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Efficient Integration of Inertial Observations into Visual SLAM without Initialization

Todd Lupton and Salah Sukkarieh

Abstract— **The use of accelerometer and gyro observations in a visual SLAM implementation is beneficial especially in high dynamic situations. The downside of using inertial is that traditionally high prediction rates are required as observations are provided at high sample rates. An accurate orientation and velocity estimate must also be maintained at all times in order to integrate the inertial observations and correct for the effect of gravity.**

This paper presents a way to pre-integrate the high rate inertial observations without the need for an initial orientation or velocity estimate. This allows for a slower filter prediction rate and use of inertial observations when the initial velocity and attitude of the platform are unknown. Additionally the initial velocity and roll and pitch of the platform become observable over time and an estimate of these values is provided by the filter. An estimate of the gravity vector is also provided.

Results are presented using a delayed state information smoother implementation however due to the linearity of the equations this technique can be applied to extended Kalman filter (EKF) implementations just as easily.

I. INTRODUCTION

An inertial measurement unit (IMU) is a useful sensor to navigation and SLAM as it provides information about the motion of the platform that it is attached to that is independent of the characteristics of the platform and does not require any external infrastructure.

The use of observations from an IMU in vision based SLAM has received some attention in recent years by a number or people such as those presented in [1]–[4].

The addition of IMU observations to visual SLAM provides many advantages. It allows:

- the tracking of high dynamic motions
- constraining the platform's position when insufficient visual observations are made in an unbiased way
- constraining of roll and pitch estimates in a drift free way
- possible scale factor observability in monocular SLAM as shown in [5]

Inertial units often operate at much higher rates than what visual observations are taken at either requiring the SLAM filter to operate at a high prediction rate, such as in [3], or to fuse the inertial observations in an external navigation solution and use the results of this solution in the SLAM filter, as in [4]. In visual SLAM the intermediate poses between camera observations, produced from the high prediction rate of the inertial observations are of little interest and do no need to be estimated.

Todd Lupton and Salah Sukkarieh are with the ARC Centre for Excellence in Autonomous Systems, Australian Centre for Field Robotics, University of Sydney, Australia {t.lupton, salah}@cas.edu.au

Inertial observations can only be integrated if the initial position, velocity and attitude of the platform are known to a high degree of certainty by using long established techniques [3], mostly derived from inertial navigation algorithms from the aerospace community [6].

If the initial conditions of the vehicle are not well known, such as in the case where no specialized initialization routine is used, then these techniques can cause instability and robustness problems due to the linearizations that need to be made and the incorrect adjustment for the gravity vector.

This paper presents a technique that allows inertial observations to be pre-integrated before being added to a SLAM filter in a way that does not require the initial conditions of the platform to be known, and that allows the initial velocity and roll and pitch of the vehicle to become observable. The result of which is an efficient, initialization stage free method of incorporating inertial observation into visual SLAM.

II. METHODOLOGY

A. Inertial Integration

The IMU measures the linear acceleration and rotation rates of the platform which can be integrated to provide estimates of orientation, velocity and position with respect to an inertial frame.

One of the drawbacks of using inertial observations is that in order for them to be integrated the initial position, velocity and attitude of the platform needs to be known to a high degree of certainty.

The accuracy of the attitude estimate is especially critical as the effect of gravity needs to be compensated for before the linear acceleration observations are integrated. If the attitude estimate, specifically roll and pitch, of the platform with respect to the inertial frame is incorrect then the gravity compensation will be incorrect and lead to a large error in the acceleration estimate.

Also the inherent non-linearity of attitude equations makes the accuracy of their estimates even more critical when a linearized filter, such as an extended Kalman filter (EKF) is used.

B. Traditional Method for Inertial SLAM

The traditional method for integrating inertial observation into SLAM is during the prediction stage in the place of the process model [7] and is based on inertial navigation techniques developed for aerospace application [6].

