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An Analysis of the Human Odometer

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Abstract

The Human Odometer is a personal navigation system developed to provide reliable, lightweight, cost-effective, and embedded absolute 3-D position and communication to firefighters, policemen, EMTs, and dismounted soldiers. The goal of the system is to maintain accurate position information without reliance on external references. The Human Odometer system provides real-time position updates and displays maps of relevant areas are to the user on a handheld computer. The system is designed to help a user place himself in a global context and navigate unknown areas under a variety of conditions. This paper provides a quantitative analysis of the in-field operational performance of the system.

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Introduction

The Human Odometer is a personal navigation system currently under development at Carnegie Mellon University's Field Robotics Center[1]. When worn, the system provides real-time position updates and displays maps of relevant areas are to the user on a handheld computer. The system is designed to help a user place (localize) himself in a global context and navigate unknown areas under a variety of conditions.

[1]Please refer to Appendix A for a detailed survey of current personal navigation technologies and to Appendix B for a comprehesive description of the Human Odometer Hardware Specifications .

Consumer personal navigation systems are quickly becoming ubiquitous; however, the technology has yet to be developed where it is needed most: in demanding and unforgiving environments. While current systems are used mainly for recreational purposes and as a matter of convenience, they have the potential to be life saving devices for personnel such as first responders. Unfortunately, they do not offer the reliability and accuracy demanded by hazard workers. The Human Odometer resolves these problems by using a novel combination of both GPS positioning and human walking analysis (pedometry).

While it makes use of GPS data whenever possible, the Human Odometer is also designed for robust localization when GPS is unavailable or unreliable. Pedometry data from inertial measurement sensors on the user's body are used to track motion using kinematic models of walking, running, and other common modes of motion. Due to the nature of inertial measurement, the pedometry system is extremely reliable, complementing the major fault of GPS. If position data from both systems is available, the two measurements are compared and fused. In addition to providing a robust localization method this also provides the ability to estimate a user's positional uncertainty.

To date, most tests of the Human Odometer have been done in very limited, controlled conditions, and in conditions in which only an approximate measure of accuracy was possible. The purpose of this analysis is to determine the accuracy of the Human Odometer under a variety of less limited conditions. Tests were conducted on both flat and broken ground, while the test subject was walking and running. This allowed the analysis to cover more complicated modes of motion. Data was post-processed using the Human Odometer's localization strategies with and without integration of GPS data, to simulate conditions in which GPS data might be sparse or unavailable as well, as well as to simulate conditions when GPS coverage might be excellent.

Test System and Procedure

Test runs for the Human Odometer system were conducted at Fort Indiantown Gap National Guard Training Center in Lebanon County, Pennsylvania. Flags were placed in the ground at selected survey points. These positions were mapped with high precision differential GPS. The survey positions for two test locations are shown in *Figures 1 and 2*, below. These locations were referred to at the training center as the "football field" and "gravel pit", respectively. (The system was also tested at the ARL robotics facility at the training center; however, these runs were conducted without previously surveyed points. These results are also included in this report.)

The football field is an area of uneven ground and weeds, creating a more challenging course for the tester. The gravel pit was a flat, empty area covered, appropriately enough, with a layer of gravel. Flags are numbered according to the order in which they were to be visited by the tester. Wearing the Human Odometer, the tester walked or ran each surveyed course several times. The system stored complete data from all measurement devices (both GPS and motion sensors) in a set of device data logs. These logs have been used in this report to reconstruct pedometry and position estimates in order to fully characterize the performance of the Human Odometry system under a wide variety of terrain types and environmental conditions[2].

[2]Please refer to the VTI TestPlan in Appendix C for the comprehesive system test procedure used at Fort Indiantown Gap.

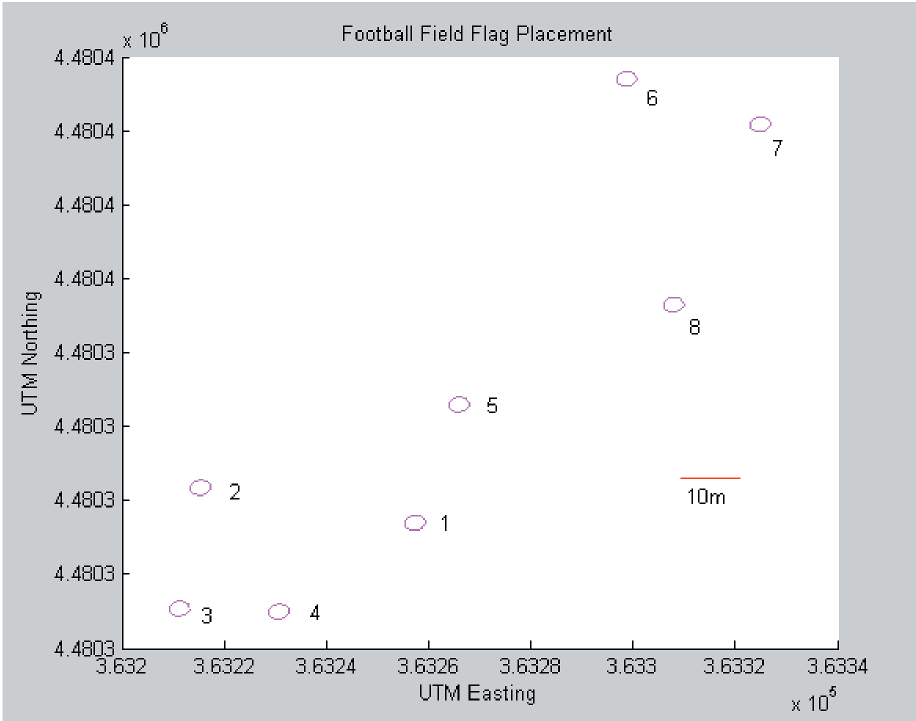

Figure 1. Football Field Flag Placement

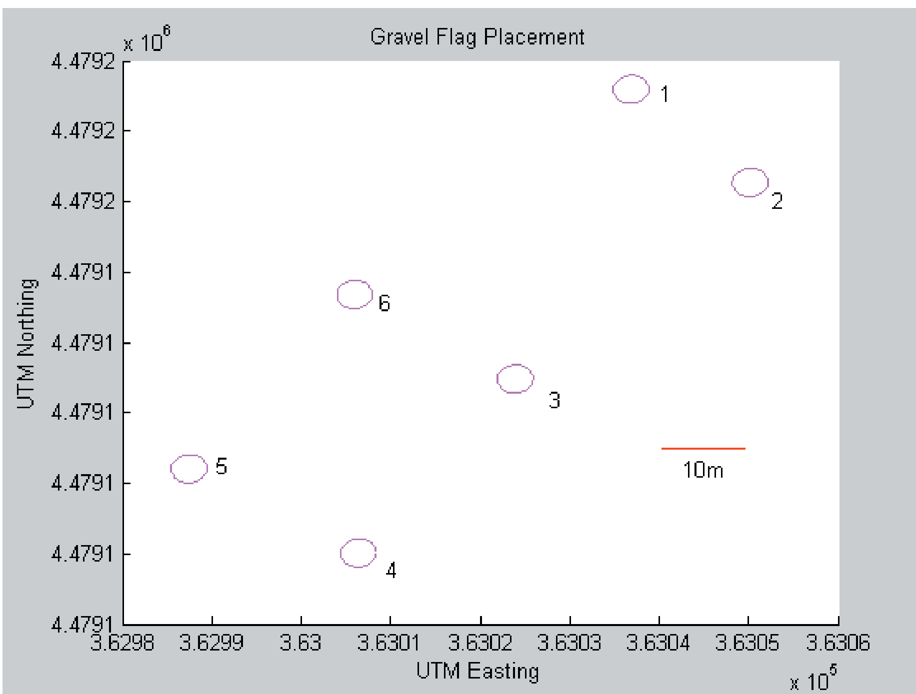

Figure 2. Gravel Flag Placement

FTIG Test Results

Included below are the graphical representations of the pedometry data and the GPS data along with annotations about the specific runs. The only treatment of the pedometry data was to manually realign some of the initial headings that became corrupted, or were severely disparate with the true value.

Normally, a system initialization phase would reject such errant heading values and calibration misalignments until an acceptable value was determined. However, during the trials data was recorded without any error handling, and no feedback was provided to the tester on the accuracy of the initial heading value. Occasional corrupted data (both GPS and pedometry) in the log files were also automatically filtered out during the system analysis. Disregarding the corrupt log data for performance calculation is consistent with the robust operational specification of the Human Odometer.

During several of the runs, the gyroscope, which is used to determine heading, failed and either started recording partially corrupt or nonsensical data. Since the gyroscope performance is usually quite robust, it is likely that the freezing temperatures (noted at 21 degrees Fahrenheit during testing) caused fluctuations in the power output of the batteries. It is possible that these power fluctuations caused the gyroscope to spontaneously reset (when power dropped below the required threshold) as well as caused the gyroscope to exhibit other peculiar behavior. This behavior is correctable with better power regulation on all hardware destined for use in extreme temperatures.

