
n_{x1} = \frac{n_y \Delta t}{\alpha} \left( \frac{v_y}{h_{ag}} - \dot{\phi}_y \right) + v_{k1}
\]

(12)

\[
n_{y1} = \frac{n_y \Delta t}{\alpha} \left( \frac{v_y}{h_{ag}} - \dot{\phi}_x \right) + v_{k2}
\]

(13)

\[
n_{x2} = \frac{n_y \Delta t}{\alpha} \left( \frac{v_y}{h_{ag} + L} - \dot{\phi}_y \right) + v_{k3}
\]

(14)

\[
n_{y2} = \frac{n_y \Delta t}{\alpha} \left( \frac{v_y}{h_{ag} + L} - \dot{\phi}_x \right) + v_{k4}
\]

(15)

which includes the rotation-rate corrections.
The filter updates using the predicted uncertainty and observation Jacobian matrix. The detailed equations are not presented here for brevity and can be found in many literatures such as [Maybeck, 1982].

### 4 Experimental Results

#### 4.1 Sensor System

The Agilent adns-2051 optical mouse chip was chosen for the experiment, illustrated in Figure 3. It is a non-mechanical tracking engine that is commonly found in computer mice. It operates using optical navigation technology, and measures changes in position by way of determining the direction and magnitude of motion from sequential surface images. The images are nominally acquired at a rate of 1500 frames per second which are then analysed by an in-built image-processing algorithm. Specific surface features on the image plane are identified and have their positions tracked with each frame. The collective motion of surface features are assigned two displacement values describing their overall motion across the image plane. The displacement values are given in terms of pixel counts.

The inertial measurement unit (IMU) was 3DM-GX1 manufactured by Micro-strain and illustrated in Figure 3. It is low-cost and contains tri-axis gyroscopes, accelerometers and magnetometers.

In preparation for experiment, several printed circuit boards were designed and manufactured to encompass the sensors, micro-controller and the necessary ancillaries for operation. An assembly was produced from the completed boards and then plotted with lens holders and lenses. The completed optical assemblies are illustrated previously in Figures 1.

#### 4.2 Results

The optic flow assembly and IMU were mounted to an arm containing two pivoting joints, and rigidly mounted to a workbench. The joints of each segment were vertical, and contained well lubricated bushes with low amounts of free play. The motion of the arm was constrained to the $x - y$ plane of the navigation frame, which was coincident with the IMU body frame at the commencement of the experiment. A large and highly textured surface was placed on a level surface beneath the optical assembly at a constant, fixed distance. A 500W lamp was placed at a distance of approximately 1.5m above and slightly adjacent to the mounting point of the arm, to ensure an adequate intensity of light and negate any adverse influences of the indoor fluorescent lighting in the vicinity of the experiment. During the experimental the arm was put through oscillatory planar motion, such that the highly textured surface was in view of both optic flow sensors.

The predicted velocity and attitude using the raw inertial data is presented in Figures 4.2 and 4.2, respectively (the position plot is not shown here since it is similar to velocity plot). They show the behaviour considered typical of low-quality inertial sensors, in that their time to exponential divergence is quite low even with the initial calibration at the beginning.

The optic-flow filtered position, velocity and attitude estimates are illustrated in Figures 6 to 8 respectively. The improvement in the estimates over the raw plots is immediately apparent. Clearly, both the $z$ position and velocity display the desired non-divergent behaviour. The last subplot in Figure 6 is the height-above-ground directly calculated from the raw measurements and shows high-noise level in measurements. The divergence of the $x$ and $y$ positions is due to the flatness of the underlying surface, preventing the position from being observable (this problem is typical in most terrain aided navigation systems where a aircraft needs to fly over undulating terrains to minimise the position error).

Figures 9 to 11 show the filter’s error in estimate for the position, velocity and attitude, respectively. It is clear that the velocity and attitude errors are constrained effectively from optic flow measurements. The divergent behaviour of the $x$ and $y$ covariance again confirms the lack of observability in position. Finally, the four optic-flow innovations with uncertainty are shown in Figure 12 also showing that the filter is tuned well.

#### 5 Conclusions

This paper presented a proof-on-concept study to show the validity of using optical-mouse chips for aided inertial navigation, aiming for flying applications. To provide the unknown depth information in optic-flows, a dual optic-flow sensor was configured. The flow measurements were then fused with a low-cost inertial sensor using extended Kalman filter. The indoor experiment showed improved navigation performances constraining errors in altitude, velocity and attitude. Implementation of this system on an actual UAV platform is currently being undertaken.
Figure 4: Raw velocity estimate using pure integration of accelerometers with raw attitude.

Figure 5: Raw Euler attitude estimate using pure integration of gyro.

Figure 6: Filtered position estimates using dual optic ow sensors.

Figure 7: Filtered velocity estimates using dual optic ow sensors.

Figure 8: Filtered Euler-angle estimates using dual optic ow sensors.

Figure 9: The filter’s error in position with $1 - \sigma$ uncertainty.
Figure 10: The filter’s error in velocity with $1 - \sigma$ uncertainty.

Figure 11: The filter’s error in Euler angle with $1 - \sigma$ uncertainty.

Figure 12: The optic flow innovations within filter with $1 - \sigma$ uncertainty.

References