The transition of the estimated vehicle position (p), velocity (v), and attitude (ϕ) from one time step to another using a single inertial observation is shown in equation 1.

$$\begin{bmatrix} p^n_{t+1} \\ v^n_{t+1} \\ \phi^n_{t+1} \end{bmatrix} = \begin{bmatrix} p^n_t + v^n_t \Delta t \\ v^n_t + \left[C^n_{bt} f^b_t + g^n \right] \Delta t \\ \phi^n_t + E^n_{bt} \omega^b_t \Delta t \end{bmatrix} \quad (1)$$

Where f^b_t and ω^b_t are the linear acceleration and rotation rate observations in the body frame at time t respectively. C^n_{bt} and E^n_{bt} are the rotation matrix and the rotation rate matrix from the body frame to the navigation frame using the attitude estimate at time t. Δt is the time between inertial observations and g^n is the gravity vector in the navigation frame.

This step has to be repeated for every inertial observation, which could be running at several hundred samples per second and the attitude of the platform must be known to a high degree of certainty at all times so that the C^n_{bt} and E^n_{bt} matrices can be formed as they are highly non-linear.

The draw back of this method is that if an EKF implementation is used, such as in [7], once the inertial observations are integrated into the filter they are fixed and can not be updated later on if a more accurate estimate of the vehicles velocity or attitude at that time is available.

If a delayed state information smoothing technique is used where all observations are retained separately, such as in [5], then the inertial observations can be relinearized at a later date but a new set of vehicle pose states needs to be added for each inertial observation leading to unnecessary bloating of the state vector and increase in the memory and computation requirements of the filter. The high non-linearity of the attitude equations can also still cause instability in this case if the initial estimate of the attitude is far from the truth.

C. Inertial Delta Observations

If inertial observations can be pre-integrated so that only one pseudo-observation incorporating all the inertial observations between two poses where images are taken in a way that is independent of the initial position, velocity or attitude of the vehicle then the ability to relinearize observations at a later date can be retained without the need to add extra pose states to the state vector or increase computational load.

This method will also allow inertial observations to be used in a filter where no initial information is know about the vehicles position, velocity or attitude as this information is no longer needed for integration of the inertial data.

These inertial pseudo-observations will be referred to as inertial delta observations.

D. Inertial Delta Observation Theory

If equation 1 is separated into its three components for the position, velocity and attitude update, and written in the continuous form so that it can cover multiple inertial observation samples, equations 2, 3 and 4 are obtained.

$$p^n_{t2} = p^n_{t1} + \int_{t1}^{t2} v^n_t dt \quad (2)$$

$$v^n_{t2} = v^n_{t1} + \int_{t1}^{t2} \left(C^n_{bt} f^b_t + g^n \right) dt \quad (3)$$

$$\phi^n_{t2} = \phi^n_{t1} + \int_{t1}^{t2} E^n_{bt} \omega^b_t dt \quad (4)$$

Where $t2 > t1$.

The inertial observation integration components from equations 2, 3 and 4 can be separated out from the components of the equations that require knowledge of the state of the vehicle at time $t1$ resulting in three inertial delta observation components as shown in equations 5, 6 and 7.

$$\Delta p^{+t1}_{t2} = \iint_t^{t+1} C^{t1}_t f^b_t dt^2 \quad (5)$$

$$\Delta v^{t1}_{t2} = \int_{t1}^{t2} C^{t1}_t f^b_t dt \quad (6)$$

$$\Delta C^{t1}_{t2} = \int_{t1}^{t2} E^{t1}_t \omega^b_t dt \quad (7)$$

The C^{t1}_t rotation matrix and the E^{t1}_t rotation rate matrix are formed using the current estimate of the attitude for the vehicle at time t relative to its attitude at time $t1$. This estimate only requires the integration of rotation rate observations from the IMU from time $t1$ to time t, which is performed in equation 7 anyway. The actual attitude of the vehicle at time $t1$ is not required for these operations.

