Passive Indoor Image-Aided Inertial Attitude Estimation Using a Predictive Hough Transformation

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Abstract—Autonomous navigation of vehicles in non-cooperative environments continues to be a significant challenge for integrated navigation systems due to the unavailability of Global Positioning System (GPS) signals. As a result, passive indoor navigation systems routinely exhibit unbounded growth in navigation errors. In this paper, we seek to stabilize the attitude errors by exploiting commonly-occurring structures within the environment using rigorously coupled image and inertial sensors.

Previous work in the literature has demonstrated the value of points on the infinite plane in projective space, also known as vanishing points. These points are invariant to position (translation) changes and are a strong indicator of attitude. If some prior knowledge regarding the location of the vanishing points is available, researchers have shown that these can be used for drift-free attitude estimation. Unfortunately, to our knowledge, research has been limited to sub-optimal implementations based on non-Bayesian techniques and various ad-hoc approaches. We seek to improve this limitation by deriving a statistically-rigorous predictive Hough transformation (PHT), based on a priori attitude information provided by an inertial sensor. The PHT update is then used to correct the inertial sensor using an extended Kalman filter algorithm.

The algorithm is tested using a combination of simulation and experimental data. The PHT is shown to improve the robustness of the image-aided navigation algorithm and reduce the effects of outliers on the solution compared to naïve approaches. In addition, the navigation solution is shown to exhibit drift-free attitude performance using experimental data collected in a typical office environment.

Keywords—Hough transform; loosely coupled navigation; recursive attitude estimation; passive image-aided navigation

I. INTRODUCTION

Over the past two decades, the Air Force has become increasingly reliant on the capabilities of precision attack and maneuver to manifest impressive operational effects [8, 18]. More recently, the conflicts in Iraq and Afghanistan have highlighted the utility of unmanned aerial vehicles (UAVs), such as the Predator and the Global Hawk, to provide a significant tactical advantage [2]. Typically, the navigation systems on these UAVs include an inertial navigation system (INS). While most INS implementations provide useful data over short periods of time, they are also subject to unbounded error growth and require an external source of information, such as the data from the Global Positioning System (GPS), to mitigate these errors. Given the lack of an alternative drift-free precision navigation sensor, there is an induced dependence on the information provided by the GPS [7, 15]. Unfortunately, the GPS signal is not available in every desired operational location. This lack of availability may arise due to the location, e.g., inside a manmade structure or in a dense urban environment, or may be the result of various forms of electromagnetic interference (possibly intentional, malicious denial of service attacks).

With a need to find a balance between this lack of availability and the desire for precise navigation, we are faced with the task of generating a source of navigation information in a GPS-denied environment. As part of this research effort, we seek to develop a source of attitude information to replace the data obtained thru GPS. While GPS is not generally considered to be an attitude sensor, in the case of a tightly-coupled GPS-INS architecture, an attitude benefit is derived by using the GPS data to bound and correct the errors committed by the INS. One potential information source may be derived from the projection of the real world scene onto the focal plane of an imaging sensor. After this projection onto the focal plane, the relative attitude of the imaging sensor is encoded in a set of special points, known as vanishing points.

Previous work related to the topic of vanishing point estimation includes the Gaussian sphere method of [1], the line cross-product method of [9, 14], the cascaded Hough transform method of [17], and the line clustering method of [12]. In [6], Johnson briefly demonstrates several vanishing point estimation techniques, to include one based on the standard Hough transform, and shows that the combination of low-rate image-based and high-rate inertial attitude data produces a bounded, drift-free estimate of attitude.

The work presented in this paper provides a method to obtain stable, drift-free attitude estimates by first formulating a predictive Hough transformation (PHT) to extract instantaneous attitude information and then combining this information with the attitude estimate from a standard inertial measurement unit (IMU) in an extended Kalman filter (EKF). Essentially, by using image-based attitude estimates to provided corrections to the angular data obtained from the IMU, we create a tightly-coupled vision-inertial attitude
determination system. The development of this PHT is based on Bayesian techniques such that the entire attitude estimation process is implemented in a recursive algorithm.

The remainder of this paper is organized into the following sections. In Section II, we review the fundamental concepts of projective geometry and the standard Hough transformation required to understand the function of the PHT. Then, in Section III, we present the development of and the justification for the PHT algorithm. Next, we discuss the general test setup in Section IV and present the analysis of data from the test cases in Section V. Finally, in Section VI, we conclude with a discussion of the benefits of the PHT and briefly discuss the future of research using the PHT.

