Doppler Velocity Log (DVL) Aided Water Column Navigation of a Descending UUV.

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Abstract

Nowadays most Unmanned Underwater vehicles (UUV's) (or Unmanned Untethered Underwater Submersibles) can travel from the surface to the seabed quite successfully. The UUV can get a position/velocity fix at the surface using a GPS. Once the UUV has descended to within tracking range of the bottom, the Teledyne RD Instruments Doppler Velocity Logs (DVLs) can provide high accuracy bottom track for dead reckoning on each single sample thanks to its proven broadband signal processing technology. The challenge currently at hand is to determine the UUV's motion during the descent when GPS signal is unavailable and the bottom is not yet within range of the Teledyne RD Instruments DVL. Each submerged observation (DVL subsurface ping) is an unknown superposition of both water motion and vehicle motion. The observed vehicle relative water motion is nevertheless a valuable measurement. The trouble is in order to determine the earth referenced water motion we must know the vehicle motion, and in order to determine the earth referenced vehicle motion we must know the water motion. We are inspired to discuss current solutions (including Doppler aided INS navigation) and try to unravel this chicken and egg problem, at least adequately enough to be useful.

Teledyne RD Instruments' Doppler Velocity Logs are multi-function Commercial-Off-The-Shelf (COTS) acoustic sensors that provide highly accurate velocity information remotely. TRDI DVLs are ideally suited for installation on a wide array of Unmanned Untethered Underwater Submersibles. The unit's compact size and low power requirements, combined with its versatile, proven technology make it the tool of choice for UUV designers and manufacturers around the world. In fact, you can find a Teledyne RD Instruments DVL installed on virtually every commercial UUV designed to date. Customized and standard Teledyne RDI DVLs are also found on a variety of military and scientific unmanned as well as manned submersibles to provide inertial system aiding, precision positioning, and speed log capability. The DVL is also used to enhance the industry standard automatic control modes (heading and depth) to include station-keeping. In case of a manned submersible the DVL excels in providing a true dynamic positioning capability, allowing the operator to automatically control vehicle motion and position while focusing on other tasks. By expanding on the same decision making and feedback loop that is used in station keeping, and extending the information throughout the available measurement of currents in the water column, information can be gathered that allows for novel methods for navigating through the water column with relatively high precision, and when added to bottom track information when bottom lock is achieved, can be immediately updated to achieve highly accurate position information,

In this presentation we will review current Navigation systems, i.e. the Doppler Velocity Logs, and how the more recent introduction of the Phased Array transducers technology and recent performance and product developments are helping our vehicles close the gap between the surface and bottom with higher degrees of precision in navigation and positioning. We will review current techniques for navigating from the surface to the bottom and present an overview of the known drawbacks when used to resolve motion of an unmanned vehicle transiting between earth referenced regions. We will finally propose new techniques for high accuracy remote speed over ground underwater methods that have been developed and modeled by Teledyne RD Instruments. We will focus on a recent method called 'Water Aided Navigation' which has been proposed and modeled by Teledyne RD Instruments. We will review why this technique is a relevant solution in the underwater motion sensor market when implemented on its own in one of Teledyne RD Instruments Doppler Velocity Logs or when complementing a navigation engine such as an Inertial Navigation system.

(Keywords: Navigation; Water column; Doppler; Sonar; DVL; Current Profiling; AUV; ROV; INS; Transit)

The Challenge

One of the biggest challenges for any kind of vehicle in any body of water is navigation. The two key challenges are knowing where you are within, quite literally, a three-dimensional sea that looks the same in all directions, and knowing that your ship, submersible, or underwater robot, is not going to accidentally impact an object that could be detrimental to the integrity of the vessel. To aid with safety of navigation, maps and charts are our key aids, providing information about depth, typical current flows, reefs, obstacles and areas where it may be too shallow to safely navigate. But if we don't know where we are within a very small margin of error in terms of latitude and longitude, all of this information is largely of no use. Not knowing position on the planet when looking down at a two-dimensional map leaves us vulnerable to potential safety risks. This situation becomes far more complex when a vehicle must navigate in three dimensions through the volume of a body of water.