Once the inertial delta observations are calculated they can be combined back with the components of equations 2, 3 and 4 that do require knowledge of the initial vehicle states as is shown in equations 8, 9 and 10.

$$p^n_{t2} = p^n_{t1} + (t2 - t1) v^n_{t1} + C^n_{bt1} \Delta p^{+t1}_{t2} + \frac{1}{2}(t2 - t1)^2 g^n \quad (8)$$

$$v^n_{t2} = v^n_{t1} + C^n_{bt1} \Delta v^{t1}_{t2} + (t2 - t1) g^n \quad (9)$$

$$\phi^n_{t2} = EulerFromRotationMatrix\left(C^n_{bt1} \Delta C^{t1}_{t2} \right) \quad (10)$$

Rotation matrices must be formed for the operation in equation 10, and then Euler angles recovered from the result instead of just using the delta Euler angles multiplied by a rotation rate matrix. This is because the integrated deltas may be over an extended period of time with a large change in orientation so the small angle approximation made with the use of a rotation rate matrix, as in equation 1, is no longer valid.

An interesting outcome from inspection of equation 8 is the proof that the initial instantaneous velocity of the vehicle in the navigation frame is observable given two consecutive position estimates. This can be seen from rearranging equation 8 to obtain equation 11.

$$v^n_{t1} = \frac{p^n_{t1} - p^n_{t2} + C^n_{bt1} \Delta p^{+t1}_{t2} + \frac{1}{2}(t2 - t1)^2 g^n}{(t2 - t1)} \quad (11)$$

The IMU sensor biases can easily be incorporated into the inertial delta observation calculations if an estimate of them is known at the time. This results in the modification of equations 5, 6 and 7 to produce equations 12, 13 and 14.

$$\Delta p_{t2}^{+t1} = \iint_t^{t+1} C_t^{t1} \left(f_t^b - bias_f^{obs}\right) dt^2 \tag{12}$$

$$\Delta v_{t2}^{t1} = \int_{t1}^{t2} C_t^{t1} \left(f_t^b - bias_f^{obs}\right) dt \tag{13}$$

$$\Delta C_{t2}^{t1} = \int_{t1}^{t2} E_t^{t1} \left(\omega_t^b - bias_\omega^{obs}\right) dt \tag{14}$$

These delta observations are then used as normal.

E. Inertial Delta Observation Creation

Algorithm 1 shows an example of how the inertial delta observations are calculated from the raw inertial measurement unit observations. This example uses first order Euler integration for clarity, however higher order integration techniques can also be used. $t1$ and $t2$ are the times at which two consecutive poses are required, such as the time two images were taken.

The deltas calculated are in the reference frame of the first position; the position at $t1$ in this case. The rotation matrix, C_t^{t1}, and rotation rate matrix, E_t^{t1}, are calculated using the intermediate delta attitude at time t, $\Delta\phi_t$, this is the estimated attitude of the vehicle at time t relative to the body frame at time $t1$ as calculated from the integrated gyro observations.

Algorithm 1 Inertial Delta Observation Creation

$\Delta p_t^+ = 0$
$\Delta v_t = 0$
$\Delta \phi_t = 0$
for $t1 < t < t2$ **do**
  $\Delta t = t_{t+1} - t_t$
  $f_t^n = C_t^{t1}\left(f_t^b - bias_f^{obs}\right)$
  $\Delta v_{t+1} = \Delta v_t + f_t^n \Delta t$
  $\Delta p_{t+1}^+ = \Delta p_t^+ + \Delta v_t \Delta t$
  $\Delta \phi_{t+1} = \Delta \phi_t + E_t^{t1}\left(\omega_t^b - bias_\omega^{obs}\right)\Delta t$
end for

$$obs = \begin{bmatrix} \Delta p^+ \\ \Delta v \\ \Delta a \end{bmatrix}$$

The biases $bias_f^{obs}$ and $bias_\omega^{obs}$ are the estimated biases of the inertial measurement unit at the time the delta observations are calculated. Derivatives with respect to these biases will be calculated so that small changes in this bias estimate at a later date can be accounted for. However, the relationship is non-linear so if a large change in the estimated bias occurs the inertial delta observations may need to be recalculated.

