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Personal Dead-reckoning System for GPS-denied Environments

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***Abstract*—**This paper introduces a positioning system for walking persons, called "Personal Dead-reckoning" (PDR) system. The PDR system does not require GPS, beacons, or landmarks. The system is therefore useful in GPS-denied environments, such as inside buildings, tunnels, or dense forests. Potential users of the system are military and security personnel as well as emergency responders.

The PDR system uses a 6-DOF inertial measurement unit (IMU) attached to the user's boot. The IMU provides rate-of-rotation and acceleration measurements that are used in real-time to estimate the location of the user relative to a known starting point. In order to reduce the most significant errors of this IMU-based system—caused by the bias drift of the accelerometers—we implemented a technique known as "Zero Velocity Update" (ZUPT). With the ZUPT technique and related signal processing algorithms, typical errors of our system are about 2% of distance traveled for short walks. This typical PDR system error is largely independent of the gait or speed of the user. When walking continuously for several minutes, the error increases gradually beyond 2%. The PDR system works in both 2-dimensional (2-D) and 3-D environments, although errors in Z-direction are usually larger than 2% of distance traveled.

Earlier versions of our system used an impractically large IMU. In the most recent version we implemented a much smaller IMU. This paper discussed specific problems of this small IMU, our measures for eliminating these problems, and our first experimental results with the small IMU under different conditions.

Keywords: *Personal Odometry, Personal Dead-reckoning, non-GPS navigation, GPS-denied navigation, Inertial Measurement Unit, IMU*

I. INTRODUCTION

This paper describes our Personal Dead-reckoning (PDR) system for measuring and tracking the momentary location and trajectory of a walking person, even if GPS is not available. Such a system is of value for military and security personnel, as well as for emergency responders. For example, our system would allow tracking the position of soldiers in urban combat operations. Another application involves the "clearing" of a large building by emergency or security personnel. Their challenge often is to keep track of rooms already cleared and areas that were not cleared, yet. Our system's ability to track each person's location provides a useful solution for this problem. Other applications for the PDR system are the interior mapping of buildings and improved situation awareness for soldiers.

As mentioned, our proposed PDR system does not require GPS. This is an important distinction, since GPS is not available indoors. Furthermore, GPS is unreliable under dense foliage, in so-called "urban canyons," and generally in any environment, in which a clear view of a good part of the sky is not available.

There are some other approaches to personal position estimation without GPS. Typically, these other systems require external references, also called "fiducials," which in most cases must be installed in the work space at precisely surveyed locations before the system can be used. This installation is time consuming and expensive, and in the cases of emergency response or urban combat completely unfeasible. Some fiducial-based systems also require an active radiation source, such as infrared light [1], ultrasound [2], or magnetic fields [3], which may be undesirable in security-related applications. Generally, fiducial-based systems perform well and are able to provide absolute position and orientation in real-time. If the application permits the installation of fiducials ahead of time, then these systems have the significant advantage that errors don't grow with time, whereas with our system they do.

Another way of implementing absolute position estimation is computer vision [4][5]. Images are compared and matched against a pre-compiled database. Computer vision has the advantage that the environment does not need to be modified, but the approach requires potentially very large databases. Work is also being done on so-called Simultaneous Location and Mapping (SLAM) methods, which don't require a pre-compiled database [5]. However, SLAM systems are not as reliable, may accrue errors over time and distance, and poor visibility and unfavorable light conditions can result in completely false position estimation.

The scientific literature offers a few approaches that do not require external references. The simplest one of them is the pedometer, that is, a device that counts steps. Pedometers must be calibrated for the stride length of the user and they produce large errors when the user moves in any other way than his or her normal walking pattern. One commercially available personal navigation system based on this principle is the Dead Reckoning Module (DRM) [6]. The DRM uses accelerometers to identify steps, and linear displacement is computed assuming that the step length is constant. Heading is measured using a digital compass, which is combined with the traveled distance (step counts) to estimate 2-D position. Under this condition, Pointresearch/Honeywell claims an accuracy of up to 5% of the traveled distance. However, we believe that the requirement for a constant step length is impractical, since step size changes as a function of operational needs, fatigue, and weight carried by the user.

A very sophisticated pedometer-like approach was introduced by Cho and Park [7]. Their system uses a two-axes accelerometer and a two-axes magnetometer located on the user's boot. Step length is estimated from accelerometers readings that are passed through a neural network, and advanced Kalman Filter techniques are aimed at reducing the effect of magnetic disturbances. While the reported results in an outdoor environment are very good, we found that indoors, especially in large steel structures, magnetic disturbances are omnipresent and varying, making it virtually impossible to filter them out.