When possible, the partially corrupted gyro data was reconstructed as-is, and the point of failure is marked accordingly on the graph of the affected trial. In the graph, it is clear that the system is no longer within functional specification after the failure of the gyroscope component. However, because of the extreme conditions which lead to this error, we do not believe that these failures are an accurate reflection of the Human Odometer performance. Thus, data recorded after such a failure is not indicative of the real system performance and is not included in the mathematical analysis of the system.

As mentioned above, the runs at the ARL building were made without surveyed flags. In addition, the GPS signal was of particularly low quality in the first test at that location (*Figure 10*) as part of the test took place inside a building, where there was poor or nonexistent GPS coverage. The second run (*Figure 11*) was conducted around the perimeter of a building as well as inside, and included fair GPS coverage along half of the path. The purpose of these runs was to collect data with actual GPS outages, in order to complement our experiments with simulated outages.

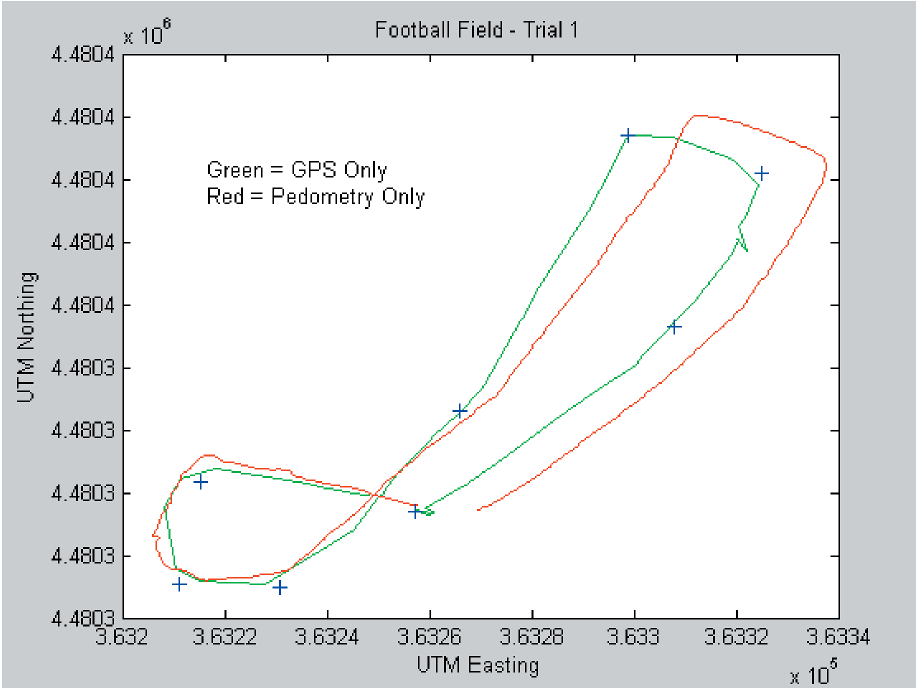

Figure 3. Football Field – Trial 1

Trial 1 of the Football Field course used a moderate walking pace to trace the path. The run was quite uneventful and there were no notable deviations from the intended course.

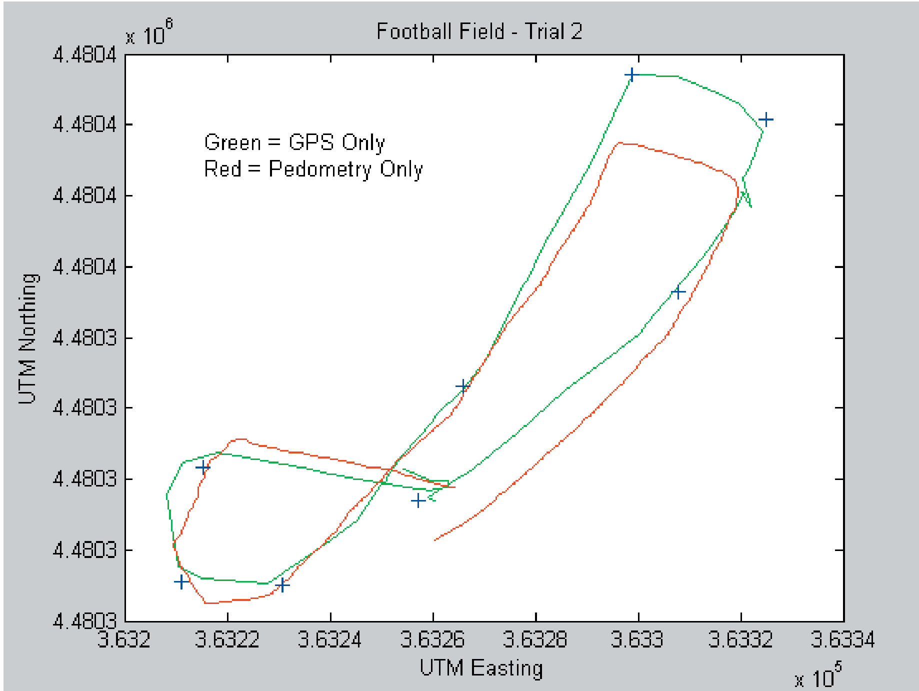

Figure 4. Football Field – Trial 2

Trial 2 of the Football Field course used a fast walking pace. A rough and notably sparse GPS signal persisted throughout the entire run. In addition, the tester tripped at one point during the middle of the run causing a brief amount of poor pedometry data.

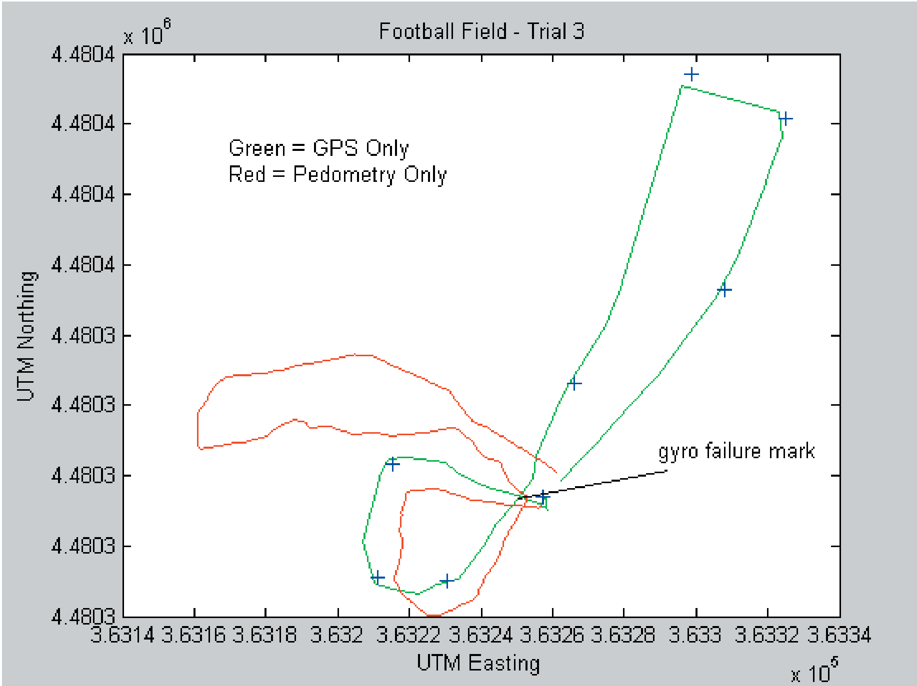

Figure 5. Football Field – Trial 3

Trial 3 of the Football Field course was conducted with a moderate walking pace. The gyro failed during the first third of the trial and the location of failure is noted above.

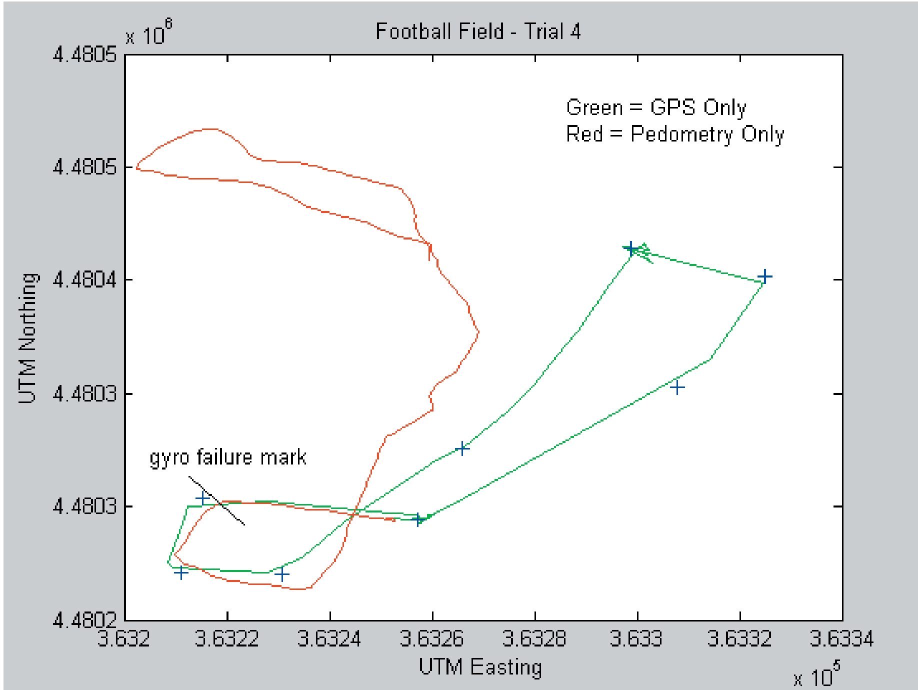

Figure 6. Football Field – Trial 4

A jogging pace was used during Trial 4 of the Football Field course. Gyro failure occurred fairly early on in this trial, making much of the later data unreliable. The tester also stopped for a short rest from jogging near flag point 6. However, this anomaly is overshadowed by the erroneous data caused by the failed gyro.