With today's Global Positioning Systems (GPS) technology, we are fortunate to have an ability to directly measure position in 2-D space, and to a lesser degree of accuracy in 3-D space, by communicating with multiple GPS satellites. GPS has several of its own sources of difficulties, including clouds, rain or severe weather, nearby transmitters or receivers, even sun spots. And of course, when we are at sea, even water on a GPS antenna can cause drop outs or difficulty for the receiver. With a typical commercial GPS, however, when a signal is adequate and enough satellites are present, we can normally triangulate our position to within a 10-meter circle (i.e. Circular Error Probability (CEP)), and with highly accurate differential systems, down to within 10 cm or less. But for a vehicle that must submerge, GPS immediately becomes unavailable when we poke under the surface of the water. And of course, this is where we most need to be able to keep track of our position. Once we are underwater, we are not only susceptible to change in position by virtue of our own motion, we are also subject to unknown position changes resulting from drift with current, and that drift can change with depth. Once we are underwater, we must find a way to track our progress relative to the point at which we entered the water. Unfortunately, we have no yard stick that can continuously or directly measure our displacement or change in position, so we have to find another way to do this. One way is to dead reckon simply by measuring our velocity and integrating this velocity over time to get displacement which is then added to an Earth Referenced starting point to resultantly obtain our track on Earth. Of course, this has two complications of its own: (1) We must know our velocity and, (2) as velocity is a vector, we must know our heading/direction and tilts at all times. Our speed is made up of three orthogonal velocity vectors, x, y, and z. Therefore, to accurately dead reckon our position through integration of velocity, we must be able to measure, in real-time and continuously, all three velocity vectors. Knowing our Tilts, i.e. Pitch and Roll, will bring the x-y plane level with the surface of the Earth and knowing our heading will give us a direction for the x-y plane. For the z-axis, we must measure the tilt corrected Up/Mast velocity of our vessel which is critical with underwater vehicles Navigation.

If we know our velocity changes in real-time and we know our heading at any given time, as well as what our depth is, we can continuously update our position in 3-D space. So the underlying question is, how do we obtain these velocity measurements? Once we are underwater, GPS and Radio Frequency devices don't work. Inspired from Radio Frequency devices used in air to measure velocity, acoustic underwater transducers have been introduced and in use for several decades now to successfully transmit and receive information underwater and the method of transmission is via acoustic pressure waves. Because of direct relationships between speed of sound and temperature, density, and in the open ocean, salinity, we can calculate how far an acoustic signal can travel in a given amount of time, assuming that we know the above variables of course. The techniques derived from this principle are named SONAR. With sonar, we can bounce sound off of objects and from the travel time of the signal, calculate distance to (and from) the object.

Unfortunately, distance doesn't help us much in terms of resolving accurately surface and more importantly sub-surface Navigation. One could argue that these types of ranging SONARs do provide, however an important piece of the puzzle, since when we add the time element, is change in distance vs. time, and since velocity can be calculated based on a change in distance with respect to time, we can obtain velocity.

This latter method, however, is still prone to numerous errors sources because we don't know much about the medium which the acoustic pulse is traveling through which directly impacts travel time, neither we know much about the reflection angle, whether we are bouncing off of the exact same spot every time, or if we are seeing the right echoes or some multiple bounced echo from the previous pulse – just like yelling "hello" when you are in a canyon and hearing multiple replies. These unknowns make calculation of velocity from range very difficult and notoriously inaccurate.

The challenge is then to be able to obtain continuous three-dimensional accurate velocity measurements underwater.

Acoustic Solutions

The first thing we might think about is building a network of sensors similar to the way GPS works with a network of satellites, but doing so underwater using acoustics. This method, which is used in Long Baseline (LBL) and Ultra-Short-Baseline (USBL) systems, is used often in the Oil & Gas and Energy sectors and employs buoys which are positioned at precisily known locations using GPS, which transmit and/or receive acoustic signals, in essence "speaking" to an underwater vehicle. From the travel time of the signals to/from the various buoys and the vehicle, a position relative to the buoys can be calculated. And by knowing the position on Earth of the buoys, we can derive position of the underwater vehicle on Earth. But this method has significant drawbacks in that it is limited in the range that it can be used, it requires that the buoys be positioned and "marked" (i.e. that they know their own position), and most important due to shorter propagation of sound in water than in air, these buoys have to be located in the ranges much shorter than satellites from the GPS receivers thus making the network grid to cover an ocean or even just a coastline unaffordable. And in terms of autonomy, when it comes to underwater vehicles it means the vehicle itself has no self-awareness of position and must rely on an external network of sensors to calculate its position. Therefore, it cannot make any decisions related to vehicle control unless it is receiving input from a central processing station, or in other words cannot get out of their respective small scale covered grid. And since these networks are susceptible to all of the same complications mentioned earlier for ranging sonar, including multiple paths and echoes, the position accuracy can often be severely degraded, a velocity cannot be reliably determined for underwater vehicle accurate control.

