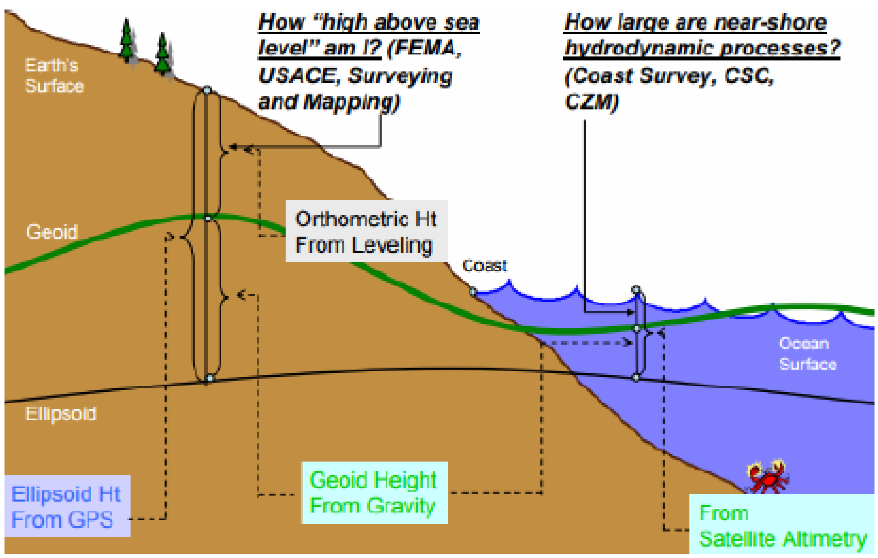
Graduation project summary, Hamza MAZIH

In many areas, determination of accurate orthometric heights cannot be achieved due to the uncertainty of the vertical reference surface –the geoid. Indeed, local gravity models are often not accurate enough, due to the insufficient amount, distribution, and quality of the incorporated ground gravity data, or they may just not be up-to-date due to ground deformation and variation in the underlying masses distribution, like in the aquifers, oil and gas reservoirs, or mines.

In nearshore regions, satellite-altimetry derived gravity models (e.g. Sandwell 2014) suffer substantial quality degradation, shipborne gravimetry cannot reach shallow water, and the sea surface is affected by non-gravitational effects –typically winds and currents; this combination prevents the determination of an accurate vertical reference surface. To fill the gap between land and deep sea, airborne gravimetry allows easily covering very large areas while providing accurate gravity measurements (few mGal), hence saving time and money. Furthermore, with the alarming effects of clime change such as rising sea levels, patch geoids specifically developed from airborne gravimetry over coastal regions will enhance the understanding of hydrodynamic processes and give access to accurate sea surface height anomaly, a key element in ocean circulation models.



(by Dru A. Smith, 2006).

The currently prevailing method in airborne gravity surveying consists in onboarding a relative gravity meter on a fixed-wing aircraft and fixing it on a gyro-stabilized platform to overcome the effect of aircraft motion on gravity signal. Despite achieving accuracies better than 2mGal, the installation process, operational inflexibility, important power consumption and huge coast of such system are limiting factors for geodetic and oceanographic applications. To overcome these limitations, strapdown airborne gravimetry (SAG), based on INS/GNSS systems, is found to be the most prominent solution. Combined with airborne LiDAR for coastal bathymetry or ground survey, it is also the most cost-effective one.

My graduation project at Fugro GEOID and Fugro INTERSITE, consisted of designing a protocol for data acquisition and processing of SAG systems, in order to evaluate whether and to what extend they can be used for geoid modelling while being implemented for positioning purpose during airborne LiDAR surveys. This study was part of an ongoing program, aiming to provide strapdown gravity data in parallel to airborne LiDAR, hence allowing geoid mapping and conversion of LiDAR's point cloud ellipsoidal heights into orthometric heights above Mean Sea Level.

Fugro LADS conducted a bathymetric LiDAR survey over the Red Sea's northern nearshore areas between December 2013 and 2015. In addition to LiDAR positioning, navigation data were made available to study strapdown airborne gravimetry capabilities of Applanix high grade IMU POS AV 610.

Inertial navigation relies on the integration of data from different sources using an inertial measurement unit (IMU) as a base. IMU structure includes basically three accelerometers and three gyroscopes, rigidly mounted to a common base along three perpendicular axes. Sensors measurements allow the determination of position, velocity and attitude of a moving vehicle, by applying strapdown equation derived from the second law of Newton.

SAG is based on combining global navigation satellite systems (GNSS) with strapdown IMU, using Kalman Filter, to estimate the magnitude of the gravity field, or the three components of the gravity vector. So typically, it requires high-grade IMU to deliver scalar gravimetry with the same accuracies as spring gravimeters mounted on gimbals-stabilized platforms.