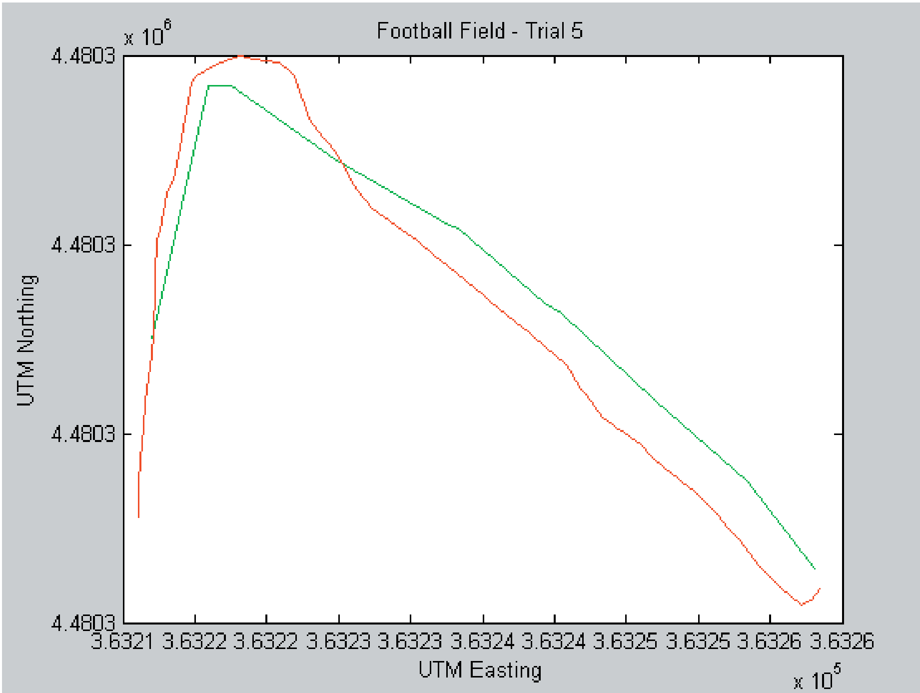

Figure 7. Football Field – Trial 5

Trial 5 of the Football Field course was conducted using a moderate walking pace. The tester tripped during the first few steps causing an initial heading misalignment, but this misalignment which was quickly rectified. Unfortunately, gyro failure also occurred along with data corruption after the second flag. A brief run was reconstructed using only the reliable data.

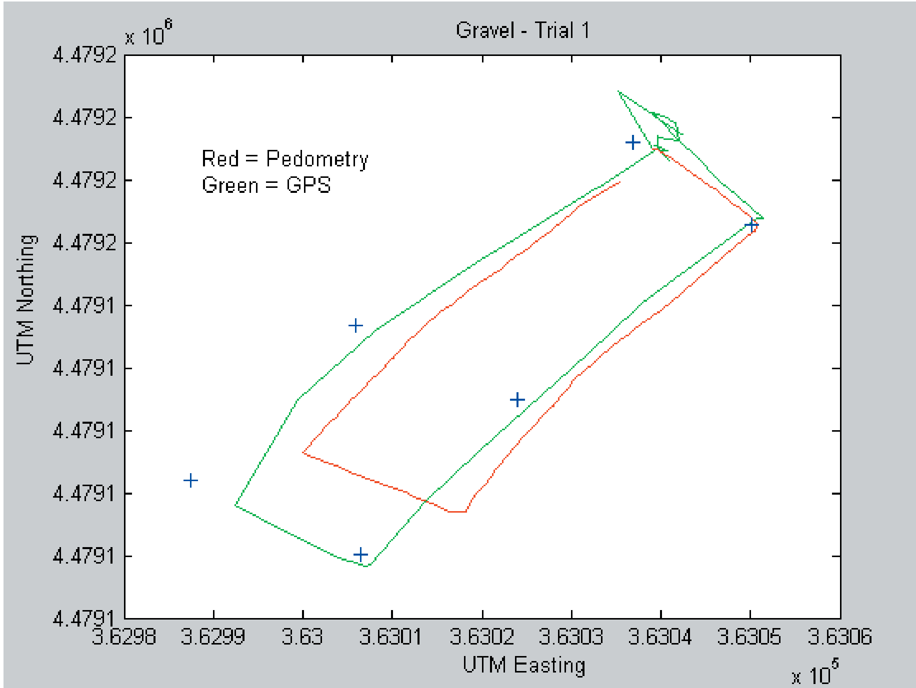

Figure 8. Gravel – Trial 1

Trial 1 of the Gravel course used a slow to moderate walking pace. Poor quality GPS data was observed during the beginning of the run, but most of the trial went according to plan.

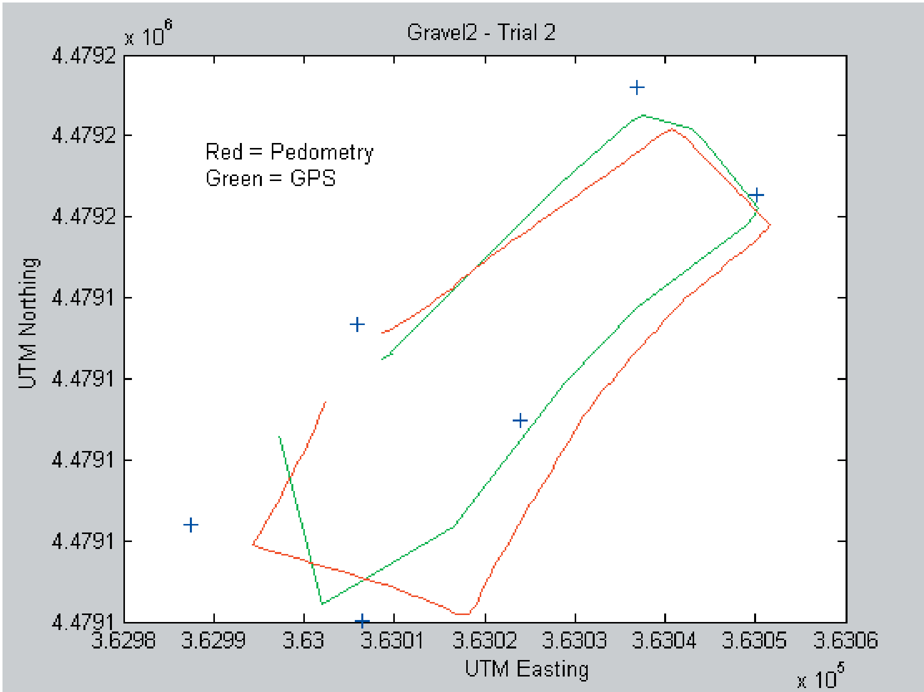

Figure 9. Gravel – Trial 2

Trial 2 of the Gravel course used a "Regular Walking" pace. The run was relatively uneventful with the exception that poor quality GPS data was observed toward the end of the run. In fact, in this case the path traced by the pedometry output more closely resembles the path walked by the tester.

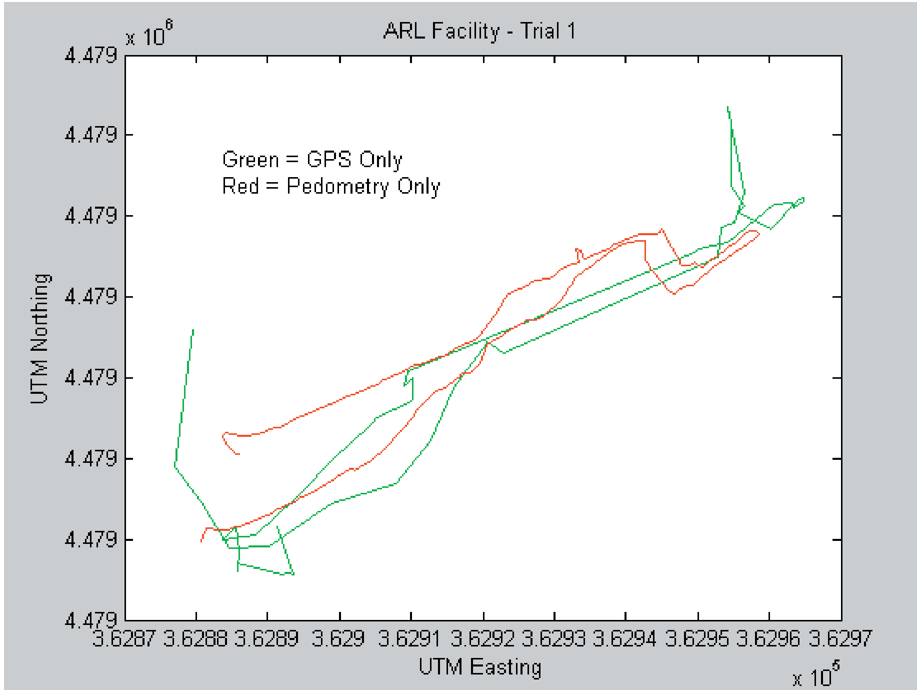

Figure 10. ARL Facility – Trial 1

The first run conducted in the ARL Robotics Facility used a "Regular Walking" pace. Most of the trial, with the exception of the beginning and end, was conducted inside of a building, making the GPS data of extremely poor quality. The pedometry data more closely resembled the true path traveled than did the GPS data.