While LBL and USBL networks can be useful for tracking equipment and divers underwater and gaining topside situational awareness within a modest degree of position accuracy, given the range limitations, lack of self-awareness, and inaccuracy of position and velocity, such networks are of limited value for any form of Autonomous Underwater Vehicle (AUV). For Remote Operated Vehicles (ROV) when they are not operating within a relatively fixed field or known area, the value of these networks also deteriorates. Since USBL and LBL are primarily focused on measurement of position.

Another method to obtain a vehicle motion measurement is to measure forces that result from their motion. Gyros and accelerometers – which measure changes in inertia due to motion by measuring the force applied to the sensor – can give us an acceleration measurement. This is helpful in understanding direction and can be used to obtain velocity by integrating these forces over time. But there are two key complications that arise: (1) when we are moving at a constant velocity (such as drift due to current), there is no acceleration. Therefore this entire time we would measure zero force, and thus have no idea how fast and in which direction we may be moving, and (2) even when we do generate a force due to a change in motion, we would have to double integrate the measurement to obtain position. These complications result in numerous integration errors, meaning that it is very difficult to use an inertial motion sensor to determine our position.

What we ideally need is a signal that changes with our speed. The phenomena of Doppler shift presents an attractive solution for this challenging situation – what you perceive as a change in frequency based on speed when something is approaching or retreating from you as the observer – manifests itself as a perceived change (frequency) directly proportional to velocity. A Doppler sensor sends out an acoustic signal at a known frequency. If the vessel on which that sensor is mounted is moving and the signal reflects off of a stationary surface, then the same sensor receives the reflected signal and it will 'perceive' the frequency shift. Since the difference in frequency is directly proportional to relative velocity of the transmitter with respect to the target, this sensor using a target fixed with respect to the Earth frame can therefore directly interpret its own speed on Earth. Thus a Doppler sensor can be thought of as the "underwater speedometer". As with any sensor, there are a few restrictions: (1) This is true as long as the reflected signal is not bouncing off of a surface that is 90-degrees to the moving sensor, (e.g. for a vessel moving horizontally, this would be the vertical axis) which results in zero Doppler shift; (2) angles near the vertical (90-degrees) result in very small Doppler shift. This means that the accuracy of a measurement suffers (becomes "noisy") when the angular change from the vertical is small. Mathematically, this means that when the Cosine of the angle relative to the direction of travel is near zero, the measurement can be inaccurate. For this reason, Doppler sonar systems are directed at a modest angle to the direction of motion, usually near 30-degrees from the normal axis from the sonar to the fixed target. As the Doppler sonar systems are usually tracking off of the seabed then the sonar beam(s) are sent 30degrees from a Earth referenced axis normal to Earth surface. Teledyne RD Instruments uses 30degrees as it proved to provide the best penetration through the water medium with respect to accuracy dependent on the surface area of the seafloor insonified at this angle.

In order to obtain velocity information instead of mere speed, we can add Doppler sensors or beams. By using two co-planar sensors/beams aimed at exactly opposite angles from the vertical (relative to the vehicle) and in-line with our direction of travel, we are able to have one sensor 'perceive' the Doppler shift as a result of a reflection that is coming back in the direction of travel of the vehicle, and another away from the direction of travel. Doppler theory says these shifts in frequency should be exact opposites. Thus we can calculate both speed and direction in the plane of the sensors. If we rotate both of those sensors around the vertical axis in any direction, the change in frequency is simply proportional by the cosine of the angle of rotation, and again opposite for each sensor. Thus no matter what rotation the vehicle is relative to Earth and no matter what speed it is traveling at (constant or not), we can calculate a velocity in the axis of these two sensors. If we duplicate this again (i.e. we now have 4-sensors) with the two new sensors at a 90-degree rotation to the first two, such that all the beams converge at the same point (resulting in 4 beams around a circular footprint, 90-dgrees apart) we can obtain velocity measurements in two (i.e. x-y) directions relative to the sensor. By adding a tilt sensor and a compass, we can then calculate our velocity relative to North and East.