Other solutions actually measure the length of every stride in real-time. One such solution using ultrasonic sensors attached to the user's boots is explained in [8]. Ultrasonic sensors require a direct line of "sight" between the boots, which may be a problem on rough terrain. In straight-line walking experiments the authors report an average and maximum error of 1.3% and 5.4%, respectively. Another approach measures the RF phase change between a reference signal located in a waist pack and the one coming from a transmitter located on each boot [9]. A drawback of these approaches is that position estimation is restricted to 2-D environments since neither system can determine altitude changes and assumes that any change is horizontal. Another potential problem is that these technologies use active emissions, which are undesirable for military applications, and they are vulnerable to external interference from the environment or from other units.

In our own previous work we demonstrated accurate 3-D position estimation using a six-Degree-of-Freedom (6-DOF) Inertial Measurement Unit (IMU) attached to the user's boot [10] [11]. The main disadvantage of our previous PDR system (shown in Fig. 1a), was that our IMU, the SiIMU01 made by BAE [12] was bulky, heavy and expensive. In this paper we present our new PDR system (shown in Fig. 1b), which uses the much smaller and lighter nano IMU ("nIMU," in short) made by MemSense [13]. The nIMU, however, has significantly worse performance specifications than the SiIMU01.

Both the old and the new version of our system compute the complete trajectory of the boot during each step. On first glance it appears that this approach is destined to fail, since measuring linear displacement using accelerometers is not very feasible. That is because data samples from accelerometers must be integrated twice to yield linear displacement and this process tends to amplify even the smallest errors, notably those due to bias drift. However, we use a practical method (explained in detail in Section B) that almost completely eliminates this problem – *under certain operational conditions*. We found that such operational conditions exist in legged motion, such as when people walk, run, or even climb. Conversely, our method does not work at all with wheeled, sea-, or airborne motion. We should also note that since the PDR system uses only passive sensors, it has a zero-radiation signature, i.e., it does not emit any signals. This makes our system "invisible" to sensors in hostile environments and immune to interference or jamming.

The PDR system offers two distinct capabilities: (1) it can measure linear displacement (i.e., odometry) and (2) it can estimate the subject's actual location in terms of *x*, *y*, and *z* coordinates, relative to a known starting location. Such a function, if performed without external beacons or landmarks, is referred to as "dead-reckoning." The simpler but less useful

Fig. 1: The University of Michigan's two IMUs mounted on rescuer's boots.
(a) The SiIMU used in our earlier proof-of-concept prototype; (b) the small-sized nIMU, described in this paper.

function – Odometry – has errors of less that 2% of distance traveled, regardless of the duration of the walk. The more complex but also more useful dead-reckoning function produces errors of up 2% of distance traveled in walks of up to about two minutes. Longer walks will produce larger errors due to bias drift in the gyroscopes. The bias drift errors in the gyroscopes can be measured and removed from subsequent readings when the user stands still for a few seconds. However, any accumulated heading error remains.

II. PDR System Hardware

Our current system uses a small IMU strapped to the side of the subject's foot, as was shown in Fig. 1. The IMU is connected to a tablet-style laptop computer through an RS-422 communication port. The IMU is powered using a small external 7.8-Volt Lithium Polymer battery, making the whole system portable. The computer runs the Linux operating system patched with a real-time extension and our algorithm runs in real-time.

III. PDR System Software

The software for the PDR system has three modules:

- Position estimation module
- Zero Velocity Updates" module (ZUPT)
- Step detection module

These modules are explained in more detail in the remainder of this section.

A. Position Estimation

In this section we give a brief summary of the navigation equations used in our system. For a more detailed explanation see [16].

We follow the convention used in aeronautics for the designation of the navigation and body frames. In mobile robotics, the so-called Euler equations are commonly used for attitude representation. However, Euler equations have singularities at ±90° – a limitation that is irrelevant in most ground-based mobile robot applications. However, since in our application the IMU is attached directly to the boot of a walking or running person, tilt angles of 90° or more are possible and likely. For this reason we chose the *Quaternion* representation, which handles any tilt angles.