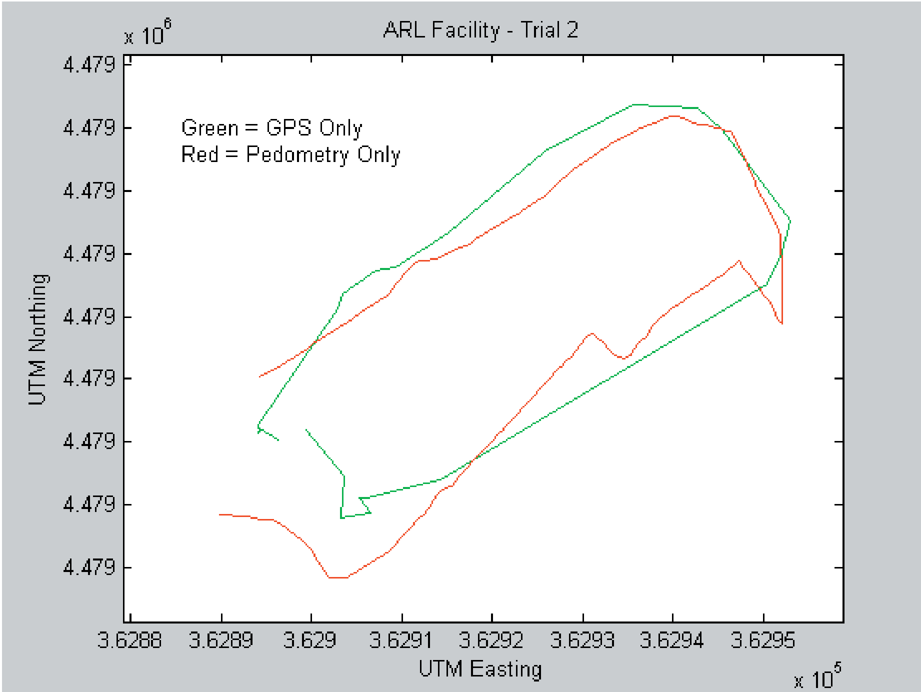

Figure 11. ARL Facility – Trial 2

The second test conducted in the ARL Robotics Facility also used a moderate walking pace. In this run, a problem with extremely inconsistent initial GPS points was filtered and so the starting location was manually entered where the good data began. A GPS outage occurred from near the first sharp turn until near the end of the trial.

Table 1, which follows, shows general statistics for all the trials conducted. The Final Position Difference is the Euclidean distance between the surveyed stopping location and the reported stopping location of the human Odometer. In the case of the ARL trials, this is the Euclidean distance between the final GPS point and the corresponding pedometry point at that timestamp. Distance Traveled is the total number of meters walked during the course of the trial and Trial Time is the duration of the run in seconds.

Run	Final Position Difference (m)	Distance Traveled (m)	Trial Time (sec)
Football Field Trial 1	8.58	442.3	626
Football Field Trial 2	10.83	400.6	616
Football Field Trial 3	N/A	116.3*	207*
Football Field Trial 4	N/A	16.9*	38*
Football Field Trial 5	4.82	59.8*	85*
Gravel Trial 1	9.88	150.8	267
Gravel Trial 2	6.83	123.8	232
ARL Facility Trial 1	10.47	189.9	335
ARL Facility Trial 2	11.6	198.9	300

Table 1. General Trial Statistics
*statistics recorded before gyroscope failure

Pedometry Analysis

The data for all test runs was post analyzed in order to calculate several statistics used to gauge system performance. Specific concern was given to characterizing the system to quantify error and uncertainty in every degree of freedom (heading and positional x-y coordinates). In order to characterize the performance of the system, there must be an accurate point of comparison. While the ideal point of comparison is "ground truth" – the exact and actual path walked – this information does not exist except in the form of the surveyed flag positions. With only 6 to 8 flag points, a reliable performance characterization is difficult for the path walked between the points. Fortunately, the majority of test runs included excellent GPS data, despite the overcast conditions at the site. With a few noted exceptions, GPS coverage frequently included 6 to 8 satellites. While the system as a whole has not been characterized, GPS itself (a proper "subsystem" of the Human Odometer) has been measured and analyzed by research institutions for many years. Therefore, knowing the unique properties of the GPS signal with respect to ground truth, the GPS data collected during the trials along with the handful of ground truth beacons can actually be used to infer the characteristics of the pedometry subsystem, which has not yet been characterized. We can then infer a total system performance from the combination of both subsystem performances.

The characterization of the pedometry subsystem itself is of particular interest as GPS is accurate, but often unavailable. Therefore the performance of the pedometry subsystem is, in many cases, the performance of the entire Human Odometer system[3]. A realistic simulation of the entire system with an intermittent GPS signal that follows form this fact, will be covered in the fourth section of this report, *Filtered System and GPS Outage Analysis*. Please refer to [2] for a more detailed explanation of statistical methods used in the following analysis.

[3] Conversely, this is never the case with a raw GPS signal. The benefit of the pedometry system lies in that it will never cease to function and its performance is never dependant on environmental conditions.

A calculation of the heading disparity between the GPS data and the pedometry data, **the Heading Offset Mean is a measure mostly of human error in initial alignment of the pedometry system** to a true value. It is calculated by running the data through a Heuristic Heading Filter (HHF) which extrapolates an average heading from consecutive GPS readings every 10 meters using simple trigonometry (arctangent(y/x)). The GPS heading, which is assumed to be true, is compared *a posteriori* to the heading given by the gyroscope which produces a value representing a local heading difference. This is factored into a global heading offset, which represents a predicted disparity in system heading, via a weighted arithmetic mean. The predicted system offset is then used to adaptively correct heading drift and also compensate for initial alignment errors. Please refer to *Table 2* for the calculated offsets of the trial runs.

The Heading Standard Deviation is a measure of the system heading accuracy and drift. Accuracy is defined as the degree of correlation between gyroscopic heading and GPS heading after removing the offset bias[1]. As such, it is calculated by taking the standard deviation of all local offsets produced by the HHF[4]. The heading deviation data in *Table 3* suggests that we should expect, on average, 68.2%[5] of heading readings to be within 9.89 degrees of the true value. This is a raw system error, without correction from GPS, of about 2.7%. This value may also be inflated, as the GPS (which is assumed to be perfectly accurate) is also subject to a small but factorable signal variation.

Positional Standard Deviation is a measure of the system positional accuracy. Specifically, it quantifies the expected variation of location in UTM Easting and UTM Northing coordinates from the true value. This value is calculated at every GPS reading by comparing the current location as given by the pedometry system (calculated since the last GPS reading) and the current GPS position. The standard deviations of all the axial component differences are then calculated. The results show that between two GPS readings, the UTM Easting value of position is expected to be within 3.69 meters and the Northing value to be within 3.49 meters of the GPS position 68.2% of the time. At an average GPS frequency of one reading every six seconds, as evidenced during testing, this translates to a compounding pedometry uncertainty of 0.61 meters (2.0ft) in the East direction and 0.58 meters (1.9ft) in the North direction every second. However, since the aggregate values (3.69m and 3.49m) are on the same magnitude as the statistical uncertainty of the GPS readings themselves (~ 2m), the deviation of the GPS signal must be subtracted to find the real accuracy of the pedometry system with respect to ground truth. After compensating for the deviation of the GPS signal in the pedometry signal variances, an average axial uncertainty of ~1.5m every six seconds is obtained, making the **system slightly more accurate than GPS for short to medium distances**. Note that due to the nature of the system, which uses a stride length in conjunction with a heading as opposed to independent axial measurements, mean values of the positional standard deviation should be statistically insignificant between East and North coordinates. The data collected agrees with this proposition.