Algorithm 2 shows how the inertial delta observation Jacobian and covariance matrices are calculated for the example shown in algorithm 1. The variable ordering used is position, velocity, attitude, accelerometer bias, gyro bias. The J matrix is the Jacobian for the observation with respect to the initial platform states at time $t1$ and bias estimates and the R matrix is the covariance for the integrated inertial observation where Q is the sensor noise covariance matrix for the inertial measurement unit.

Algorithm 2 Inertial Delta Jacobian and Covariance Creation

$J = \mathbf{I}_{15}$
$R = \mathbf{0}_{15}$
for $t1 < t < t2$ **do**
  $\Delta t = t_{t+1} - t_t$
  $\alpha = \frac{dC_t^{t1}\left(f_t^b - bias_f^{obs}\right)}{datt_t}$
  $\beta = \frac{dE_t^{t1}\left(\omega_t^b - bias_\omega^{obs}\right)}{datt_t}$

$$F = \begin{bmatrix} \mathbf{I}_3 & \mathbf{I}_3\Delta t & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{I}_3 & \alpha\Delta t & -C_t^{t1}\Delta t & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 + \beta\Delta t & \mathbf{0}_3 & -E_t^{t1}\Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix}$$

$$G = \begin{bmatrix} \mathbf{0}_3 & \mathbf{0}_3 \\ C_t^{t1}\Delta t & \mathbf{0}_3 \\ \mathbf{0}_3 & E_t^{t1}\Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix}$$

  $J = FJ$
  $R = FRF' + GQG'$
end for

The Jacobian and covariance matrix calculations use intermediate results from the delta observation calculations from algorithm 1 so these two calculations should be performed simultaneously as the Jacobian and covariance matrices can not be recovered directly from the delta observations. As the delta observations are fixed in the initial position, velocity and attitude frame of the vehicle at time $t1$ only the last two columns of the J matrix are actually required for later use when the deltas are incorporated in the filter as these columns relate to the estimated inertial measurement unit bias values. The full J matrix is required for the intermediate calculations in algorithm 2.

If only one inertial observation is used in the inertial delta observation then the covariance matrix for that delta observation will only be of rank 6 as in this case the delta velocity and the delta position plus components can not be independently observed.

F. Inertial Delta Observation Use

Once the inertial delta observations and their Jacobian and covariance matrices have been calculated, they can be incorporated into a SLAM filter in the same way as any other observation. Only the prediction of the inertial delta observation given the current state estimates, $h(\hat{x}_t)$, and the predicted observation Jacobian matrix, H_t, still need to be calculated.

Equations 8, 9 and 10 can be rearranged to obtain the equations for the predicted inertial delta observations given the current state estimates as is shown in equations 15, 16 and 17.

$$h_{\Delta p+}(\hat{x}_t) = \widehat{C}^{n'}_{bt1}\left(\widehat{p}_{t2} - \widehat{p}_{t1} - \widehat{v}_{t1}\Delta t - \frac{1}{2}g\Delta t^2\right) + \frac{d\Delta p^+_t}{dbias_f}\left(\widehat{bias}_f - bias^{obs}_f\right) + \frac{d\Delta p^+_t}{dbias_\omega}\left(\widehat{bias}_\omega - bias^{obs}_\omega\right) \quad (15)$$

$$h_{\Delta v}(\hat{x}_t) = \widehat{C}^{n'}_{bt1}\left(\widehat{v}_{t2} - \widehat{v}_{t1} - g\Delta t\right) + \frac{d\Delta v_t}{dbias_f}\left(\widehat{bias}_f - bias^{obs}_f\right) + \frac{d\Delta v_t}{dbias_\omega}\left(\widehat{bias}_\omega - bias^{obs}_\omega\right) \quad (16)$$

$$h_{\Delta\phi}(\hat{x}_t) = EulerFromRotationMatrix(\widehat{C}^{n'}_{bt1}\widehat{C}^{n}_{bt2}) + \frac{d\Delta\phi_t}{dbias_\omega}\left(\widehat{bias}_\omega - bias^{obs}_\omega\right) \quad (17)$$