The Quaternion, q, is a vector that defines attitude using four parameters, a, b, c and d. q propagates as a function of the body angular rates, ω_b, according to:

$$\dot{q} = \frac{q \cdot p}{2} \quad (1)$$

where $p = [0, \omega_b]$ and $\omega_b = [\omega_x, \omega_y, \omega_z]$.

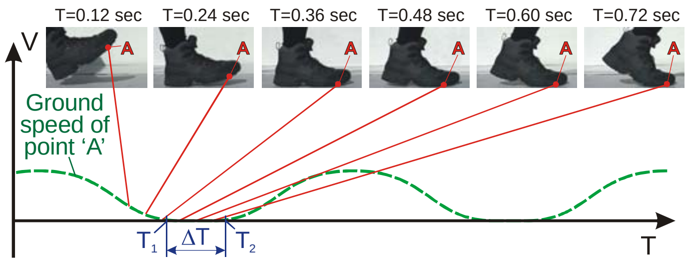


Fig. 2: Key phases in a stride. During ΔT, all velocity components of point A in the sole of the boot are zero.

Once attitude is computed, the body acceleration, a_b, can be computed in terms of the navigation reference frame, a_n, using the quaternion vector

$$a_n = q\, a_b\, q^* \quad (2)$$

where $q^*=(a - b - c - d)$ is the complex conjugate of q.

In order to minimize the errors associated with the digital implementation of these algorithms, we used optimized discrete-time algorithms as explained by Savage [17].

Velocity, v_n, can be computed by integrating the accelerations in the navigation frame after eliminating the local gravity component g_l

$$v_n = \int \dot{v}_n\, dt = \int \left(a_n + g_l\right) dt \quad (3)$$

Finally, position can be computed as the integral of the velocity over time

$$p_n = \int v_n\, dt$$

B. Zero Velocity Updates (ZUPT)

Fig. 2 shows some of the phases of a stride during normal walking. As is evident from the motion sequence, Point A on the bottom of the sole is in contact with the ground for a short portion of time, ΔT. ΔT lasts roughly from just before *Mid-stance* (T_1= 0.48 sec) to just after *Terminal Stance* (T_2 = 0.72 sec) and is ~0.24 sec in the example here (terminology based on [18]). During that time and unless the sole is slipping on the ground, 'A' is not moving relative to the ground and the velocity vector of 'A' is $\boldsymbol{V}_A = 0$. The non-slip assumption is warranted because during that phase almost all of the body's weight rests solely on the area of the sole around 'A', thereby increasing traction.

Since the condition $\boldsymbol{V}_A = 0$ is maintained for the significant period of time ΔT and not just for an instance, we reason that at least sometime during ΔT the velocity vector of Point A is also zero. We expect the three velocities to show readings of zero during this time. If the reading is not zero, then we assume that the difference between zero and the momentary reading is the result of accumulated errors during the step interval. It is now trivial to reset the velocity error to the known zero condition. This way we can effectively remove the accumulated errors from the accelerometer output, at least for a few seconds. Luckily, it is the nature of walking or running that the next footstep is just a second away, allowing us to repeat this cycle over and over without accumulating significant errors. This frequent resetting of velocities to the known and absolutely true value of zero assures that any error produced during one step is not carried over to the next ones. For example, if the subject's foot actually slipped during one step, then the resulting error in velocities exists for just the duration of this one step. Subsequent steps are again error-free. The resulting error in position is just a few centimeters and it remains constant for the remainder of the walk, unless new errors occur.

In the scientific literature, this method of counteracting drift is called "Zero Velocity Update" (ZUPT) and is commonly used in underwater navigation [19]. ZUPT is also used in oil drilling, where it provides real-time monitoring of the position and orientation of the bottom hole assembly [20]. In these applications, ZUPT has been used successfully with update intervals between two to ten minutes depending on the quality of the sensors. The accuracy of the ZUPT-based solution depends on the time interval between ZUPT points. As mentioned, for walking or running these conditions occur once on every footfall, that is, about once every second. A detailed explanation of the ZUPT method can be found in [21].

The elegance of this approach lies in the fact that in each stride we know at least once the true velocity and acceleration of Point A. Our knowledge of the velocity and acceleration being zero and the resulting ZUPT correction is always absolute, not relative to the previous correction. Therefore, at least once during every step the accumulated errors can be removed or bounded.

After applying the ZUPT algorithm, there is an additional stage of conditioning the sensor data. A detailed discussion of this stage is beyond the scope of this paper. The experimental results of the following section, however, reflect the application of the additional data conditioning stage.