In actuality, the Doppler sensor is measuring a Doppler shift along the direction of the beam. This is known as beam-radial velocity. This can be viewed as having a vertical component, and a horizontal component. When we combine all four beams, what this does is allow us to obtain three-dimensional velocity. Technically, all we really need are three beams and a matrix of solution across all the pairs of beams to resolve three dimensional velocities. But using a fourth beam with two paired beams adds redundancy and thus allows us to maintain measurement accuracy when a vehicle is pitching and rolling and one beam may find that it cannot reach the fixed reflecting surface because of its angle and/or the absorption of the acoustic energy in the water; and also provides an additional measurement of the same velocity made by the 3 Doppler sensors which because it is an independent measurement made by an independent sensor, it will help drive the measurement noise down thus improving velocity accuracy and thus reducing motion tracking error when performing dead-reckoning.

The limitation of such sensor is obviously that it needs to be at range of a target fixed or moving. The challenge currently at hand in underwater navigation today is to determine the vehicle's motion during the descent when GPS signal is unavailable and the fixed bottom is not yet within range of the Doppler sensor. We are inspired to discuss current solutions available to resolve this underwater navigational challenge at least adequately enough to be useful.

Doppler Velocity Logs

As mentioned above, today's Doppler sonar systems typically use four beams to create acoustic signals that allow us to resolve velocity in three dimensions. For a Doppler Velocity Log (DVL), these beams are normally at or near 30-degrees from the vertical. The device and its beam pattern therefore look like this:

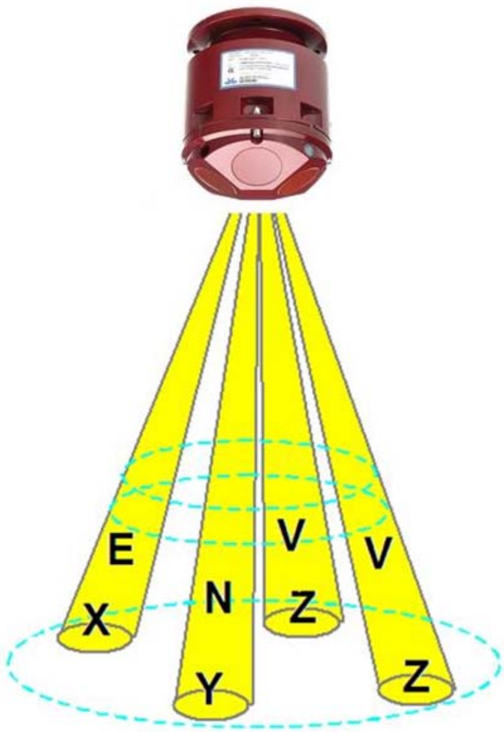

Figure 1. A Doppler Velocity Log and its acoustic beam pattern

The three key performance measures of a DVL are (a) range, (b) measurement Standard Deviation (also referred to as “single ping precision” or “noise level”), and (c) long term accuracy.

Range is primarily dependent on frequency and absorption. Commercial DVL’s are available in frequency ranges from 1200 kHz down to 38 kHz. We tend to think of range as the vertical range, but it is actually the range along the beam’s axis. By multiplying by Cos(beam-angle), we can calculate the possible altitude or vertical range at which the device can measure a signal.