The $bias^{obs}_f$ and $bias^{obs}_\omega$ variables are the estimated IMU biases used in the creation of the deltas in algorithm 1 and the $\widehat{bias}_f$ and $\widehat{bias}_\omega$ variables are the filter's current estimate of these biases.

The $\frac{d}{dbias}$ terms in equations 15, 16 and 17 are obtained from the final J matrix from algorithm 2. The final J matrix is of the form shown in equation 18.

$$J = \begin{bmatrix} \frac{d\Delta p^+_{t2}}{dp^{t1}_{t1}} & \frac{d\Delta p^+_{t2}}{dv^{t1}_{t1}} & \frac{d\Delta p^+_{t2}}{d\phi^{t1}_{t1}} & \frac{d\Delta p^+_{t2}}{dbias_f} & \frac{d\Delta p^+_{t2}}{dbias_\omega} \\ \mathbf{0}_3 & \frac{d\Delta v_{t2}}{dv^{t1}_{t1}} & \frac{d\Delta v_{t2}}{d\phi^{t1}_{t1}} & \frac{d\Delta v_{t2}}{dbias_f} & \frac{d\Delta v_{t2}}{dbias_\omega} \\ \mathbf{0}_3 & \mathbf{0}_3 & \frac{d\Delta \phi_{t2}}{d\phi^{t1}_{t1}} & \mathbf{0}_3 & \frac{d\Delta \phi_{t2}}{dbias_\omega} \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \frac{dbias_f}{dbias_f} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \frac{dbias_\omega}{dbias_\omega} \end{bmatrix} \quad (18)$$

Therefore the total predicted inertial delta observation is:

$$h(\hat{x}_t) = \begin{bmatrix} h_{\Delta p+}(\hat{x}_t) \\ h_{\Delta v}(\hat{x}_t) \\ h_{\Delta \phi}(\hat{x}_t) \end{bmatrix} \quad (19)$$

The predicted observation Jacobian matrix, H_t, is made by taking the derivatives of equations 15, 16 and 17 with respect to the estimated vehicle position, velocity and attitude at both time $t1$ and $t2$ and the current estimates of the biases.

G. Observability and Convergence with Unknown Initial Conditions

If the initial velocity of the vehicle is unknown then it can become observable once estimates of the first two positions are available as has been shown in equation 11. From differentiating the inertial delta observation prediction equations (equations 15, 16 and 17) with respect to the initial velocity, as shown in equation 20, it can be seen that given the initial attitude the relationship becomes linear and therefore easy to estimate.

$$\begin{aligned} \tfrac{d\Delta p^{+t1}_{t2}}{dv^{n}_{t1}} &= -C^{n'}_{bt1}\Delta t \\ \tfrac{d\Delta v^{t1}_{t2}}{dv^{n}_{t1}} &= -C^{n'}_{bt1} \\ \tfrac{dd\Delta \phi^{t1}_{t2}}{dv^{n}_{t1}} &= 0 \end{aligned} \quad (20)$$

This result is useful for both filtering and smoothing (delayed state) techniques if the initial attitude is know to a high degree of accuracy as then initial velocity estimation becomes a highly linear problem.

However even if initial attitude is not know to a high degree of accuracy, or at all, the initial velocity and roll and pitch estimation can become a linear problem with a slight change to the estimated states.

The reason that attitude has to be known accurately when using inertial observations is because the gravity vector needs to be subtracted from the accelerometer observations before being used. The vehicle attitude with respect to the gravity vector needs to be known so that this subtraction can take place.