The standard deviation values in *Table 4* and *Table 5* are combined using a simple Cartesian distance[6] to obtain a worst-case stride length error. This error is recorded in *Table 6* as the Step Standard Deviation. This is an estimate of how well each stride's predicted length resembles the true stride length of the stride, which is derived from GPS. This is a particularly "bad case" measurement as we assume that readings in both axes are exhibiting behavior along the limits of the expect value. The data shows that with an average GPS frequency of 1/6 Hz and an average of 2.0 steps a

[4] The standard deviation is calculated using the formula $\sqrt{m'_2 - m^2}$.

[5] The percentage of points corresponding to one standard deviation.

second, we can expect each step to be within 0.43m (1.4ft) of the true stride length.

[6] Cartesian distance is calculated using the formula $\sqrt{x^2 + y^2}$

Run	Heading Offset Mean (degrees)
Football Field Trial 1	16.12 CCW
Football Field Trial 2	17.275 CW
Football Field Trial 3	14.78 CW
Football Field Trial 4	N/A
Football Field Trial 5	6.220 CCW
Gravel Trial 1	0.0184 CW
Gravel Trial 2	2.264 CCW
ARL Facility Trial 1	5.00 CW
ARL Facility Trial 2	9.600 CCW
Mean	**N/A**

Table 2.

Run	Heading Standard Deviation (degrees)
Football Field Trial 1	8.620
Football Field Trial 2	8.9738
Football Field Trial 3	11.953
Football Field Trial 4	N/A
Football Field Trial 5	8.930
Gravel Trial 1	5.2767
Gravel Trial 2	10.702
ARL Facility Trial 1	n/a
ARL Facility Trial 2	14.79
Mean	**9.892**

Table 3.

Run	UTM Easting Positional Standard Deviation (m)
Football Field Trial 1	2.8928
Football Field Trial 2	3.1899
Football Field Trial 3	1.5726
Football Field Trial 4	N/A
Football Field Trial 5	2.2338
Gravel Trial 1	3.2674
Gravel Trial 2	4.0445
ARL Facility Trial 1	5.977
ARL Facility Trial 2	6.3583
Mean	**3.6922**

Table 4.

Run	UTM Northing Positional Standard Deviation (m)
Football Field Trial 1	3.2326
Football Field Trial 2	4.104
Football Field Trial 3	4.0271
Football Field Trial 4	N/A
Football Field Trial 5	2.8838
Gravel Trial 1	2.7909
Gravel Trial 2	3.949
ARL Facility Trial 1	4.4696
ARL Facility Trial 2	2.5078
Mean	**3.4956**

Table 5.

Run	Step Standard Deviation (m)
Football Field Trial 1	4.3379
Football Field Trial 2	5.1979
Football Field Trial 3	4.3232
Football Field Trial 4	N/A
Football Field Trial 5	3.6477
Gravel Trial 1	4.2970
Gravel Trial 2	5.6526
ARL Facility Trial 1	7.4633
ARL Facility Trial 2	6.8349
Mean	**5.2193**

Table 6.

Filtered System and GPS Outage Analysis

The Human Odometer makes use of GPS points to help correct heading and positional errors as well as compensate for initial heading offsets. An initial sample of GPS readings greatly enhances the accuracy of the pedometry data. Under normal circumstances, **a semi-reliable GPS signal with moderate frequency is sufficient to keep the system from drifting and provides an optimal estimation of position between GPS updates.** However, a GPS reading may not be available for some extended period, for example during use in a building. During these periods, the system is expected to continue to perform reliably.

Simulated tests were conducted on the full Human Odometer system to measure resilience against prolonged GPS outages. Pedometry data was fused with GPS data using the HHF and an Extended Kalman Filter (EKF)[7] during an initial calibration phase, during which the heading and stride-length biases are calculated. After this, the GPS is data is "turned off" and the pedometry allowed to run until the end of the trial. The graphs in *Figure 12 and 14* show the "total system output" which incorporates all GPS and pedometry data along the entire length of the path and is representative of system performance with a good GPS signal on negotiable terrain. The graphs in *Figure 13* and Figure 15 show the result of correcting for the heading offset and stride length bias with only a small amount of initial GPS data. The GPS data, which is considered a good estimate of ground truth[8], is also plotted for comparison. It is notable that the pedometry performs almost as well as a high quality GPS signal, indicating the the Human Odometer exhibits near GPS performance in situations where GPS is unavailable.

[7] The Extended Kalman Filter is a mathematically optimal method of fusing two estimates of location (pedometry and GPS) to produce a combined position and error estimate. The Kalman Filter can also estimate and correct for an offset in the stride length data. It is used in the full Human Odometer system for this purpose [3].

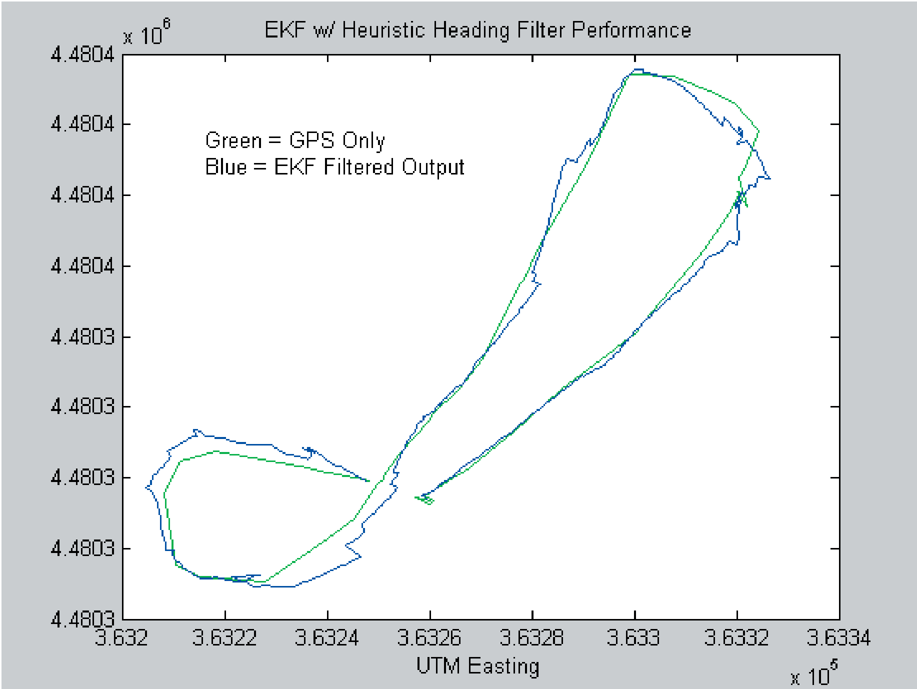

Figure 12. System Output for Football Field

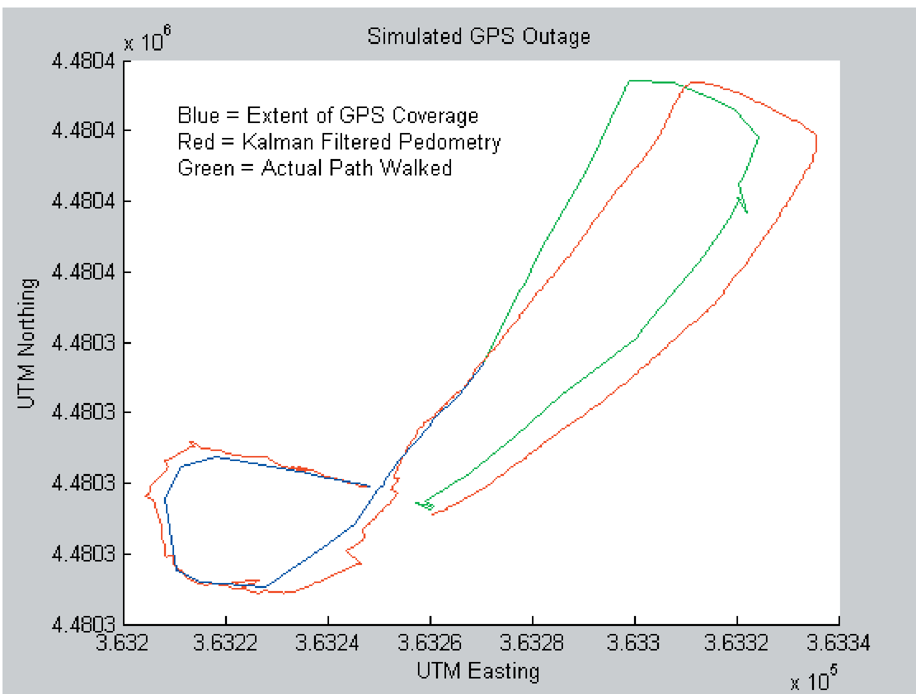

Figure 13. System with Simulated Outages on Football Field

[8]GPS data was a good estimate of ground truth for these specific trials. GPS accuracy depends on a wide variety of conditions and is normally significantly less exceptional in quality and quantity.

