Short Paper

Assemblability Based on Maximum Likelihood Configuration of Tolerances

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***Abstract*—An assembly is defined by a configuration of parts of known geometries subject to tolerances in the pose, dimensions, and mating relations among part features. Using a tolerance model based on matrix transforms and Gaussian models of geometric variations [1], the pose and dimensional tolerance models are considered as *a priori* models of the assembly with nominal and variational components for both position and orientation. The mating relations are regarded as linear relational constraints, also with nominal and variational components. With this formulation, estimation of the configuration of parts may be posed as a maximum likelihood problem and solved by a Kalman filter algorithm. The resulting maximum likelihood configuration of the assembly may be used to evaluate the required deviation from nominal and the *assemblability* as defined by the maximum likelihood clearance from constraints. In addition, application of the technique to intermediate subassemblies may be used to evaluate assemblability of specific steps and discriminate among alternative assembly sequence plans.**

I. Introduction

The design of products for assembly requires careful consideration of many factors which influence the functionality and manufacturability. While stability and relative precision of part positions are often essential for the functional performance of assemblies, these same requirements may make the product difficult to manufacture. At the same time, dimensional clearance among parts is essential to create paths for assembly operations, fine motion strategies may utilize contact between parts to guide the assembly motions, and often the addition of fixtures and supports may be necessary to maintain stable intermediate configurations of the parts during assembly. The planning of part designs, subassembly groupings, and assembly sequencing [2] is critical to efficient and reliable manufacturing processes.

In practice, part geometries are not manufactured precisely and there is also uncertainty in each positioning operation. These uncertainties may be represented by tolerance specifications on the parts and the assembly relations. Reasoning about these tolerance uncertainties is important to the understanding of the difficulty of the assembly and may be critical to the determination of a sequence which is *feasible*. A given sequence may cause the tolerances among parts to accumulate ("propagate") as the assembly operations proceed, and the accumulated tolerances may result in an infeasible operation for some percentage of the assemblies which are produced. Tolerance is a representation of a stochastic geometry of the parts and positions, so the resulting analysis and reasoning is inherently probabilistic. The question is: Even if an assembly sequence is feasible for the *nominal* geometry of the parts, what is the *probability* that, in practice, tolerances may accumulate to make the resulting assembly infeasible? Are there some assembly sequences which will increase, or guarantee, the probability of successful assembly? How should the design of the parts, or the tolerancing of the parts be changed to improve the *assemblability*? When is it cost-effective to loosen the tolerance on parts in order to improve the reliability of manufacturing?

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The representation of tolerance information has been key to the analysis of this problem. The basic engineering standard for specifying tolerance relations is given by the ANSI Y14.5M-1982 [3] standard, and these tolerances are applied to parts and standard sub-part geometric features. In standard practice, dimensions and positions are bounded by minimum and maximum values, and these bounds are used to define the allowable variations among the features. While form tolerances, such as variation in surface flatness, are also of practical interest, they will not be discussed in this paper.

Two classes of tolerance representation have been used for assembly analysis. First, the direct interpretation of standard tolerance specification suggests the use of inequality constraints and bounded intervals. Fleming [4] analyzed the extremal configurations associated with inequality constraints, and used symbolic reasoning to solve for bounds. Takahashi *et al*. [5] analyzed sets of vertex-face contacts and successively added contacts to find feasible configurations. Turner [6]–[8] formulated the problem as a mathematical linear programming problem and solved for configurations which satisfy the set of linear inequalities associated with tolerances on three-dimensional polyhedral models. In practice, this approach requires an ordering specification to define chains of tolerance relations, and this ordering of relations has been developed through manual analysis, or must be specified by the designer. Inui *et al*. [9], [10] have used bounding polyhedra in the configuration space and sought to optimize an objective function with the tolerance bounds.

A second approach to tolerance analysis is based on the representation of geometric variations by probability distributions in the kinematic configuration space of the parts. Whitney and Gilbert [1] used Monte Carlo simulation techniques to choose optimal Gaussian approximations to bounded distributions. They showed that matrix transformations representing part and feature relations could be used to propagate variational models through the assembly model. The approach of Lee and Yi [11] is based on this representation and evaluates the assemblability of two subassemblies with respect to the pose tolerance and clearance of mating features among parts. They use a bounding ellipse related to the Gaussian model, and examine discretized samples of the bounding points of the ellipse to check the existence of sufficient clearance to compensate for the pose tolerance. The resulting characterization of the uncertainties is based on a type of Monte Carlo simulation of the distributions and requires extensive computation time for realistic examples.