IV. Experimental Results

In this paper we present results of an experiment on level terrain (2-D) and the result of a 3-D experiment. All algorithms were implemented in C++ on a Lippert LiteRunner PC-104 computer, under Linux with real-time extensions.

A. *Walk on 2-D Terrain*

In this experiment the subject walked along a rectangle-shaped path (Fig. 3). The longer side of the rectangle was just over 30 meters in length, and the shorter one about 20 m, resulting in a total path length of $D = 104$ m. We ran five experiments in clockwise (CW) and five experiments in counter-clockwise (CCW) direction. In all cases the subject walked at the normal walking pace of 1 m/sec. After completing each loop, the subject stood still for about 30 sec. This zero motion condition was detected by our software, which updated the bias drift using the new information. The same experiment was performed by five different subjects.

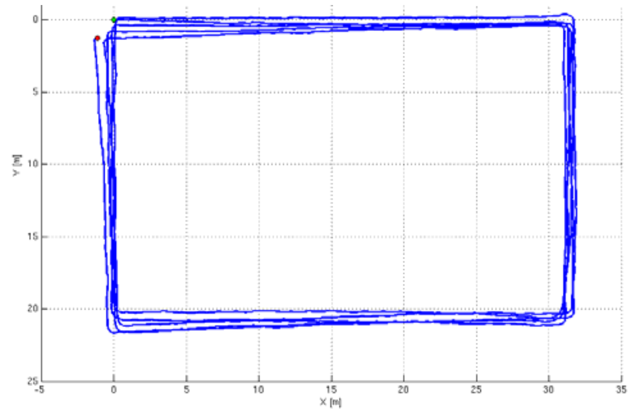


Fig. 3: Recorded trajectory of a subject walking on the 2-D terrain.

The absolute return position error in the x-y plane was computed as

$$E_a = \sqrt{x_e^2 + y_e^2} \tag{5}$$

where
x_e – return position error in X-direction.
y_e – return position error in Y-direction.

We also computed the *relative* error, E_r, which expresses the average error as a percentage of total travel distance, D

$$E_r = 100\frac{E_a}{D} \tag{6}$$

Tables 1 and 2 summarize the return position errors for these runs. Without our ZUPT implementation, the errors in

Table 1: Summary of return position errors for the 2-D terrain clockwise (cw) walks.

	X_e [m]	Y_e [m]	D [m]	E_a [m]	E_r [%]
Walk 1	-0.77	1.5	524.2	1.69	0.32
Walk 2	-0.75	4.04	524.3	4.11	0.78
Walk 3	1.94	-5.12	519.5	5.48	1.05
Walk 4	3.26	-4.68	525.0	5.7	1.09
Walk 5	0.46	-2.23	511.9	2.28	0.44
Average			**520.9**	**3.85**	**0.74**

Table 2: Summary of return position errors for the 2-D terrain counter-clockwise (ccw) walks

	X_e [m]	Y_e [m]	D [m]	E_a [m]	E_r [%]
Walk 1	-1.05	0.43	531	1.13	0.21
Walk 2	-0.92	-0.17	527	0.94	0.18
Walk 3	-1.22	-0.16	522	1.23	0.24
Walk 4	2.59	1.14	524	2.83	0.54
Walk 5	-2.24	-2.01	507	3.01	0.59
Average			**522**	**1.83**	**0.35**

this experiment would be on the order of hundreds or even thousands of meters!

B. Walk on 3-D Terrain

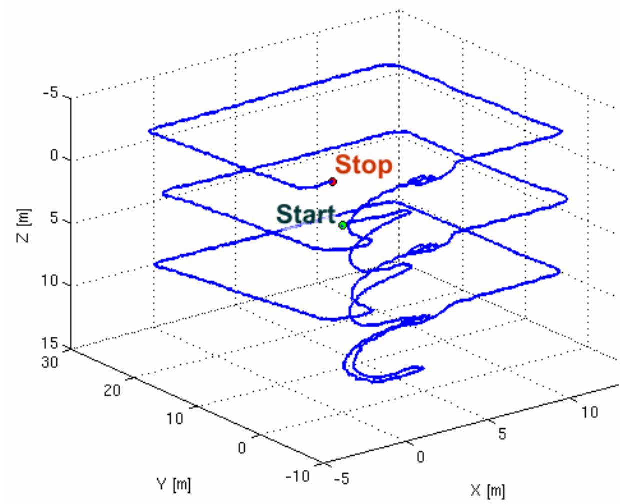
Fig. 4a shows a complex 3-D environment: a 4-story spiral staircase, and parts of three sets of square-shaped open corridors surrounding the atrium of the Computer Science and Engineering building at the University of Michigan. In the experiment described here, the subject started walking down the depicted spiral stair case from he top of the stair case on the fourth floor. The subject walked down the stairs all the way to the bottom of the stairs. Then, the subject walked up again. However, on the way up, on each floor the subject left the spiral stair case and walked around the square corridor, once on every floor, before continuing on to the next higher floor on the spiral stair case. After completing this ~324-meter walk in 5.3 minutes, the subject stopped at the exact same location where he had started. Fig. 4b shows a 3-D plot of the subject's trajectory.