Standard Deviation is, in essence, the variance that can be seen from ping to ping for a fixed measurement due to the measurement noise of the device at the relevant beam angle. Long term accuracy is a measure of the devices ability to accumulate position after long periods of time by continuously integrating the velocity measurement, including its potential instantaneous standard deviation error (which are Gaussian in nature and tend to cancel by mean of averaging successive measurements together). Choices of commercial sensors have performance specifications that are roughly as follows:

Frequency	Max Range – Current Profiling	Max Range – Bottom Track	Standard Deviation	Long Term Accuracy
38 kHz	800 -1,000 meters	2,500 + meters	± 0.8cm/s	± 1% ±0.5 cm/s
150 kHz	375 – 400 meters	560 meters	± 0.7cm/s	± 0.6% ±0.2 cm/s
300 kHz	80-100 meters	250 meters	± 0.6cm/s	± 0.6% ±0.2 cm/s
600 kHz	35-50 meters	90 meters	±1.2 cm/s	± 0.4% ± 0.2 cm/s
1200 kHz	16-18 meters	30 meters	±1.2 cm/s	± 0.3% ± 0.2 cm/s

When a DVL’s signal is able to reach the bottom of the body of water in which the vehicle is navigating, it has “bottom-lock”, which means that it is now able to provide the vehicle with its speed with respect to the bottom or in GPS terminology, Speed Over Ground (SOG). At that point, velocities are extremely accurate and as long as bottom-lock is maintained, position accuracy can be maintained for a rather long period of time. But the moment bottom-lock is lost – i.e. because we simply can’t ‘see’ the bottom because it is too deep - we must find something else to reflect off of. Fortunately, a Doppler Velocity Log can measure velocity not only relative to a fixed surface, but to backscatterers present in the water. Typically, those backscatterers (e.g. zooplanktons, sediment, krill, etc.) are moving with the water current (or are suspended in the water if no current). Thus, the velocity measured in this case is the relative velocity of the sensor relative to the current velocity, which means in GPS terminology that the DVL is able to provide the vehicle with its speed through water (STW). If the sensor is mounted on a non-moving vessel and the water is moving, or if the sensor is moving and able to get a bottom-lock and the water is moving, we have a direct measurement of the water velocity. If the water is not moving and the vessel is, we have a direct measurement of the vessel by measuring the scatterers in the water. But if the vessel is moving and the water is moving, then we have simply the relative difference of the water velocity to the vessel velocity. And in this case, we have no way of knowing either the individual water current velocity or the vessel velocity, or at least not without adding another absolute reference.

Finally, the TRDI DVLs come in many flavors to accommodate all platforms and application needs but in terms of transducer, Teledyne RD Instruments introduced a new technology of Doppler sensors which is called the Phased Array technology having which pushes the limits of Doppler sensor capabilities by resolving many of the challenges pertaining to integrating acoustic velocity sensing to underwater vehicles getting smaller, going deeper, using less energy and yet with maintained similar or improved accuracy of measurements:

- Size
    - Size of only a single Piston sensor

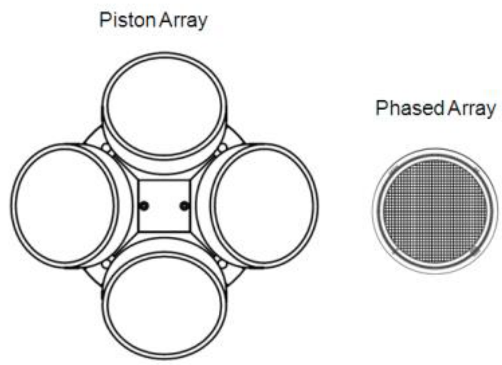

Figure 2. Size comparison between same frequency DVLs – 150KHz.

- Weight
- Extended Range for same footprint
    - Same Size, increased accuracy, greater range
    - Smaller size sensor at same accuracy and range
- Reduced Flow Noise
- No correction For Speed of Sound on Horizontal Velocity.

Surface-to-Bottom Gap Navigation solutions

The goal of resolving navigation is for a UUV (Unmanned Underwater Vehicle) equipped with a DVL(Doppler Velocity Log) to descend to the bottom, and know its position at the bottom with as much accuracy as possible. A UUV can have a position fix from GPS at the surface, and can use bottom track for dead reckoning once it has descended to within tracking range of the bottom. The challenge is to determine the vehicle's position at the bottom, by tracking its motion through the transition from surface to bottom. That is: The challenge is to determine the UUV's motion through the Water Colum, during the descent when GPS is unavailable and the bottom is not yet within range.