Kalman filtering requires the knowledge of the system's noise characteristics, since it is based on probabilistic properties of input data. Its algorithm relies first on the estimation of the parameters forming the state vector, and then corrects these estimations based on aiding information. GNSS positions and raw IMU data are combined with their respective offsets using Fugro's FineTrack integrated positioning solution. The later models the difference between the measured gravity and the normal gravity, so-called gravity disturbance, as a stochastic process and estimate it as an element of the state vector X.

$$X = [\phi \quad \lambda \quad h \quad V \quad \Theta \quad B_a \quad B_g \quad Sf_a \quad Sf_g \;\; \delta g]$$

where each element of X corresponds, respectively, to position, velocity, attitude, accelerometer bias, gyros bias, accelerometer scale factor, gyros scale factor and gravity disturbance.

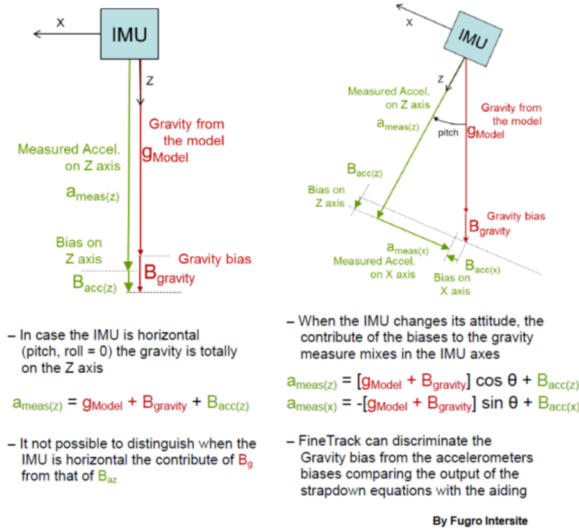
Kalman filter parameters are the core of FineTrack processing, because they define the noise levels in the system, the temporal correlation of the measurements and the modelling coefficients of the state vector elements. So, before starting processing navigation datasets with FineTrack, Kalman filter parameters are to be defined for all four levels of the inertial navigation process. Level 1 refers to the initialization and contains initial standard deviations of the state parameters. Level 2 has settings related to the initial alignment phase on the ground known as coarse alignment, for instance threshold configuration to detect if a vehicle is static (used for alignment purpose). Parameters for fine alignment and navigation modes are respectively defined in levels 3 and 4.

To run FineTrack, at least 21 a priori Kalman filter parameters are to be defined, and datasets needs to be decoded and converted to match FineTrack's format and navigation frame. Kalman filter is known to be the best linear estimator only for parameters affected by Gaussian noise, so all systematic errors are to be removed from data before starting processing.

Since the inertial navigation system (INS) true parameters are unknown, they need to be defined based on the collected data within a tuning process. In practice it involves evaluating the performance of the system with many different possible a priori settings. The parameters providing the best results are then refined by successive reiterations until getting the expected results.

The tuning process is performed in two steps. First, Fugro's automated tuning is applied to evaluate different sets of settings. Second, the selected settings are manually adjusted to get reliable gravity results, by making gravity estimates match their expected results.

The gravity is estimated in the navigation frame, and the biases are in the IMU body frame. Consequently, the Kalman filter needs big attitude changes to be able to distinguish between gravity signal and z accelerometer bias. Therefore, improving the observability, with optimal flight trajectories like successive circles (clockwise/anticlockwise), will allow the filter to fully differentiate accelerometer biases from gravity data by spreading the correction from measurement update adequately.