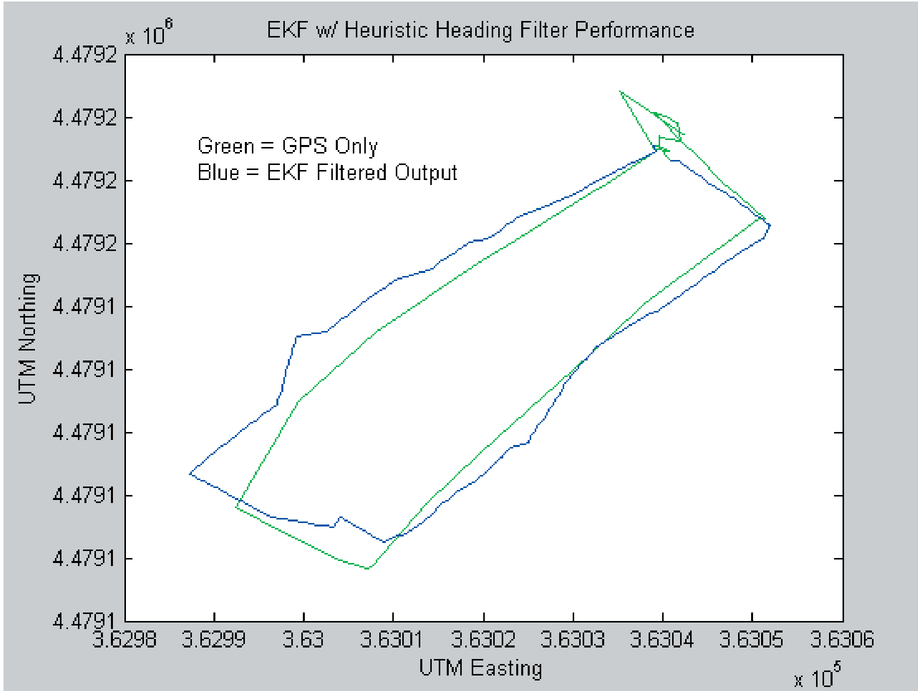

Figure 14. System Output for Gravel Pit

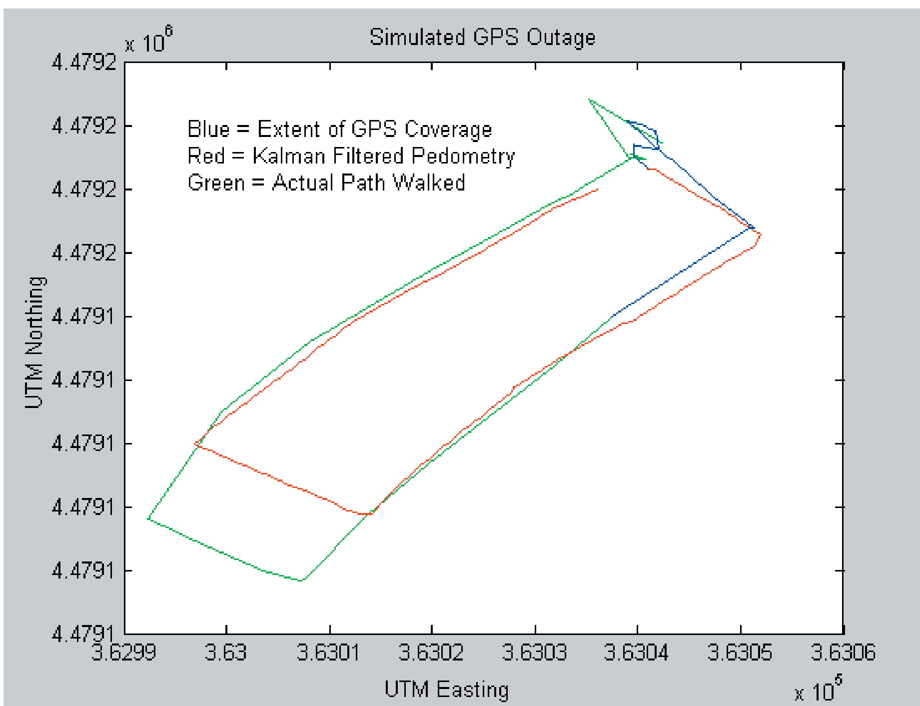

Figure 15. System with Simulated Outages on Gravel Pit

Conclusion

The Fort Indiantown Gap test of the Human Odometer served primarily as a proof of product, as well as establishing baseline performance characteristics of the system and providing insight into the limitations of the current hardware and software setup.

The basic operational aspects of the Human Odometer system were demonstrated and proven to be successful during strenuous testing. Running for an extend period of over 10 minutes, the system reported a cumulative error of less than 10 meters. This amounts to a drift rate of .05 feet per second, significantly better than other pedometry and inertial-based solutions in the same price range. Performance was also shown to be stable and consistent over many runs and through system resets.

The field test also provided the oportunity to assess the performance of the system's localization algorithms and to verify the correctness of several theoretical assumptions made in the design of the software. Firstly, pedometry-based inertial motion detection has been shown to be a reliable short term estimate of position with a short-term expected uncertainty to be less than that of high precision GPS. Additionally, it has been shown even with a frequently updating GPS signal, pedometry provides consistently reliable positioning at a much finer granularity. Secondly, long term GPS data has been shown to provide a suitable basis for accurate heading correction and also step size parameter correction for the pedometry data. Lastly, the fusion of locally-optimal pedometry data with globally optimal GPS data provides an operationally robust method for human localization in dynamic and demanding environments.

The FTIG tests also revealed a few areas of improvement and recommendations for future work.

Firstly, a correctable flaw was discovered in the power regulation of the gyroscope where cold temperatures caused a drop in the power output of batteries. DC voltage converters were added to the system shortly after to remedy the problems with fluctuating power.s. The voltage converters provide the clipping feature of standard linear regulators in addition to a step-up ability if the power output of the battery source ever falls below the required voltage. Power upgrades to the rest of the system are planned in the future.

Secondly, pedometry analysis suggested that further accuracy could be attained by a more principled approach to the calculation and correction of step size. In several of the runs, inaccurate step size prediction caused a scale disparity between the pedometry and GPS graphs. While the addition of GPS data attenuates the effect in the fused data, total system accuracy and reliability during GPS outages can be improved. Algorithms for learning and automatically adjusting step sizes for multiple users of a system are currently being investigated.

Lastly, the current system does not factor elevation changes into the estimate of position. Small height discrepancies such those that are the result of uneven terrain, are detrimental to the accurate determinat of step size. While the experiment did not specifically test for particularly rugged terrain, it is believed that compensating for the user's pose will greatly enhance the accuracy of the system[9].

[9]The system is being developed to handle stairclimbing, but there are no immediate plans to factor in smaller altitude changes.

Appendix A:
Background Information

Section A: Introduction

Section B: GPS

Section C: Inertial

Section D: Pedometric

Section E: Radio Frequency

Section F: Laser

Section G: Photogrammetric

Survey of Human Navigation Technology

Human movement tracking technology can be divided into three main categories: Inside-Out (exteroceptive), Outside-In (proprioceptive), and Inside-In (interoceptive) sensors. Inside-Out sensors measure internal state with respect to an external reference. These sensors include accelerometers, gyroscopes, and Global Positioning System (GPS). Outside-In sensors measure a person's state by tracking externally detectable changes in pose and are generally the least obtrusive of the sensor types. Cameras and RF transmitters are examples of Outside-In technology. Inside-In technology seeks to emulate internal feedback sensors like the nervous system to extrapolate body state from the movement of limbs. Inside-In sensors like flex-wires and potentiometers are rarely used in human localization as the sensors are neither a direct nor accurate measure of position and they often interfere with the user by providing points of resistance.

Personal navigation systems sometimes use a combination of sensors in the three categories to complement the weaknesses of the individual sensors, known as sensor fusion. However, the vast majority of systems today use Inside-Out sensors for their ease of deployment and relative accuracy. It is much more common to pair two Inside-Out sensors, one that detects natural sources and one that detects an artificial source. Natural source sensors detect changes in natural phenomena such as acceleration or magnetic orientation. Artificial source sensors detect changes with respect to synthetic phenomena such as a GPS signal or a radio beacon. Natural sources are usually noisy, but can be measured almost anywhere at anytime. Artificial sources can be made arbitrarily accurate, but are subject to signal availability problems [7].

A brief survey of popular localization sensing solutions follows.

GPS

Most commercial personal navigation systems rely primarily on the Global Positioning System. GPS is an absolute measure of position based on a global reference frame. GPS signals are provided by a grid of satellites in synchronous orbit and position is extrapolated by triangulation between the satellites. GPS is considered a fair measure of position, with 95% of readings falling within 10-meters accuracy for civilian uses [19]. Using WAAS, a method for improving on the accuracy of standard GPS, a 2-meter accurate signal can be achieved.

GPS lends itself naturally to pedestrian navigation because the required hardware is small, affordable and accurate. However, GPS can only be used in environmental conditions where the receiver can detect clear signals from several satellites. This means that

GPS usability and accuracy are a direct function of the number of visible satellites and the prevailing weather conditions. While many systems use GPS in conjunction with another sensor, most use other types of data as a supplement a constant GPS stream. As such, a system relying primarily on GPS cannot normally be used inside of buildings or in cloudy weather.