Each submerged observation (DVL subsurface ping) -nevertheless a valuable measurement- is an unknown superposition of both water motion and vehicle motion. The trouble is in order to determine the earth referenced vehicle motion we must know the water motion, and in order to determine the earth referenced water motion we must know the vehicle motion. The following is a discussion on the most common and current solution, i.e. including Doppler aided INS navigation) and try to unravel this chicken and egg problem, at least adequately enough to be useful.

INS aided

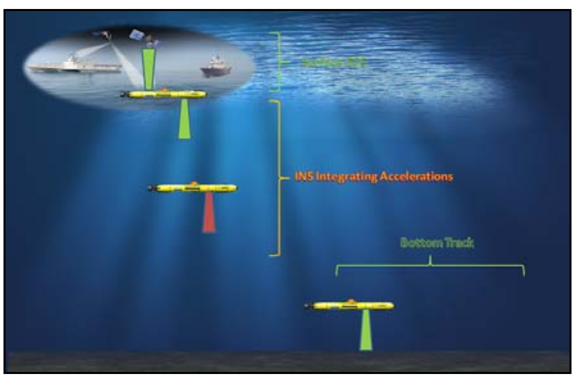

Figure 3. INS Aided Navigation diagram.

Most UUVs navigate using a fusion of several motion sensors. The most common combination comprises an Inertial Motion Unit (IMU), a Doppler Speed Log (DVL) and a GPS. It can also include a series of additional sensors which despite their lesser accuracy present advantages by bringing redundancy in the Navigation solution or by applying to a lesser budget offering. These sensors can be any of the following: MEMs based sensors such as AHRS attitude sensors which are proven to maintain a few degrees of accuracy when subject to highly strong magnetic transients, Ultra-Short or Long Baseline systems, Magnetic Pipe following sensor, Cameras, LIDAR, etc.

Teledyne RD Instruments Doppler Velocity Logs (DVL) have been integrated to the most accurate INSs over the years thus offering a low drift navigation solution for unmanned underwater navigation as well as surface navigation most commonly in GPS denied and mission critical high accuracy autonomous applications. The two systems which most commonly integrated our DVL are the Kearfott T-18/24 RLG and the IXSEA PHINS III FOG. Each of these systems will fusion their internal sensors with the DVL and use pressure/depth sensor, and speed of sound sensor inputs while submerged to achieve the desired navigation accuracy. Both INS are comparable in accuracy specification and have a stated position drift of less than 0.1% of distance travel Circular Error Probability. CEP refers to a circle of possible measurements by the sensor about the true value including 50% of the population of possible values – similar to a noise cloud around the true value. For instance, assume an UUV which would not surface for 2km between GPS fixes, then 50% of the times the UUV will have a position drift of only 2m.

Although FOG and RLG technologies are based on the same physical principle discovered at the beginning of the 20th century that is called the Sagnac effect -this effect shows that the propagation time of light along a closed-loop path depends on its rotation rate- the main differences between these Gyroscopes are derived from the technology implemented internally.

Kearfott T-18/24 uses Monolithic Ring Laser Gyros, which is based on measuring phase/frequency shift from interfering counter-propagating laser sources going through a path created by mirrors redirecting the light into a loop thus increasing the light path which in terms increases the Gyroscope's accuracy. This technology has been proven for years and continues to be chosen in high accuracy applications some 30+years later. Indeed, the RLG technology had been in study in the sixties and it took about 15+years for it to get to its maturity, economy, and produceability to enable it to be used on a large scale in production Inertial Navigation Systems. This time was mostly due to studying and overcoming the most difficult obstacle to making the technology as versatile as it is today, i.e. resolving frequency locking at slow rotations. The problem was mostly due to imperfections in the mirror or optical components causing backscattering energy that would ultimately cause the 2 sources to oscillate at the very same frequency. This phenomenon common to all oscillators has been well studied in the domain of radio physics [ADLER (R.). - 1973, *Proceedings of the IEEE*, Vol 61, N10]. The most common solution is referred to as "Dithering", which consist of adding random noise to the signals using a motor control loop creating random light noise by controlled vibration of the laser gyro block. This dithering in the Kearfott T24 produces an audible tone at the dithering frequency.

In the case of the IXSEA PHINS III, the technology used is the Fiber Optic based Gyro (FOG) which is based on measuring phase/frequency shift from interfering counter-propagating laser sources going through a long optical fiber to create the increased light beam path which in terms defines the Gyroscope's accuracy. A FOG is more of a solid-state sensor as there is no need for moving parts thanks to the use of a passive interferometer which prevents the risk of lock-in between counter-propagating.