If instead of trying to estimate the initial attitude of the vehicle in the inertial frame, the gravity vector in the frame of the first vehicle position can be estimated. This way the initial attitude of the vehicle can be considered to be perfectly known, making the derivatives in equation 20 constant (as $C^{n'}_{bt1}$ is now a constant), and the gravity vector unknown.

The advantage of this arrangement is that not only does the estimation of the initial velocity become linear, but the estimation of the gravity vector given a fixed initial attitude is also a linear problem where as the estimation of the initial attitude relative to a fixed gravity vector is highly non-linear.

The linearity of the gravity vector estimation can be seen from the derivatives of equations 15, 16 and 17 with respect to the gravity vector as shown in equation 21.

$$\begin{aligned} \tfrac{d\Delta p^{+t1}_{t2}}{dg} &= -\tfrac{1}{2}C^{n'}_{bt1}\Delta t^2 \\ \tfrac{d\Delta v^{t1}_{t2}}{dg} &= -C^{n'}_{bt1}\Delta t \\ \tfrac{dd\Delta \phi^{t1}_{t2}}{dg} &= 0 \end{aligned} \quad (21)$$

Which with a fixed initial attitude (making $C^{n'}_{bt1}$ constant) makes estimation of the gravity vector a linear problem.

A beneficial side effect of this approach is that if no initial estimate of the vehicle attitude is available an all zero (or any arbitrary value) prior on the gravity vector can be used for the starting point of the solution instead of having to use a heuristic for the initial attitude.

III. RESULTS

A. Experimental Setup

To test the inertial pre-integration technique described in this paper data was collected using a Honeywell HG1900 inertial measurement unit and a Point Grey Research Bumblebee 2 stereo camera custom fitted with 2.1mm focal length wide angle lenses. Inertial observations were recorded at 600Hz and images were taken at 6.25Hz, at this sample rate 96 inertial observations are integrated into each inertial delta observation.

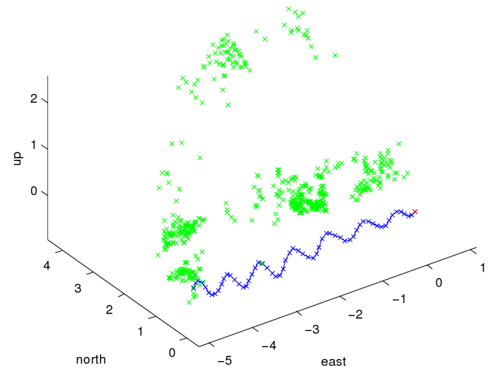

Fig. 2. Estimated map and trajectory. Landmarks are shows as green crosses. The connected blue crosses are the estimated poses with the red cross being the first pose.

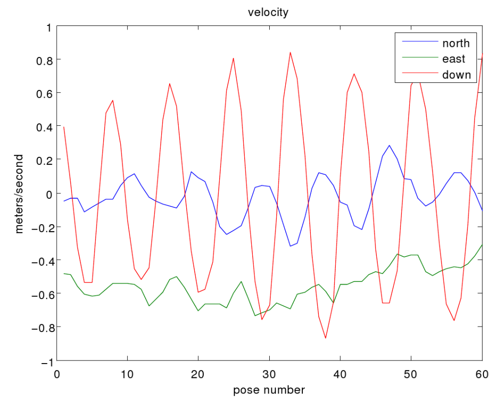

Fig. 3. Estimated velocity over the 60 image sequence in the north, east and down directions in the frame of the first pose.