II. BACKGROUND

Before delving into the details of the PHT, a discussion of the fundamentals of projective geometry and the standard Hough transformation is presented. In the discussion of projective geometry, a definition of special image points, known as vanishing points, is provided and the nature of these vanishing points is explored. Then, in the section on the standard Hough transform, the foundation of a method to detect these vanishing points in an image is explained. The insights gained from these basic concepts provide a starting point for the development of the PHT approach to attitude estimation.

A. Projective Geometry

By using an imaging sensor as a source of navigation information, there is an inherent loss of information due to the projection of a three-dimensional world onto a two-dimensional imaging plane. The study of the geometric properties which are invariant under a projective transformation (e.g., the transformation induced by an imaging sensor) is known as projective geometry [4]. Within the framework of projective geometry, any pair of lines in 3-space (even parallel lines) may be shown to intersect in a single point. In the case of parallel lines, this intersection point is referred to as an ideal point. Alternatively, these ideal points are referred to as vanishing points, especially when there are a significant number of mutually parallel lines under consideration.

In [4], Hartley and Zisserman show that the vanishing points are invariant to translation and that, after projection onto the imaging sensor, the pixel location of the vanishing point is given by

\[ \mathbf{y}_{\text{pix}} = K R \mathbf{y}_{\text{world}} \]  \hspace{1cm} (1)

where \( \mathbf{y} \) is the location of the vanishing point in either pixel or world coordinates (as specified by the superscript), \( K \) is the projection matrix associated with the imaging sensor, and \( R \) is a rotation matrix. The representation in (1) implies that the pixel coordinates of the vanishing point are, conceptually, an encoded form of the imaging sensor’s attitude with respect to a specified reference frame. By choosing an appropriate reference frame to define the world coordinates, the rotation matrix may be estimated from knowledge of the pixel coordinates of the vanishing point.

B. Standard Hough Transformation

In 1962, Hough presented his work on defining a parameter space for use in detecting specific patterns in images [5]. The parameters Hough used to define lines took the form of the standard slope-intercept geometric description of a line. This choice of parameter space is actually unbounded in both parameters, specifically for vertical lines.

Realizing the fundamental utility of the Hough transformation, Duda and Hart [3] proposed an alternative definition of the parameter space for use in describing lines in images. This new parameter space defines lines with angle and radius values specified by a radial line passing thru a predefined origin and normal to the line of interest, as shown in Fig. 1. Mathematically, this is equivalent to

\[ \rho = x \cos(\theta) + y \sin(\theta) \]  \hspace{1cm} (2)

where \((x, y)\) is any point on the line of interest and \((\rho, \theta)\) are the parameters in Hough space. This angle-radius parameter space defines what is commonly referred to as the standard Hough transformation. To compute the Hough space data, (2) is evaluated, for all possible values of \(\theta\), at each pixel in an edge-detected image. Fig. 2 shows the result of performing Canny edge detection on the image of a hallway scene obtained from a commercial webcam. Fig. 3 depicts an example of the data available in the standard Hough space representation for the edge-detected image in Fig. 2. In general terms, the data in Hough space may be thought of as a collection of votes regarding which lines are present in an image. Since (2) operates on each edge-detected pixel, the amount and quality of data in Hough space is inherently dependent on the edge-detection scheme.

By inspection of (2), we observe that there is a relationship between the image space and Hough space such that points in the image space correspond to sinusoidal curves in Hough space, while points in Hough space correspond to lines in the image space. Extending this relationship, the pair of \((\rho, \theta)\) values which define two intersecting lines will lie on the Hough space curve specified by their point of intersection. Remembering the definition of vanishing points, the Hough space data should display consensus along the curves which represent the various vanishing points under consideration.

With the fundamental concepts of vanishing points in projective geometry and the standard Hough transformation, we may now proceed to develop a predictive Hough transformation.

![Graphical depiction of the standard Hough transform parameters.](image)
III. PREDICTIVE HOUGH TRANSFORMATION

Recall that the overall goal of this research is to provide a reliable and accurate source of attitude information in order to remove the drift induced by a standard IMU. By defining vanishing points in a local navigation reference frame and utilizing the insights of [4] with respect to the nature of the location of these vanishing points after projecting the world onto the image plane, we may begin to develop the PHT.