The first approach, using bounded intervals, is most consistent with the engineering standard representation, and yields hard bounds on assemblability. However, the computational complexity grows quickly with the number of parts, and is particularly difficult if orientation is included. The second approach, the Gaussian model, takes advantage of the computational properties of the distribution and simplifies the serial propagation of tolerances. In addition, the Gaussian model may capture many actual physical characteristics of tolerances which the standard bounds do not.

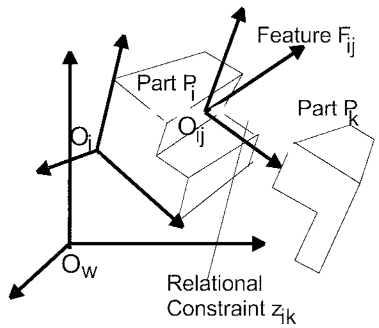

Fig. 1. Representation of assembly relations.

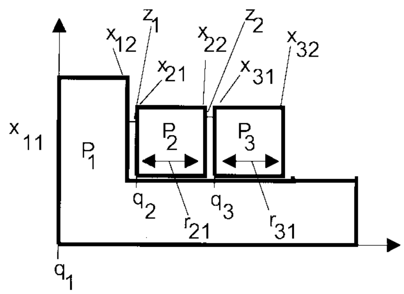

Fig. 2. Three part assembly with principal mating constraints in the x-direction.

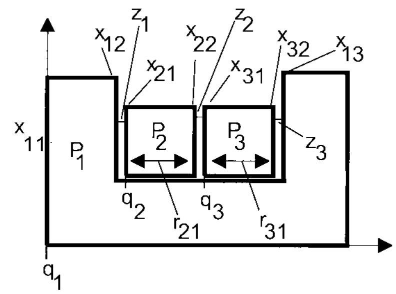

Fig. 3. Three part assembly with added constraints.

In this paper, the Gaussian approximation to tolerance distributions [1] is used as a basis for maximum likelihood estimation of a parts configuration which satisfies both *prior* distributions defined by pose and dimensional tolerances and mating constraints defined by linear feature relations. The probability distribution of the resulting *maximum likelihood assembly configuration* (MLAC) [12] provides a basis for evaluating the consistency of the tolerance specifications and the resulting assemblability of the parts. The intent of this approach is to provide a relative assemblability, rather than an absolute criterion for assemblability. The relation of the MLAC to the nominal configuration and clearances may be used to rank alternative designs and sequences. In addition, the comparison of the MLAC for two subassemblies may be used directly to assess the feasibility of an individual assembly step in a sequence, and therefore may be used to evaluate the sequence itself. Because the Kalman filter estimation is effectively a closed-form analytical solution to the estimation problem, the computational requirements of this approach are far less than in a Monte Carlo approach [11].

In Section II of this paper, we define the tolerance representation for an assembly. In Section III, we describe the MLAC algorithm for estimate of the maximum likelihood assembly configuration. In Section IV, we describe results of four examples and their evaluation for assemblability. Section V presents conclusions.

II. Tolerance Representation

In this paper, an assembly, A, is represented as a set of parts, $\{P_i\}$, configured in a global coordinate frame, F_G, with origin O_G. Each part, P_i, has a local coordinate frame, F_i, with origin, O_i, as shown in Fig. 1, which will be used to define the position of the part in the global frame. Each part, P_i, has a set of geometric features, $\{F_{ij}\}$, where F_{ij} designates the jth feature on part P_i. Each feature, F_{ij}, uniquely defines a local geometry (e.g., face, hole, tab etc.) and will usually be chosen from a library of available features with parameterized geometries (e.g., diameter of the hole). Each feature, F_{ij}, therefore also has a local feature coordinate frame, F_{ij}, which will be used to define the position of the feature in the part coordinate frame.