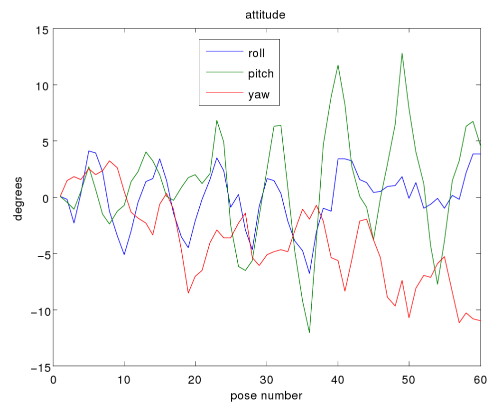

Fig. 4. Estimated attitude over the 60 image sequence in roll pitch and yaw in the frame of the first pose.

A sideways trajectory with sinusoidal up and down motion at an average walking pace was used in an indoor office environment. Sample images from the dataset can be seen in figure 1 and the trajectory itself can be seen with the estimated map in figure 2.

A delayed state information smoothing implementation similar to that described in [5] was used with initial estimates for the camera to IMU alignments provided with some associated uncertainty which was refined in the estimation by the filter. IMU biases, the gravity vector and the initial velocity of the sensor unit were also estimated as described in section II-G.

B. Analysis

Figure 2 shows the reconstructed feature map and trajectory estimated by the filter. The connected blue crosses are the pose locations with the red cross being the first pose.

Figure 3 shows the estimated velocity of the sensor unit in the north, east and down directions in the frame of the first pose. The sinusoidal motion can be seen in the down component of the velocity and the translation can been seen in the negative offset of the east component.

The initial velocity was estimated to be $[-0.0516, -0.4841, 0.3932]'\,m/s$ in the north, east and down directions respectively.

The estimated attitude of the sensor unit during the experiment is shown in figure 4, as with the position and velocity estimates the attitude estimate is in the frame of the first pose and that is why the initial estimates for roll, pitch and yaw are all zero.

The final estimate of the gravity vector in the first poses frame, as described in section II-G, for this experiment is $[0.5473, 0.1131, 9.7847]'\,m/s^2$ giving an estimated magnitude of the gravity vector of $9.8006 m/s^2$ which is within 0.04% of the true value which is $9.797 m/s^2$ in Sydney, Australia.

From this gravity vector estimate an initial roll and pitch in the inertial frame of 0.6621^o and -3.2015^o respectively can be calculated.

Figures 5 and 6 show the estimated velocity and attitude of the sensor unit during the first 20 images along with the estimates obtained if standard inertial observations fusion was performed where every inertial observation creates a new pose. The crosses on the figures indicate the estimated poses and it can be seen that there is a strong agreement between the two cases as should be expected.

The normalized innovations for the camera observations can be seen is figure 7, the horizontal line indicates the 2σ value. With the exception of a few points near the end of the run, which are outliers due to misassociation of features, the innovations are largely under the 2σ line indicating that the estimated trajectory and landmark locations are consistent with the feature observations made by the cameras.

IV. CONCLUSION

This paper has presented a new technique for the incorporation of inertial observations in a visual SLAM implementation that avoids many of the complications traditionally associated with using IMUs.

With the described method of pre-integrating inertial observations into inertial delta pseudo-observations the high filter prediction rates associated with IMU observations can be avoided.

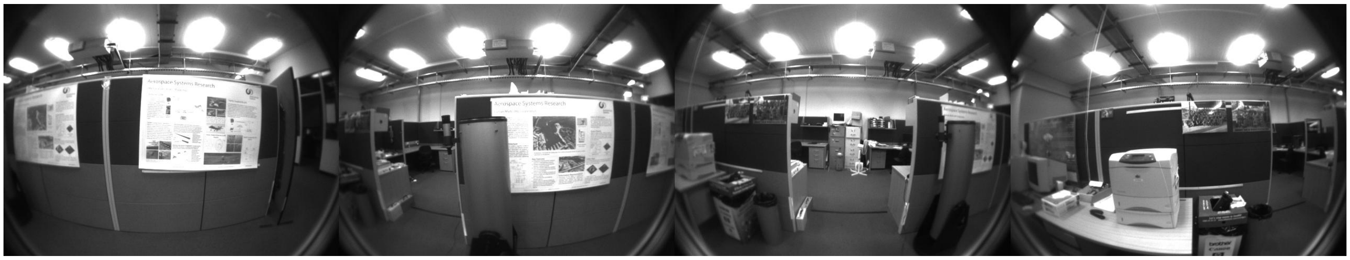

Fig. 1. Sample images taken from the dataset. The sensor unit was hand held and moved sideways towards the left while also being moved up and down in a sinusoidal motion.