For the purpose of this development, a more insightful version of (1) is

\[ \mathbf{v}_{\text{pix}} = T_{\text{c pix}} C_{\text{b c}} C_{\text{b n}} \mathbf{v}^n \mathbf{v}_z^c \]  

(3)

where \( \mathbf{v}^n \) is a unit vector in the direction of the vanishing point in the navigation reference frame, \( C_{\text{b n}} \) is the direction cosine matrix (DCM) from the navigation frame to the body frame, \( C_{\text{b c}} \) is the DCM from the body frame to the camera frame, \( \mathbf{v}_z^c \) is the z-coordinate of the vanishing point in the camera frame, and \( T_{\text{c pix}} \) is the projection matrix which transforms coordinates in the camera frame to pixels on the image plane. The utility of the expanded form of (3) is that, at any given time, the only unknown (uncertain) quantity on the right-hand side of the equation is the \( C_{\text{b n}} \) term. This assertion is reasonable since we are free to rigidly attach the camera to the host platform, such that \( C_{\text{b n}} \) is fixed and predetermined, and \( T_{\text{c pix}} \) is obtained by calibrating the camera. Additionally, by choosing the navigation reference frame, we may inherently specify unit vectors in the direction of the vanishing points in this frame. The PHT seeks to exploit the relationship between this uncertain term and the pixel coordinates of the vanishing point to predict where the relevant information is located in the Hough parameter space. The overall process, from integration of inertial angular rates thru the incorporation of a PHT-based attitude measurement, is shown in the flow chart of Fig. 4. The remainder of this section is dedicated to describing and justifying the PHT core and the PHT-based measurement generation portions of this integrated attitude determination system.

Figure 2. Edge-detected image of a hallway scene obtained by using Canny edge detection on an image from a commercial webcam.

Figure 3. Sample of data in standard Hough space corresponding to the edge-detected image in Fig. 2. Note the collection of sinusoidal shapes, each corresponding to an edge-detected pixel in Fig. 2. Conventionally, a vanishing point is found by searching for dominant peaks in this data and then computing the sinusoid that contains these peaks.

Figure 4. Overall process flow of the integrated attitude determination system which uses PHT-based measurements of a vanishing point to correct attitude errors in an inertial navigation system.
In the most basic form, the concept of the PHT may be stated as, given an expected pixel location of a vanishing point, what is the likelihood that a particular \((\rho, \theta)\) coordinate pair in Hough space corresponds to a line which supports the vanishing point. Postulating that the expected pixel location of the vanishing point is properly characterized by a Gaussian density function, the likelihood function sought by this development, for each potential value of \(\theta\), is

\[
f_\rho(\rho) = \mathcal{N}(\rho_{\text{mean}}, \sigma^2_{\rho})
\]

where \(\rho_{\text{mean}}\) and \(\sigma^2_{\rho}\) are the expected value and variance, respectively, of \(\rho\) corresponding to (2) evaluated at the expected vanishing point. By evaluating (4) for each of the possible values of \(\theta\), we may build up a representation in standard Hough space of where the relevant information should appear. This representation is hereafter referred to as the predictive Hough space. Using the predictive Hough space as a basis, we may select a desired threshold and construct a windowing function that can be applied to the actual data obtained in the standard Hough space for a given image. This statistically-based windowing function is the core of the PHT. Fig. 5 shows an example of the data in the predictive Hough space.

Until this point, the development of the PHT has relied on the assumption that the expected pixel location of a vanishing point is adequately described by a Gaussian density function. We will now demonstrate the validity of this assumption via an inductive proof. First, recall the discussion following (3) regarding the nature of the quantities used to determine the pixel location of a desired vanishing point. Let us assume that, at some arbitrary initial time, the uncertain quantity \(C_{\text{n}}^b\) may be sufficiently described by Gaussian statistics. This implies that, after the computations of (3), the expected pixel location, \(\nu_{\text{pix}}\), may also be characterized by Gaussian statistics. Now, since the expected pixel location of the vanishing point is described by Gaussian statistics, for any value of \(\theta\), the linear relationship of (2) between \(\rho\) and \(\nu_{\text{pix}}\) shows that \(\rho\) may also be fully described by Gaussian statistics. Finally, by incorporating inertial angular rate data from an IMU, the uncertain quantity \(C_{\text{n}}^b\) may be propagated from a set of initial conditions (specified by Gaussian statistics) to any arbitrary time by solving [13, 16]

\[
C_{\text{n}}^b = C_{\text{n}}^b \Omega_{\text{ab}}^b
\]

where \(\Omega_{\text{ab}}^b\) is the skew-symmetric form of the angular rate data from the IMU. The solution to (5) is known to be of a linear form, so the propagation of \(C_{\text{n}}^b\) from one time to another does not invalidate the assumption that \(C_{\text{n}}^b\) may be specified using Gaussian statistics. We are now back at our initial assumption from the start of this proof, so the assertion that the expected pixel location of the vanishing point may be adequately described by a Gaussian density function is fully justified.