Fig. 4c shows a zoomed-in top view of the start/stop area. The green and red dots indicate the starts and stop position of the subject, respectively, as computed by our PDR system. Since in reality the subject started and stopped at the exact same location, the distance between the green and red dot in Fig. 4c represents the error of our system in the x-y plane. In the case here, the error in this run was 1.1 m, or 0.32% of the total travel distance of 324 meters. This is especially remarkable in light of the excessive vertical travel, and in light of the fact that the subject's gait differed significantly in the three modes of walking during this experiment: horizontal walking, as well as climbing up and down the spiral stair case. The error in vertical direction was larger, about 4.0 m or 1.2% of distance traveled.

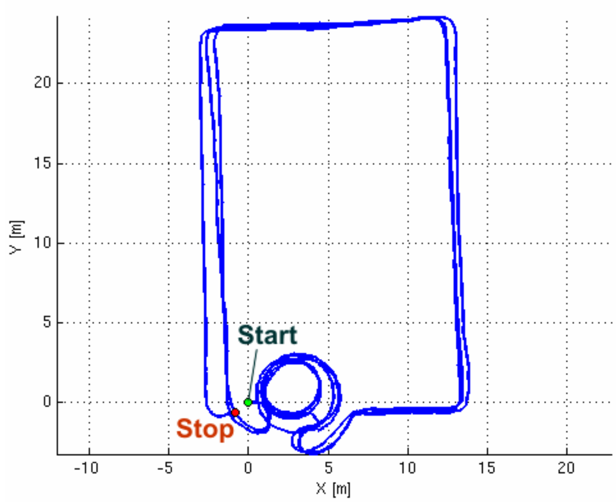
We should note that this run (the only one we performed on this 3-D terrain with the nIMU), appears to have uncommonly small errors. In other, less carefully recorded experiments of this duration, we found that the high drift rate of the nIMU's gyros resulted in larger errors.

a

Fig. 4: Experimental result of a 3-D walk. (a) Four-story atrium and spiral staircase in the University of Michigan Computer Science Building. (b) Trajectory of walking subject as recorded by our PDR system. (c) The return position error in the x-y plane (difference between the start and stop position, i.e., the green and red dot, respectively) is about 1.1 m.



b



c

V. CONCLUSIONS

Our earlier work with the bulky SiIMU01 proved the feasibility of the PDR concept. This paper here presents a snapshot of the current state of development of our PDR system using the small-sized nIMU. Since this project is far from being completed, we could present in this paper only a limited set of experimental results. Nonetheless, these limited results, together with the extensive experimental results obtained with the SiIMU01 in our earlier work, suggest that the PDR system can indeed be based on a small-sized IMU, despite that nIMU's performance limitations.

As tested to date, the nIMU-based system is very accurate in measuring linear displacements (i.e., distance traveled, a measure similar to that provided by the odometer of a car), with errors being consistently less than 2% of distance traveled. The PDR system is also indifferent to pauses or changes in walking gaits. The accuracy of the PDR system degrades gracefully with extreme modes of legged locomotion, such as running, jumping, and climbing.

In the second mode of operation, dead-reckoning, the PDR system measures relative position in terms of X-Y-Z coordinates. Because of the limited performance of the gyroscopes inside the nIMU, the heading errors and the position estimation accuracy are larger than with the SiIMU01, and these errors grow faster than those of the SiIMU01 as a function of time. We are currently investigating methods for reducing these problems such as using a magnetometer or implementing a Kalman filter to estimate some of the random errors.