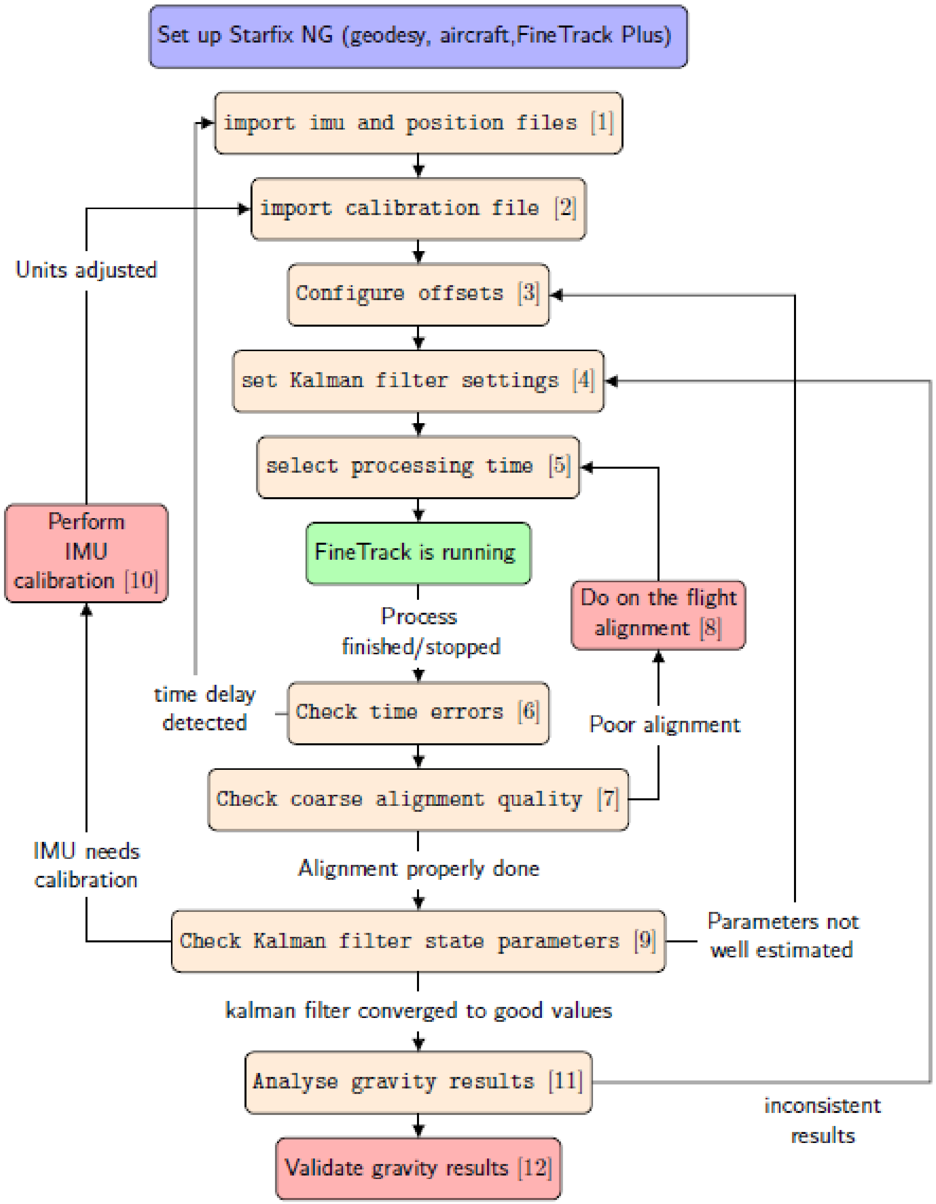


A large amount of flight datasets was available for this study, so it was necessary to set up a good methodology to select adequate datasets for the gravity extraction. Alignment quality of the INS and the required observability were the main criteria of the selection process.

Gravity results from FineTrack processing are to be corrected for a time lag and a linear drift before proceeding with gravity analysis. The latest is based on the following:

- Compare adjacent and overlapping lines.
- Compare each survey line with global gravity model (GGM). In this step only long wavelengths are considered due to GGM shortcomings at short wavelengths (incorporating questionable ground gravity data).
- Compare gravity data with least squares downward continuation reference model. The Least Squares Downward Continuation method allows the identification of outlying data points, in addition to evaluating discordance of measurements with gravity field harmonic behavior.

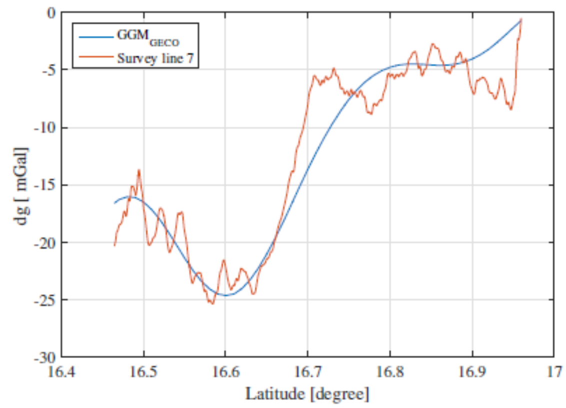
Datasets are processed and analyzed individually in FineTrack using an iterative process. The following diagram summarizes the main steps of the processing. Each step depends on the results of the previous one. Therefore, this processing is all the more crucial as an error would propagate and be amplified if not detected and corrected as soon as it occurs.



When the gravity results are not coherent with the GGM or between overlapping lines, then the Kalman filter settings are adjusted and FineTrack process is reiterated. Once consistent results are obtained for a selected flight, checks using the Kalman filter settings from the validated flight are performed with respect to other flights acquired with the same IMU. The Kalman filter settings are defined for each IMU and not for each flight, so unless the gravity results are validated for at least two datasets, the settings may not be fully validated. However, considering that the available datasets were not dedicated to strapdown gravity, but only to LiDAR positioning, the validation process has turned out to be especially challenging.

The internal accuracy of the system, based on comparisons between repeated lines, application of Least Squares Downward Continuation process, and comparison to a reliable GGM, was found to be better than 2 mGal at 2 km along-line resolution (half wavelength) and up to 1 mGal at 6 km resolution. The lack of accurate ground gravity data limited the external accuracy evaluation of the system.

The gravity results of the system have shown that Applanix POSAV 610 IMU can be used for strapdown gravimetry dedicated to geoid modelling while being implemented for airborne LiDAR positioning.



This study confirmed that defining Kalman filter parameters is the most challenging step of the strapdown gravity process. These parameters are crucial for geoid modelling applications, and to estimate them properly dataset must fulfil some requirements such as a lot of observability (i.e. aircraft attitude variations), fully static periods (or initial attitude) and accurate GNSS positions. The lack of accurate external gravity data and the absence of crossover points were a limiting factor to consolidate the system's accuracy.