Next, we show how the PHT may be used to extract a useful and statistically appropriate measurement of the observed vanishing point in the scene. This process begins by applying the PHT to the representation of the edge-detected scene in the standard Hough space. Conceptually, the application of the PHT in this manner may be thought of as a filtering operation performed in Hough space. After this filtering step, we search for peaks in the data by finding local maxima in the filtered Hough space representation. Then, for the set of ordered pairs of standard Hough parameters \((\rho, \theta)\) corresponding to these peaks, the simple linear regression of (6) may be solved to obtain the measured \((\bar{x}, \bar{y})\) pixel coordinates of the observed vanishing point

\[
[p.] = [\cos(\theta) \sin(\theta)] \nu_{\text{meas}}.
\]

In summary, given an estimate characterized by a Gaussian density function, of the host platform’s attitude with respect to the navigation reference frame, the PHT is defined by the likelihood function of (4), such that a measurement of the observed vanishing point may be obtained by solving the linear regression implied by (6) using data from the filtered Hough space. In the next section, the details of the fusion filter portion of the process shown in Fig. 4 are presented.

IV. FUSION FILTER DESIGN

In this section, the estimation algorithm used to optimally fuse the high-rate IMU attitude estimates and the low-rate PHT-based attitude measurements is presented. This estimation algorithm is an adaptation of the perturbation-state EKF scheme presented in [11]. The design of this EKF-based fusion filter begins with a definition of the perturbation states, such that

\[
\delta \psi_k = \psi_{k,i} - \psi_{k,n}
\]

where \(\psi_{k,i}\) and \(\psi_{k,n}\) are, respectively, the true and nominal orientations of the host vehicle at discrete time \(k\). Given the
state definition of (7), the purpose of the fusion filter is to estimate the 3-element perturbation state vector based on the IMU angular rate data and the PHT-based vanishing point measurements. Next, a vehicle dynamics model is required in order to make use of this EKF formulation. For the purpose of this development, let us assume that the host vehicle’s orientation is modeled as a random constant, such that

$$\delta \psi_{k+1} = \delta \psi_k + w_k$$

(8)

where \( \delta \psi_k \) is the 3-element perturbation state vector at discrete time \( k \), and \( w_k \) is a 3-vector of discrete-time white Gaussian process noise of strength \( Q_k \). Within the framework of the standard EKF scheme, the state dynamics equation of (8) is actually a linear relationship and the time propagation portion of this fusion filter may be implemented with the linear Kalman filter propagation equations of [10]. Now, a measurement model is required to complete the foundation of this EKF-based fusion filter. Assuming that the angular perturbation states specified by (7) remain small, a small angle approximation to the measurement model is

$$\delta_k = T_c^{\text{pix}} C_b^c C_b^\Psi \left[ I - \Psi_k \right] \nu^b + \nu^c + v_k$$

(9)

where \( C_b^\Psi \) is the nominal direction cosine matrix (based on the current orientation estimate) from the navigation frame to the body frame, \( \Psi_k \) is the skew symmetric form of the perturbation state vector \( \delta \psi_k \), and \( v_k \) is a 3-vector of discrete-time white Gaussian measurement noise of strength \( R_k \). Algebraic manipulation of (9) shows that the measurement model contains all of the non-linearities of the system model for this EKF-based fusion filter. Using the perturbation-state EKF formulation presented in [11], along with the dynamics model of (8) and the measurement model of (9), the high-rate IMU attitude estimates and the low-rate PHT-based vanishing point measurements are optimally fused, in terms of mean square error, recursively in a predictive-corrective manner. In the next section, the test equipment and the general test setup are discussed.

V. Test Setup

The test equipment used in this stage of the research consists of a consumer-grade Crista micro-electromechanical system (MEMS) IMU and a tactical-grade Honeywell HG1700 strapdown IMU for high-rate angular rate measurements and a pair of PixelLINK PL-A741 machine vision cameras for low-rate image collection. The test equipment is bolted onto a rigid plate, as shown in Fig. 6, and placed on a wheeled cart. Then the cart is pushed along a closed loop path thru the hallways at the Air Force Institute of Technology (AFIT).