Assuming that all the parts, P_i, are rigid, then we can define a configuration, q_i, of P_i as a specification (for example, a parameterized homogeneous transformation, T [13]) of the position and orientation of part frame F_i with respect to global frame F_G. The complete assembly, A, is then specified by the configuration of all the parts in F_G, where $Q = (q_1, q_2, \cdots, q_N)$ is the parameter vector of the transformation. Each feature, F_{ij}, of a part, P_i, is specified by its parameterized configuration, r_{ij}, in the local part coordinate frame, F_{ij}. Given a nominal configuration, Q, the linearized configuration of the feature, F_{ij}, can be expressed in F_G

$$x_{\text{in}} = T\{q_i, r_{ij}\}. \tag{1}$$

The resulting set of all nominal feature configurations in the global coordinate frame is $X = (x_{11}, x_{12}, \cdots, x_{21}, x_{22}, \cdots, x_{N1}, x_{N2}, \cdots)$.

In practice, designers usually do not specify assembly designs in terms of independent nominal parts positions, but rather in terms of relations between features from different parts. For example, a mating contact between surfaces, or between a peg and hole, are common constraints which define the final configuration of the assembly. In this work, we will assume that such relative constraints can be expressed as *linear* functional constraints on the global feature positions, X

$$Z = HX \tag{2}$$

where $Z = (z_1, z_2, \cdots z_M)$ is a vector of constraint parameters (e.g., clearance values) and H is a matrix defining the feature constraint relations. For example, a simple clearance constraint in the x-direction between face 1 of P_2 and face 3 of Part 4 might be written

$$z_{1x} = [1 \quad -1]\begin{bmatrix} x_{21} \\ x_{43} \end{bmatrix}. \tag{3}$$

Such linear relations on the parameters of X can account for most of the common mating, clearance, and alignment constraints in common use for specification of assemblies. If parts placements and geometries were precise, then the nominal specification of the assembly, Q, would always be consistent with the relational specification given by (2). As described below, this is not the case in practice, though for purposes of the analysis here we will assume that the assembly constraints have been provided by the designer and define a unique nominal configuration, Q_N.

Parts are not manufactured exactly to their nominal geometries, and therefore the feature configurations described by r_{ij} will vary from their nominal values

$$r_{ij} = r_{ij} + u_{ij} \tag{4}$$

where u_{ij} is a random vector of noise variation terms. For the analysis here, we will assume that u_{ij} is described by a Gaussian distributed random vector with mean zero and covariance C_{ij}. We will also often assume that the random variations in feature geometries are independent among features, though this is not strictly necessary to the formulation. r'_{ij} may be thought of as a parts feature tolerance model, and the Gaussian assumption used for the representation of part feature geometries adopts the model of Whitney and Gilbert [1].

The placement of parts in the assembly process is also not precise, and we adopt a similar Gaussian model for the variations in part positions defined by

$$q_i = q_i + v_i \tag{5}$$

where v_i is a random vector of noise variation terms, also with zero mean and covariance C_{vi}.

The combination of the random models of part and placement geometries provides a representation of the random configuration of parts features in the global coordinate frame

$$x_{ij} = T\{q_i + v_i, r_{ij} + u_{ij}\} \tag{6}$$
$$= T'\{q_i, r_{ij}, w_{ij}\} \tag{7}$$

where w_{ij} is also a Gaussian random vector defining the random component of the convolution of the two distributions and having zero mean and covariance C_{wij}. The set of random vectors $X' = (x'_{11}, x'_{12}, \cdots, x'_{N1}, \cdots)$

$$X = T'\{Q, R, W\} \tag{8}$$

will be considered the *a priori* model for the assembly configuration, since it incorporates placement and parts variations, but does not impose relational constraints.

The second part of the formulation is based on a similar stochastic model for the constraint relations. Each relative constraint parameter, z_{kl}, may also be specified with some tolerance, d_{kl}. The resulting constraint equations take the form

$$Z = HX + D \tag{9}$$

where $D = (\cdots, d_{kl}, \cdots)$ is a random vector described by a Gaussian distribution with mean zero and covariance C_D. It should be noted that these constraint tolerances are usually represented as uniform or skewed and bounded distributions, and therefore it is not obvious that a Gaussian model will be meaningful. However, as described in [1], they still provide a useful description, and in particular the goal of this work is to formulate a *relative* assemblability measure, rather than an absolute model. We will again assume that the constraint tolerances are independent, though that is not strictly necessary.