GPS is widely available to the public in the form of lightweight, small form factor personal receiver units such as the Socket Bluetooth GPS and the Garmin GPS 17N [19, 20]. GPS receivers typically interface with a Handheld Computer which can then display user location information along with any maps available in a database. For most civilian uses, GPS itself is a sufficient personal localization device. However, for hazardous use, the drawbacks of a 1-sensor system, especially if that sensor cannot work indoors, is immediately obvious. Therefore, it is common practice to combine GPS with another form of positional measurement such as pedometry, radio or inertial systems so that the system operates at a partial capacity at least most of the time.

Inertial

Inertial sensors primarily measure the acceleration of the user. However, the position of a person relative to a starting location can be inferred by the double integration of the acceleration data. When mounted in an appropriate manner, three axial accelerometers in addition to three axial gyroscopes, usually packaged as an Inertial Measurement Unit (IMU) are sufficient to track and position a person in three dimensions. While, position by integration of acceleration remains popular in mobile robotics, personal navigation systems using direct inertial measurements are becoming increasingly rare. Unlike robots which have a rigid body frame on which an accelerometer can be easily mounted, human bodies constantly shift and distort such that the sensor's position relative to the body is not constant. A robot with a single axis accelerometer mounted in the direction of travel will always report an acceleration if the robot is moving. However, a human with a back-mounted accelerometer may not report any acceleration if the torso is turned while walking. To compensate for the uncertainty in sensor position with respect to the body pose, systems have been designed with tilt sensors, gyroscopes and GPS in addition to axially mounted inertial sensors [11]. While the additional sensors fix the rigidity problem, they also add overall cost and weight to the navigation system. Moreover, there is still the problem with the double integration of a discrete signal. Double integration magnifies small accelerative inaccuracies, present in all discrete systems, so that they compound and eventually amount to a significant positional inaccuracy [13]. Currently, no commercial personal navigation systems use this approach to localization.

Pedometric

Many personal navigation solutions today utilize the fact that, unlike most robots, humans move by actuating the legs and feet in an intentional fashion to take steps. Pedometry (step sensing) data is usually collected with inertial sensors mounted to detect the motion of the legs. Analysis reveals that certain positions on the leg always exhibit the same repeating motion/acceleration pattern unique to individual movement modes, called occurrences. Two consecutive occurrences denote that a step has transpired and movement is recorded in relation to the user's step size. While the occurrential approach often uses inertial sensors, it detects pattern frequencies in the signal as opposed to using actual inertial values. Thus, pedometry is much more accurate than the direct inertial approach while retaining the ability of inertial sensors to be used anywhere [10].

Using the graphical features of the acceleration profile instead of the actual values does create additional complication however. Detection of a step alone is not enough to position a person in a space; the length of the step must also be known. One approach is to assume a fixed step size for each individual user. If the assumed step size is very close to the true mean, this is generally an acceptable approach; however, accuracy suffers as the user traverses different types of terrain. The step size of user varies depending upon the inclination and consistency of the terrain and the mechanics of walking changes completely with a grade of more than 10% [4]. As personal navigation systems are intended to be used in hazardous situations and environments, this is serious problem. Consequently, most current pedometry research is being conducted in step-adaptive systems.

The systems being developed by Kourogi and Kurata [15], Vildjoiunate [12], Randell [6], Bieber and Korten [13], Ladetto [8] and Jirawimut [14] are among those that utilize pedometry sensing. Variations in the commercial pedometry systems include placement, quantity and utilization of sensors. The complexity and quantity of sensors utilized to measure steps is usually correlated to the type and number of other positional sensors present in the system.

The simplest pedometry setup is a human center of gravity (COG) mounted IMU that measures antero-posterior motion (bumps in torso movement) [15]. Bump detection is popular because it requires only a single sensor; however, motion of the torso is not as prominent as that of the limbs, making feature extraction more difficult and output is prone to erroneous predictions. Standalone step detectors using this method are also made commercially, much like their GPS counterparts. The Dead Reckoning Module by Point Research (DRM) is one such sensor that combines an inertial sensor with a built-in bump detection function. Kourogi, Jirawimut and Ladetto all use the bump detection method. Kourogi's system used the bump detection method in addition to an impressive network of gyroscopic, magnetic and photo-correlative sensors simultaneously to produce an estimate of user position. Alternatively, Jirawimut and Ladetto both approached the localization problem traditionally by pairing pedometry with GPS to adaptively correct for step features and length.

Vildjoinuate and Beiber both use a single IMU mounted on one leg to detect steps. Single leg detection also requires only a single sensor; however it trades step accuracy for feature extraction ease. Leg motion exhibits more prominent acceleration peaks and troughs than torso motion, but by only sensing a single leg, this method does not provide for robust handling of false positives that may be produced when the user is turning in place or adjusting the sensor leg while standing still. In addition to the single leg sensor, Vildjoinuate and Beiber both use strategically placed infrared beacons for indoor positional correlation, while Vildjoinuate adds an additional magnetometer to track user heading.

Randell uses sensors mounted on both legs to both detect steps and adaptively scale step sizes. While the occurrence signatures remain the same for both feet during the process of walking, the delay between the detection of an occurrence on each foot is proportional to the step size. If the mean step size and occurrential delay is known, then the effective step size can be inferred by scaling the observed delay with the mean step size to delay ratio. The added sensor also provides the potential for operational redundancy which is a very appealing point for users in hazardous environments.

Radio Frequency

Radio localization systems consist of transponders and interrogators. Transponders (RFID Tags) are passive receiver/transmitters that react to specific radio waves by producing a unique response signal induced by the first. The interrogator is a transmitter that will broadcast the correct signal. With sufficient signal coverage in an area, localization is achieved through response time triangulation of the user to various interrogators.

RFID sensors have the benefit of not requiring an external power source as the interrogator's signal is enough to activate the sensor. This in turn reduces the weight and size of sensors on the user. Most commercial RFID tags are thinner than paper and little larger than a quarter. While a radio solution provides the user low-clutter GPS quality localization indoors, many groups have found that using RFID for field use is impractical. RF Transponders are large and must be installed in the field around the area of interest before the system can be used. This creates additional external setup time and complexity to deploying the system that is detrimental to the design of mission critical systems.

Several commercial radio solutions are currently available. The seven.Five platform by Comarco Wireless is a commercially available indoor navigation system that couples standard RFID with inertial sensing [16]. However, a price tag of $20,000 makes this solution a very costly investment. The Ensco Ranger is a limitedly available precise RF localization system with an operational range of more than a kilometer and 8-inch precision. The system also uses available outdoor geophysical information when connected to an electromagnetic detector [17].

Laser

Laser scanners have long been used on mobile robotics to make 3D maps of spaces. A point laser, which measures distance, is fired many times about an arc which is then adjusted to a different pitch and the process is repeated to produce a discrete, point representation a 3D void. In addition to providing mapping via point clouds, they are also exceptionally accurate at determining distances to landmarks which can be used for relative localization. However, use of laser scanners on humans poses many problems. Most notably, laser scanners are large and require similarly unwieldy support and computation equipment. Secondly, laser scanners only produce location data in reference to previously surveyed landmarks. If the geographic locations of the landmarks are poorly measured, the system will be adversely affected. Lastly, the laser scanner is a short range sensor with a max distance of around 80m and an effective detection distance of much less [21].

The Sick Corporation makes the most widely used laser scanner in robotics, the LMS 200 series. It is primarily for indoor use and has a 180 degree scan arc at a maximum range of 80m. Saarinen's Personal Navigation System [18] is currently the only one in its class that uses the Sick laser scanner. The 5kg (11lbs) scanner is mounted on the abdomen of the user through the use of a harness. The system uses the laser scanner to simultaneous map and localize along with doubled legged pedometry sensors, digital compass and a gyroscope.

Photogrammetric

Photogrammetry is the analysis of two 2 and 3-dimensional spaces from photograms (imaging media such as CCD, radiation sensors, and stereo cameras). Photogrammetry is used much like laser scanning in localization: to infer distances from landmarks. Usually, pictures of landmarks taken with a camera during runtime are compared to images of the same landmark taken at previously surveyed locations. Fitting algorithms are then used to find the direction and orientation skew between the two images, with which the position of the user can be determined by adjusting from the surveyed location.

There is much research being conducted in this field, but current technology is still in the developmental phase. In addition to noisy image processing, vision and placement algorithms, limited computing resources also force a long response time. It is also very difficult to infer position in a 3 dimensional world using 2 dimensional photograms, so many systems must rely on stereo vision. However, this approach also adds more computational and sensing real estate to the system, making current photogrammetry setups impractical for use as a primary sensor in human navigation systems.

Photogrammetric technology is currently being used on the Portable Mobile Mapping system designed by Ellum and El-Sheimy [9]. The walking measurement system uses high-precision differential GPS to characterize the user's pedometric parameters, after which, the system can go for extended periods without a GPS signal. Using GPS based pedometry correction is The Portable Mobile Mapping system is a both a localization and mapping system that uses GPS and a digital magnetic compass for positioning and a digital camera for landmark detection and correlation. The PMM is intended for outdoor use only, and the photogrammetric system is still in development. The designers have admitted to running into serious problems with image compression interfering with landmark correlation and how to deal with comparing potentially skewed images.