![Figure 6. Rigid platform, used as a surrogate for the host vehicle, with the Crista IMU, HG1700 IMU, and PixelLINK cameras bolted down.](image)

The Crista IMU is used as a representative low-quality IMU that could be utilized on a small UAV, while the HG1700 IMU is used as a source of truth reference data for the test runs. Additionally, since the intent of this research is to utilize monocular imaging techniques, the left camera from the pair of PixelLINK cameras is arbitrarily chosen as the representative monocular imaging sensor. One of the major disadvantages of these PixelLINK cameras is that they have a fixed exposure time. By fixing the exposure time, the camera lacks the ability to adapt to varying levels of ambient light intensity. During several time periods throughout the test run, there are significant variations in the ambient light intensity, such that the image becomes either saturated or extremely dim in appearance. Given that the Canny edge detection method utilized in this research relies on intensity gradients to detect edges, the saturated and dim images result in sparsely populated edge-detected images. In an attempt to counter this effect, the detection thresholds used by the Canny edge detector are manually adjusted throughout the test run.

All of the monocular images and IMU data are saved for evaluation in a post-processing environment. In the post-processing setup, the PHT approach is implemented within a simple perturbation-state EKF and the full-state estimates are examined for accuracy and drift characteristics. Finally, this PHT-based approach is compared to free-inertial and non-predictive Hough transform implementations. In the next section, the specific details of each case and the analysis of the post-processed data are presented.

VI. Analysis

For purposes of comparison and to highlight the benefits of the PHT-based approach, this post-processing analysis considers three cases:

- Free-inertial case, where the data from the Crista MEMS IMU is integrated over the duration of the experiment and no image-aided updates are applied.
- Unaided Hough transform case, where the Crista MEMS IMU data is integrated throughout the experiment and image-aided updates, based on the unfiltered data in standard Hough space, are incorporated at a rate of approximately 2 Hz.
Predictive Hough transform case, where the Crista MEMS IMU data is integrated throughout the experiment and image-aided updates, based on the filtered data in standard Hough space, are incorporated at a rate of approximately 2 Hz.

In all three cases, the EKF is given a simple attitude update, in addition to the IMU data and any image-based information, when the host platform rests on the cart. This extra attitude update exploits the knowledge that the vehicle's orientation is constant, with respect to the x, y, or z axes, as the cart is rolled down the hallway. For the PHT case, this supplemental update was used solely to ease the transition between hallways. The other two cases use this extra update to provide a fair comparison among the test cases. Additionally, the inertial data from the HG1700 IMU is numerically integrated to produce a history of truth data for the angular orientation of the host platform. The first case considered is the free-inertial case.

A. Free-inertial Case

In this case, no image-based updates are supplied and the angular rate data from the Crista MEMS IMU is simply integrated to determine the attitude of the host platform, with respect to the local navigation frame, at any given time during the experiment. In practice, the full DCM for $C_{bn}^n$ is obtained directly by solving (5) and the individual relative angles are extracted from $C_{bn}^n$ by using the inverse trigonometric relationships as specified in [16]. Fig. 7 shows the full-state estimate of the rotation about the x, y, and z axes, the corresponding estimate of the +/- 1-$\sigma$ bounds, and the truth reference data for this free-inertial case. Although the full test run completes a closed loop around the hallways, the data shown in Fig. 7 is truncated to display the same timeframe as the data in the PHT case. Comparing the estimated orientation with the truth reference, the typical drift characteristic of an unaided free-running IMU is observed after an initial alignment period. The collapse of the error bounds on the roll state occurs because of the artificially supplied measurement when the host platform rests on the cart. This artificial update was provided to maintain parity among the test cases. The next case considered is the unaided Hough transform case.

B. Unaided Hough Transform Case

In this case, the angular rate data from the Crista MEMS IMU is integrated, as in the previous case, but no corrections are passed back by estimating the observed vanishing point from the unfiltered Hough data and extracting attitude data from this estimated vanishing point. Fig. 8 shows the full-state estimate of the rotation, the corresponding estimate of the +/- 1-$\sigma$ bounds, and the truth reference data for this unaided Hough transform case.