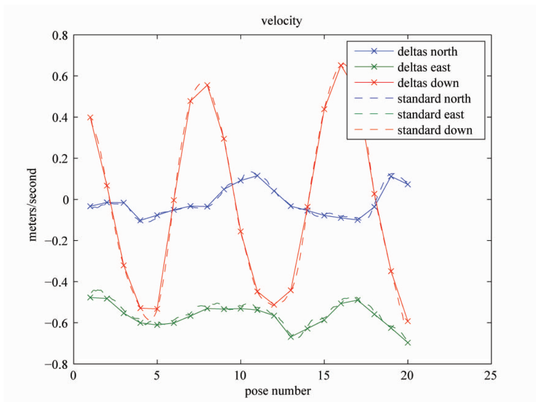

Fig. 5. Comparison of the velocity estimates for the same dataset using the inertial deltas as described in this paper and using standard inertial observations where each observation generates a new pose.

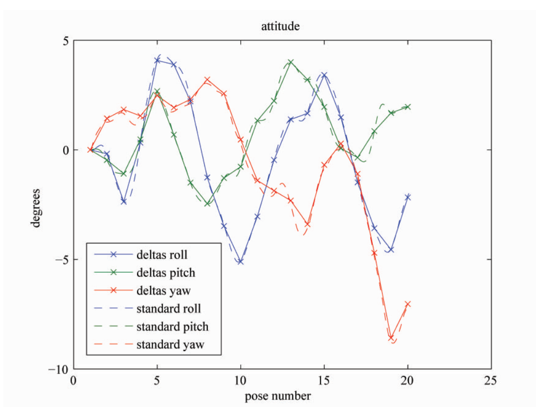

Fig. 6. Comparison of the attitude estimates for the same dataset using the inertial deltas as described in this paper and using standard inertial observations where each observation generates a new pose.

Also the combined use of inertial delta pseudo-observations and the estimation of the gravity vector in an attitude fixed frame allows inertial observations to be used in a SLAM implementation without the need for an initialization stage to obtain the initial attitude and velocity of the platform. This is true even if a filter structure with fixed linearizations, such as an EKF, is used.

Results have been presented to demonstrate the consistency of the solution and the estimation of the unknown initial velocity and attitude of the platform.

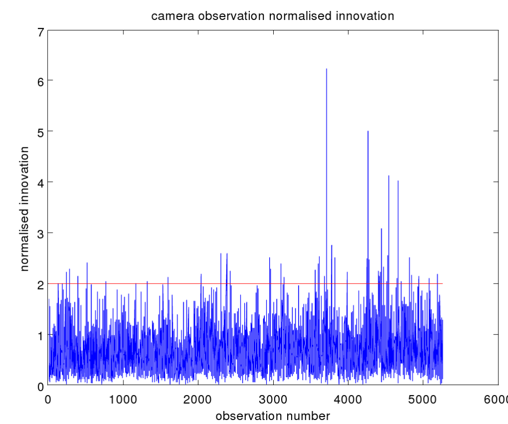

Fig. 7. Normalized innovation of the camera observations over the 60 image sequence. The horizontal red line indicates the 2σ value. It can be seen that the majority of the innovations are below this line indicating that the estimated trajectory is consistent with the camera observations.

The authors are currently looking into how this technique can be extended to include the estimation of the initial vehicle yaw in an absolute frame if it is observable as well as how absolute position information, such as that obtained from GPS observations, can be integrated into the solution.

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