III. Maximum Likelihood Assembly Configuration

Given a stochastic model of the assembly tolerances and relations, we can address the question of assemblability in terms of the *probability* that parts will fit together as specified. In this formulation, the model developed in Section II and summarized in (8) and (9), provides the basis to estimate the *expected* configuration of the parts and the likely *variance* in the configuration of the parts given all the tolerance information. The variance or range of configurations within which the assembly is probably feasible may be interpreted as a criterion for assemblability.

From (8), we consider X' as an *a priori* model of the configuration of the assembly, including both position and orientation. The relations among parts described by (9) impose a set of constraints on the final configuration, and the actual assembly and its feasible variations will be described by satisfaction of both equations. In this section, we wish to estimate the configuration X which minimizes the mean square error

$$J = E\{\hat{X}^T \hat{X}\} \tag{10}$$

where E is the expected value. The general form of (8)–(10) define a problem in mean-square estimation of a random variable with a linear measurement model with statistical independence of the process and measurement noise. In this case, the constraint vector, Z, takes the place of a traditional measurement process [14]–[17].

Based on this linear constraint model and Gaussian probability density functions, the minimum mean-square error estimator is found to be a *linear* estimator, $\hat{X}$, for the assembly configuration, X, and is given by the following expression [16]:

$$\hat{X} = C_X H^T C_D^{-1} Z \tag{11}$$

where the covariance of the estimate X is given by

$$C_{\hat{X}} = \left[C_X^{-1} + H^T C_D^{-1} H\right]^{-1}. \tag{12}$$

The same estimator could be written in terms of the Kalman gain, K

$$C_{\hat{X}} = [I - KH]C_X \tag{13}$$

where

$$K = C_X H^T (H C_X H^T + C_D)^{-1}. \tag{14}$$

Equations (11) and (12) may be used to compute the estimates of X and the covariance estimates for any set of *a priori* distributions and any set of relational constraints on the assembly. Given N parts in the assembly, their nominal configuration, Q_N, and their placement and parts covariances (tolerances), the computation requires the following steps.

1) Specify the parts relations, H, which define the assembly, as well as the constraint parameters, Z, and the constraint tolerances, C_u.
2) Use (12) to compute the estimate of the covariance matrix, C_x, for the assembly configuration which is most likely to satisfy the constraints given the nominal configuration.
3) Use (11) to compute the maximum likelihood estimate of the assembly configuration, $\hat{X}$.
4) Integrate (numerically) the resulting Gaussian distribution of parts configurations with respect to the actual constraint tolerance bounds in the configuration space of the assembly. The resulting integral, P_A, is the probability that the maximum likelihood configuration lies within the specified tolerance bounds, and may be interpreted as a measure of *assemblability*.
5) Examine the probability of individual degrees of freedom of the distribution relative to their constraint tolerance bounds, and identify those specific parts and degrees of freedom which are least likely to be within constraints. These may be interpreted as a measure of assemblability of the specific parts and identifies parts and features which may be good candidates for redesign.
6) For any two subassemblies $B1, B2 \; \varepsilon \; A$, repeat steps (2), (3). The resulting $\hat{X}_{B1}$ and $\hat{X}_{B2}$ are the maximum likelihood estimates for each of the two subassemblies. For each specific constraint relation between $B1$ and $B2$, the probabilities of meeting tolerance constraints, P_{B1} and P_{B2} can be computed, and serve as measures of assemblability for the two subassemblies. Any set of candidate assembly sequence steps may be compared in terms of these probabilities, and the total probability for the sequence may be used to evaluate alternatives.

IV. Examples

Based on the formulation of the problem in Section III, several examples may be used to illustrate this approach. In order to visualize these tolerances, one-dimensional cases will be emphasized in the

TABLE I
VARIANCE AND ASSEMBLABILITY FOR THE ASSEMBLY IN FIG. 3 WITH SEQUENCE 1-2-3 FOR INCREASING PARTS TOLERANCES

σ_r^2 (x.01)	P_A
0.06	0.94
0.25	0.84
1	0.61

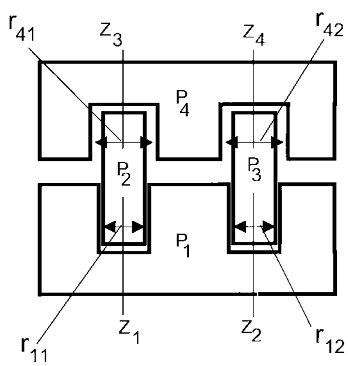

Fig. 4. Four part assembly example.