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VI. BIBLIOGRAPHY

[1] Butz, A. Baus, J. And Kruger A. (2000). "Augmenting buildings with infrared information." *Proc. Int. Symp. on Augmented Reality, IEEE Computer Society Press*, pp. 93-96.

[2] Newman, J., Ingram, D. and Hopper A. (2001). "Augmented reality in a wide area sentient environment." *Proc. IEEE and ACM Int. Symp. on Augmented Reality*, pp. 77-86.

[3] Liu, Y., Wang, Y., Dayuan Y. And Zhou Y. (2004). "DPSD algorithm for AC magnetic tracking system." *IEEE Symp. on Virtual Environments, Human-Computer Interfaces and Measurement Systems*, pp. 101-106.

[4] Kourogi M. and Kurata T. (2003). "Personal positioning based on walking locomotion analysis with self-contained sensors and a wearable camera." *Proc. 2nd IEEE and ACM Int. Symp. on Mixed and Augmented Reality*, pp. 103-112.

[5] Galindo, C. et al. (2005). "Vision SLAM in the measurement subspace." *Proc. IEEE Int. Conf. Robotics and Automation*, Barcelona, Spain, pp. 30-35.

[6] PointResearch/Honeywell, (2006), http://pointresearch.com/products.html#DRM, last accessed: 03/2007.

[7] Cho, S.Y. and Park (C.G., 2006). "MEMS Based Pedestrian Navigation System." *Journal of Navigation*, vol. 59, pp. 135–153.

[8] Saarinen, J., Suomela, J., Heikkila, Elomaa, M., and Halme, A. (2004). "Personal navigation system." *Proc. 2004 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, vol 1, pp. 212-217.

[9] Brand, T. And Phillips, R. (2003). "Foot-to-Foot Range Measurement as an Aid to Personal Navigation." *59th Institute of Navigation Annual Meeting.* Albuquerque, NM.

[10] Ojeda, L., Borenstein, J. "Non-GPS Navigation for Emergency Responders." *2006 Int. Joint Topical Meeting: Sharing Solutions for Emergencies and Hazardous Environments*. Salt Lake City, UT, Feb. 12-15, 2006.

[11] Ojeda, L., and Borenstein, J. (2007). "Non-GPS Navigation for Security Personnel and Emergency Responders." *Journal of Navigation*. Vol. 60 No. 3, Sept. 2007. In Print.

[12] BAE Systems, plc, http://www.baesystems.com, London, United Kingdom, last accessed: 04/2007.

[13] MemSense, LLC, http://www.memsense.com, Rapid City, SD, last accessed: 03/2007.

[14] Ojeda, L., Chung, H., and Borenstein, J. (2002). "Precision Calibration of Fiber-optics Gyroscopes for Mobile Robot Navigation." *Proc. 2000 IEEE International Conference on Robotics and Automation*, San Francisco, CA, pp. 2064-2069, April 24-28.

[15] IEEE Std.952-1997. (1998) "IEEE Standard Specification Format Guide and Test Procedure for Single-Axis Interferometric Fiber Optic Gyros" IEEE Standards, Piscataway, NJ, USA, 1998

[16] Titerton, D. and Westaon, J. (2004). "Strapdown Inertial Navigation Technology, 2nd Edition." *Progress in Astronautics and Aeronautics Series*, Published by AIAA.

[17] Savage, P. (1998). "Strapdown Inertial Navigation Integration Algorithm Design. Part 1: Attitude Algorithms", *Journal of guidance, control, and dynamics*, vol. 21, no. 1, pp. 19-28

[18] Ayyappa, E. (1997). "Normal Human Locomotion, Part 1: Basic Concepts and Terminology." *Journal of Prosthetics & Orthotics*, vol. 9, no. 1, pp. 10-17.

[19] Huddle, J. (1998). "Trends in inertial systems technology for high accuracy AUV navigation." *Proceedings of the 1998 Workshop on Autonomous Underwater Vehicles*. AUV'98. pp. 63-73.

[20] Ledroz, A. et al. (2005). "FOG-based navigation in downhole environment during horizontal drilling utilizing a complete inertial measurement unit: directional measurement-while-drilling surveying." *IEEE Transactions on Instrumentation and Measurement*, vol. 54, no. 5, pp. 1997-2006.

[21] Grejner-Brzezinska D. A., Yi Y, and Toth C. K. (2001). "Bridging GPS Gaps in Urban Canyons: Benefits of ZUPT", *Navigation Journal*, vol. 48, no. 4, pp. 217-225.