Appendix B:
System Hardware Specification

System Hardware Specification

The current Human Odometry system is comprised of a PocketPC (a HP iPaq or a Dell Axim) and several measurement devices: two Inertial Measurement Units (IMUs), a fiber optic gyroscope (FOG), and an optional Bluetooth GPS unit. The PocketPC uses the data from the other devices to detect and measure motion and calculate position. The data from the IMUs is used to measure distance traveled, while the data from the fiber optic gyroscope is used to calculate heading. For the most precise position estimates, the GPS data can be used to correct for drift. GPS may also be used alone instead of the other devices.

All devices are connected via Bluetooth, to form a Personal Area Network (PAN). Each measurement device is connected to a Bluetooth transmitter so that the data can be transmitted wirelessly. The Bluetooth devices are simple serial to Bluetooth transmitters that can be configured to output at seven different baud rates. The Bluetooth devices stream the data from their respective devices to the PocketPC, which can then interpret the data to be used in the application.

The inertial sensing unit has two major items, a 6-degree of freedom IMU and a serial Bluetooth board. The existing Human Odometer units currently use two varieties of the IMU units. The first, the ONAVI FalconGX, has all IMU components on one board. The second variety, the ONAVI Gyrocube 3F, contains the inertial sensor headers on one board and the digitizer on another. This allows for an easier and more compact design. Both versions of the ONAVI IMU output the same exact data - inertial angular rate and acceleration - as binary format at 20hz and 9600 baud. Two 3V CR-2 batteries power both the Bluetooth and IMU devices. These components are all packaged into a small box which straps around the user's leg.

The fiber optic gyroscope currently used is a KVH DSP-3000 and is wired for digital asynchronous operation. It outputs an angle corresponding to the user's orientation, at a frequency of 100 Hz. The FOG is connected directly to a serial-to-Bluetooth device, which outputs data at 50hz and 38400 baud. The Bluetooth device connects to the FOG via serial cable. To power the FOG, four external AA batteries and a 5v DC-DC converter are required. These components are packaged into a single heading unit mounted on a belt, such that the FOG is positioned on the small of the user's back.

Appendix C:
Human Odometer TestPlan

Test Plan

The purpose of this test plan is to establish a well defined procedure for quantifying the accuracy of the CMU Human Odometer system. Previously, this system has only been tested in an ad-hoc manner, and accuracy has been visually approximated by looking at the path drawn on a mapping application. This test plan will use a more structured approach to gathering and analyzing Human Odometry data.

The following tests measure baseline functionality and performance, and are not meant to test robustness of the system under extreme conditions. That said, baseline performance should not be defined so narrowly that basic functions of the system are ignored. Tests should be conducted with various modes of motion, over various types of terrain, to fully test both detection and measurement in a variety of conditions.

In order to measure accuracy of a localization system, a reliable source of position information must be available as a benchmark. The system must be set up and used in a well documented and repeatable manner, and all data and results must be logged for later analysis or comparison. A set of statistics which quantify the accuracy of the system in meaningful terms should be generated from the logged data. The methods which generate these statistics must also be well documented and repeatable. A set of steps intended to satisfy these criteria are outlined below.

Procedure

The following documents the precise set of steps the tester must take to gather all necessary information for analysis. Some of these steps may be done well ahead of time, while others can only be completed on the test site, or shortly before testing. Any deviations from the plan should be noted for consideration in later analysis.

A. Preparation Phase

The Human Odometer consists of a set of wirelessly connected hardware components and a software application. These require certain configuration steps to work together, as outlined below.

1. Hardware preparation

• Gather necessary components for the system. The system requires two IMU nodes, a gyroscope belt unit, a Bluetooth GPS receiver, and appropriate batteries. The belt unit should hold a KVH DSP 3000 gyroscope, a battery pack, and a Bluetooth node. When the tester is wearing the hardware, the belt unit should fit snugly against the small of the back.

• Place fresh batteries in the IMUs and the gyroscope. Charge the GPS receiver. All baseline tests should be done on full power. If you are specifically testing the effects of battery power on performance, this will require a different set of tests.

• Make any necessary wire connections, such as connecting the gyro to a corresponding Bluetooth node and attaching the apparatus to the belt.

• Verify the connections by turning on the IMUs and checking that the power indicator lights turn on.

2. Course Designation

• Select an appropriate course or set of courses that will allow for at least 100m (328 feet) of uninterrupted travel or 3 minutes of data. Ideal conditions will include excellent GPS coverage and no interfering traffic which may force the tester to change their course.

• Preferably, the course will have consistent, passable terrain. At least one course should be set up over level ground, to test baseline performance of level forward motion. Another course should be set up over hilly and/or broken ground to test the tolerance of the system to uneven terrain.

• Clearly delineate the path to be traveled through the course. For example, the use of flags, painted lines or other visual beacons may help guide the tester. The test is not accurate if the tester cannot stay on the path. Beacons should be placed at all turns or hills, and should be close enough to each other that the tester can always see the next beacons.

• Survey the obstacle course. Characterize the course numerically by measuring distances between landmarks. Landmarks can be the visual beacons used to designate the course, or natural features of the terrain. Alternatively, a precision GPS reading for landmarks may be obtained by standing still for an extended period or using a differential GPS device. If the test is indoors, a precise set of building blueprints, if available, may be used to measure distances between path segments. However, these must be completely accurate, and experience has shown most maps of buildings to be somewhat poorly proportioned.

3. Software Preparation

• Obtain the latest software from the revision control system. Note the date of checkout, and tag the files you are testing for future reference.

• The software needs to know which device you are using.

All devices are connected to the PocketPC via Bluetooth communications. In the future, device connections will be set in an XML file, but currently all connections are hard coded. Therefore, the Bluetooth addresses for the nodes that will be used must be included in the code. The correct Bluetooth address can be determined by the labels on the nodes. Be sure to note which IMU node the software will expect on the tester's right leg, and which on the tester's left leg.

• If you wish to run the map tracking software while collecting data, make sure the initial position given to the Human Odometer is set as the first point in your surveyed path. Also make note of the initial heading expected by the software.

• Compile the software for data logging mode to log GPS, IMU and Gyro data. Make sure the localization system is set up to look for all of these devices, since many tests of the system do not include GPS.

• Load the software onto a PocketPC. Currently supported platforms are the HP iPaq 5555 and Dell Axim.

4. System verification

Perform a basic test of the software build in order to ensure that compilation settings were correct and all devices are connecting properly. Sufficient verification should include the following:

• Wearing the measurement devices, run the application and walk around normally, to verify that a path is drawn on the application's maps.

• After running the application, check the device log files to ensure that all devices are receiving reasonable data at expected rates. IMU logs should have data rates of about 20 Hz, gyro logs tend to have rates of 60 to 100 Hz. IMU logs should not contain zeros. Gyro logs should show an initial output of angular rate, followed after a few samples by an output of integrated angle data only.

B. Testing Phase

1. Wearing the System

The Human Odometer's measurement units are very sensitive to location. In order for measurements to be accurately scaled, each wearer must use a consistent placement of the hardware every time they use the system.

• Strap the two IMUs to each leg, ensuring proper tightness such that they are rigid against the leg axis to prevent jostling. The best place to wear the IMUs is directly below the knee. They should be on outside of the leg, with the power switch facing forwards. They must be aligned with the direction of motion. In other words, when looking straight down at the IMUs they should not appear to be tilted inwards or outwards; the cover of the boxes should face directly outwards.

• Put on the belt, ensuring that the gyroscope assembly is snug against the small of the back. The gyroscope itself should be perfectly horizontal, or heading data will quickly accumulate error.

• The GPS device needs to be placed wherever it will get the best coverage. It is recommended that the GPS device is affixed to the top of a hat with Velcro.

2. Starting Up

• The tester must be at the first surveyed point in the planned course before starting the application.

• The tester should be facing in the direction expected by the software, noted in the Software Preparation step. A compass is helpful.

• Turn on the PocketPC.

• Start the application.

• Switch on power to the IMUs, gyroscope and GPS receiver. It is recommended that these are switched on in the order they are searched for by the application. Therefore, turn on first the gyroscope, then the IMUs, then the GPS. After turning on each device, wait for the application to connect to it before turning on the next device. The application should print "Device Matched" to the log screen when it has completed a connection.

• Wait for the GPS device to get a lock. When it has received enough satellite data to get a good lock, the current position indicated on the map will stabilize.

3. Course Completion

• Walk or run the obstacle course by visiting the predetermined path, allowing for as little deviation as possible.

• Shut down the application.

• Turn off power to the devices (IMU, Gyro, GPS etc).

• Save the log files generated for the trial.

• Record any observations and errata for the trial. Important things to note are significant deviations from the path and any system anomalies.

• Check for appropriate battery power and replace if necessary.

• Repeat the obstacle course trial with various speeds and user modes (i.e. walking, running, jogging etc).

Appendix D:
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