TABLE II
ASSEMBLABILITY FOR THE ASSEMBLY SHOWN IN FIG. 4 FOR TWO DIFFERENT SEQUENCES AND TWO DIFFERENT PARTS TOLERANCES

Sequence	σ^2 =.0025	σ^2 = .0050
1-2-3-4	0.93	0.81
4-2-3-1	0.77	0.62

examples. The analysis applies to arbitrary dimensions including orientation.

Fig. 2 shows a three-part assembly with principal mating constraints in the x-direction. The nominal parts positions, q_1, q_2, q_3, and geometries r_{21}, r_{31} are shown in the figure. The tolerances are described as bounds on part placement q_i and part geometries r_{ij}. These tolerances are modeled by Gaussian distributions with variances in the x-direction for placement: $\sigma_1^2 = \sigma_2^2 = 0.01$, and for parts geometries: $\sigma_{ij}^2 = 0.0025$. The problem is formulated as described in Sections II and III with resulting expressions (omitting x_{11} for simplicity)

$$X = [x_{12}, x_{21}, x_{22}, x_{31}, x_{32}]^T \tag{15}$$

$$H = \begin{bmatrix} -1 & 1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 1 & 0 \end{bmatrix} \tag{16}$$

$$C_x = \begin{bmatrix} \sigma_{11}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{20}^2 & \sigma_{20}^2 & 0 & 0 \\ 0 & \sigma_{20}^2 & \sigma_{21}^2 + \sigma_{20}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{30}^2 & \sigma_{30}^2 \\ 0 & 0 & 0 & \sigma_{30}^2 & \sigma_{31}^2 + \sigma_{30}^2 \end{bmatrix}. \tag{17}$$

The resulting covariance depends on the order of assembly. For sequence 1-2-3, the resulting variance $\sigma_{20}^2 = 0.0050$ and the probability of feasible assembly is $P_A = 1.0$, since this sequence is always feasible. However, the sequence 1-3-2 results in a probability $P_A = 0.5$ and $\sigma_{20}^2 = 0.0100$ for the cases when assembly is feasible.

Fig. 3 shows a more difficult assembly with an additional constraint in the x-direction by feature F_{13}. For this case the expressions become (omitting x_{11} for simplicity)

$$X = [x_{12}, x_{13}, x_{21}, x_{22}, x_{31}, x_{32}]^T \tag{18}$$

$$H = \begin{bmatrix} -1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 \end{bmatrix}. \tag{19}$$

For this case, the resulting probability P_A may be calculated for several possible values of the parts tolerances. Results of these calculations for this model are shown in Table I. As the parts tolerance becomes larger, the final assembly configuration tends to deviate more widely from the nominal and the resulting probability of feasible assembly decreases.

Fig. 4 shows an example with two degrees of freedom, x and O. This example is derived from an industrial case study of high-tolerance connector assemblies for fiber optic cable connectors. The tolerance on both position and angle of these devices is quite high due to the requirements for alignment of optical paths. In addition, the assembly steps are critical to the process in order to enable proper alignment of both of the parallel paths.

In this case, the clearance on the upper holes is wider than the clearance on the lower holes, $r_{11} > r_{41}, r_{12} > r_{42}$, so that the order of assembly becomes important to the assemblability. Table II shows results of the assemblability analysis for the four obvious assembly sequences with calculation of the assemblability of the final part for each case. This result shows that the first sequence, 1-2-3-4 (1-3-2-4), is less difficult to assemble than 4-2-3-1 (4-3-2-1).

V. CONCLUSION

The formulation of the assemblability problem described in this paper is an exploration of techniques which would provide a more efficient and computationally tractable approach to determining the assemblability of a given design and assembly sequence. The approach suggests a relative measure based on Gaussian approximations to actual parts distributions and the use of maximum likelihood as a means to achieve analytical solutions. The results described here from relatively simple problems and geometries are promising and consistent with an intuitive interpretation of the problems. Further investigations and experiments with more realistic problems and larger numbers of parts will be necessary to evaluate the practical feasibility of this approach.