Once again, due to a specific situation with the PHT-based approach, the timeframe shown in Fig. 8 is a truncated portion of the closed loop traveled during the test run. The first observation is that, by using the data from the Hough transform to provide corrections to the IMU estimates, the estimate of the uncertainty is now bounded. However, the collapsing of the uncertainty bounds is from the perspective of the filter and does not accurately reflect the true errors of the estimated orientation. This becomes evident by comparing the estimated states with the truth data and noting that the estimated orientation angles do not always reflect the true attitude of the host vehicle. This occurs because, in the naive approach, the estimated vanishing point is based solely on the strongest lines in the edge-detected image. No guarantee can be made whether or not these lines actually correspond to a valid (useful) vanishing point, so they primarily serve to confuse the attitude estimate with inaccurate information.

Finally, the PHT case is considered. The expectation is that the PHT-based approach will rectify the errors of this unaided Hough transform case and the free-inertial case.

C. Predictive Hough Transform Case

In this case, the angular rate data from the Crista MEMS IMU is integrated, as in the free-inertial case, but now corrections are passed back by estimating the observed vanishing point from the filtered Hough data and extracting attitude data from this estimated vanishing point. Fig. 9 shows the full-state estimate of the rotation angles, the corresponding estimate of the +/- 1-$\sigma$ bounds, and the truth reference data for this predictive Hough transform case. Now, not only are the drift and unbounded growth of uncertainty issues mitigated, a
comparison of the orientation estimates with the truth reference data demonstrates how the attitude estimates also provide an accurate accounting of the true path followed throughout the test run. This occurs because, unlike in the unaided Hough transform case, there is now a high confidence that the detected lines provide valid support for the observed vanishing point, from a statistical perspective.

As mentioned during the analysis of the previous two test cases, the timeframe shown in Fig. 9 is truncated from the full duration of the test run. This truncation was required because of a problem induced by the PixelLINK camera’s fixed exposure time. Shortly after the end of the data shown in Fig. 9, the cart entered a dimly lit interior room which, due to the fixed exposure time, led to a difficulty in reliably detecting edges within the images using the Canny edge detection method.

Fig. 10 shows an example of the predicted and measured vanishing points, the detected lines which support this measured vanishing point, and a 90% error ellipse around the predicted vanishing point. In this image, we can clearly see that the PHT-based method selects the proper vanishing point and also identifies lines which support this selection.

Another observation based on the image in Fig. 10 is the fact that the PHT method is dependent on the detection of edges. This occurs because the Hough transform, which forms the core of the PHT approach, operates on the individual pixels of an edge-detected image. Throughout the cases presented in this paper, a Canny edge detector was used to obtain the edge-detected images required by the Hough transform. The only lines that can be selected using this method must be composed of the edge pixels, although a small degree of interpolation is permissible. The implication here is that the use of a better edge detection method should result in a more complete set of lines that support the vanishing point. However, as is evident, the PHT-based method still performs adequately, even with a fairly rudimentary edge detection scheme.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, the PHT is proposed and developed as a statistically rigorous method to facilitate an image-aided update to the attitude estimates provided by a low-quality MEMS IMU. This PHT-based method is feasible because of a strong relationship between the orientation of a host vehicle, with respect to a desired navigation frame, and the projection of a vanishing point, which is realized as the intersection of parallel lines, onto the pixel array of an imaging sensor rigidly attached to the host vehicle.

The fundamental concept behind this PHT-based method is that, by predicting where a specific vanishing point should occur in an image, we may accurately and consistently detect the observation of this vanishing point in a real image, such that an updated attitude may be estimated. The development of this algorithm proceeded in a Bayesian manner to facilitate the use of an EKF as the optimal estimator. Experimentation with imagery obtained by following a closed-loop circuit around the halls of AFIT demonstrated the ability of this PHT-based orientation estimation scheme to provide stable and accurate attitude estimates, whereas other unaided and naïve methods could not provide adequate performance.

However, this PHT-based method does have significant room for improvement. Most notably, the Canny edge detector is sensitive to the saturation or dimness of the base image. This sensitivity was a limiting factor during several time periods because of the fixed exposure time of the PixelLINK camera. Additionally, throughout the tests conducted thus far, only the vanishing point in front of the nose of the host vehicle (within the visible image) has been considered as a source of attitude information.

Future research with this PHT-based method will utilize a better imaging sensor with the ability to vary the exposure time based on the ambient light intensity. This would remove the constraint imposed by using the PixelLINK camera. Furthermore, future research efforts will seek to make...
observations of at least two vanishing points, one of which being infinitely outside the image in either the vertical or lateral directions, in order to provide continual access to data for all three of the orientation angles without the need for artificial attitude updates. This would remove the need to provide the artificial measurements which tell the filter that the host vehicle is in a static orientation on the cart.

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