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A High Integrity IMU/GPS Navigation Loop for Autonomous Land Vehicle Applications

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***Abstract*—This paper describes the development and implementation of a high integrity navigation system, based on the combined use of the Global Positioning System (GPS) and an inertial measurement unit (IMU), for autonomous land vehicle applications. The paper focuses on the issue of achieving the integrity required of the navigation loop for use in autonomous systems. The paper highlights the detection of possible faults both before and during the fusion process in order to enhance the integrity of the navigation loop. The implementation of this fault detection methodology considers both low frequency faults in the IMU caused by bias in the sensor readings and the misalignment of the unit, and high frequency faults from the GPS receiver caused by multipath errors. The implementation, based on a low-cost, strapdown IMU, aided by either standard or carrier phase GPS technologies, is described. Results of the fusion process are presented.**

***Index Terms*—Autonomous systems, global positioning system, inertial measurement unit, Kalman filter, navigation.**

I. Introduction

The commercial development of large autonomous land vehicles in applications such as open-cast mining, agriculture and cargo handling requires the corresponding development of high integrity navigation (localization) systems. Such systems are necessary to provide knowledge of vehicle position and trajectory and subsequently to control the vehicle along a desired path. The need for integrity in such systems is paramount: undetected, erroneous, position or trajectory data can lead to catastrophic failure of the autonomous vehicle.

A growing number of research groups around the world are developing autonomous land vehicle systems for various applications (see [2], [4]–[6], and [13] for example). However, few of these works make explicit the essential need for system integrity that will be necessary in any future commercial development of this technology. Further, while many systems use Global Positioning System (GPS) and inertial technology, there has been no real application to understand, quantify and overcome the issue of failure and integrity in navigation systems based on these sensor technologies. This paper specifically addresses this issue in the context of autonomous land vehicle applications.

The focus of this paper is on the implementation of fault detection techniques that increase the integrity of the inertial measurement unit (IMU)/GPS navigation loop for land vehicle applications. The implementation processes adopted follows a decentralized data fusion philosophy and have been developed to ensure modularity. This ensures that the ability of the loop to detect the occurrence of faults is not prejudiced by the specific accuracy of the IMU or GPS sensors employed. This paper begins in Section II by providing the essential background on IMU and GPS sensor technologies in the context of sensor faults and the sensors specifically used in this paper. Section III presents the IMU error model implemented which forms the basis of the Kalman filter state model. Section IV focuses on faults, their nature and the means of detection in IMU and GPS systems. The nature of these faults and the means for detecting them are described. Section V details the implementation of this system with respect to the tuning of the filter and the resulting error growth. Section VI presents the vehicles used to test the loop along with the effect of the environment on the sensors. Finally, Section VII provides a series of experimental results that demonstrate the accuracy and integrity of the resulting system. Conclusions are then provided.

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II. Sensors

The accuracy of the navigation loop is dependent on the accuracy of the IMU and GPS sensors implemented. The greater the accuracy of these sensors, the greater the accuracy of the overall navigation loop. Brief descriptions of IMU and GPS sensors follow. For further detail on IMU's refer to [3] and [11]. For GPS refer to [9].

A. IMU

The primary advantage of using an IMU on outdoor land vehicles is that the acceleration, angular rotation and attitude data is provided at high update rates. Thus the velocity and position of the vehicle can also be evaluated. Unlike wheel encoders, an IMU is not affected by wheel slip, which is encountered by the majority of land vehicle applications. There are however disadvantages to using an IMU. The errors caused by bias in the sensor readings accumulate with time and inaccurate readings are caused by the misalignment of the unit's axes with respect to the local navigation frame. These errors will be discussed in Section IV-A.

The IMU implemented in this work comprises of three accelerometers, three gyros and two pendulum gyros. These sets of sensors provide the acceleration, rotation rate and tilt of the vehicle respectively, in the body frame, at a frequency of 84 Hz.

B. GPS

The GPS receiver is an external or absolute sensor, thus the errors in the data it provides are bounded. However, the GPS unit is a low frequency sensor, thus providing the state information at low update rates. There are two forms of accurate GPS receiver technologies implemented in this work: standard differential and carrier phase differential. High frequency faults arise when the GPS signals undergo multipath errors. These errors occur when the GPS signal is reflected off one or more surfaces before it reaches the receiver antenna. This results in a longer time delay of the signal and hence affects the fix of the standard differential receiver and also alters the phase of the signal thus affecting the carrier phase