As aforementioned these devices have comparable performances but differing properties which need to be taken into account when designing your UUV Inertial Navigation Solution. For instance here, the differing properties lies on physical size and weight, the KEarfott T24 is significantly smaller than the IXSEA PHINS III; power draw, the PHINS III draws less power; and acoustic noise, PHINS III is acoustically silent.

The main reason for integrating TRDI DVLs to an INS with an IMU such as the ones presented above is due to its ability to drastically reduce these sensors systematic position drift and random walk.

The following will discuss basic concepts which underline the foundation for the aforementioned statement.

First and foremost, the most common idea to get across is that the INS usually contains sensors which will measure accelerations, either angular or horizontal but anyway accelerations.

In comparison, the DVL will measure Velocity.

The ultimate goal of the INS is to provide an Earth referenced motion/position of the tracked vehicle (whichever it is: AUV, ROV, ASV, UUV, Manned Surface Vessel, etc.). Therefore, from a mathematical standpoint the INS will have to integrate its acceleration twice to get to a delta position.

In comparison the DVL will have to integrate its velocity once to get to the same result.

Assumptions

Assumption1: One can assume with some confidence that both the DVL and the INS would have a constant bias b and a dynamic bias d.

Assumption2: For the sake of simplicity for this paper let's assume that these biases are the same for both the DVL and the INS.

Constant Bias

Such a Constant bias error when integrated once by the DVL would result in a position error which would grow linearly with time:

s(t) = b_DVL . t

In comparison, when integrated twice by the state machine on an INS it would cause a position error which would grow quadratically in time:

s(t) = b_INS . T^2/2.

The resulting drift caused by integrating a measurement with a constant bias would obviously grow much faster on the accelerometer than the DVL as depicted in the figure below.

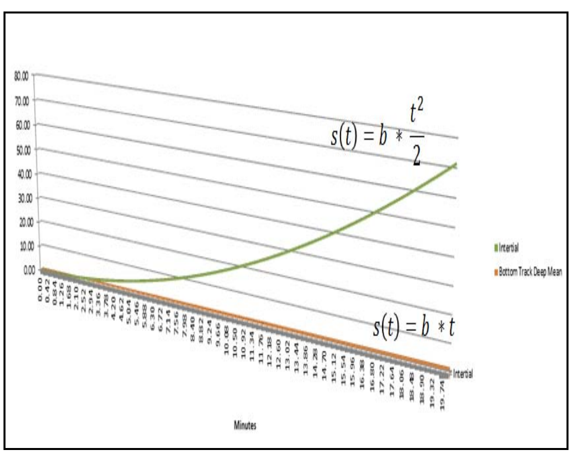

Figure 4. CPE Inertial vs. DVL Bottom Track Constant Bias

Now the Engineers are IXBlue and Kearfott have found some very efficient ways to reduce this constant bias. Please refer to them for more details. In just a few words:

It is possible to estimate the bias by measuring the long term average of the accelerometer's output when it is not undergoing any acceleration. Unfortunately this is complicated by gravity, since a component of gravity acting on the accelerometer will appear as a bias. It is therefore necessary to know the precise orientation of the device with respect to the gravitational field in order to measure the bias.

In practice this can be achieved by calibration routines in which the device is mounted on a turntable, whose orientation can be controlled extremely accurately.

In any case the math still pertains here and the point is:

By integrating a DVL to the INS, we have added the capability to compensate for these exponential-like errors from the accelerometer.

Dynamic Bias

To understand what a dynamic bias is, let's picture the true velocity or acceleration as a single point and every time your sensor tries to measure it the result is a randomly offset point. As the sensor is taking more and more measurements other dots around the True Velocity or Acceleration single dot will appear thus forming a cloud around that perfect measurement of the velocity or acceleration.

A direct result from this cloud of measurements in terms of position is a random walk, that is if we integrate all these slightly imperfect velocities or accelerations, we would be integrating could of points, thus obtaining a cloud of larger size/diameter now around the true perfect measurement of position. As these measurements are randomly appearing in the cloud this will result in the INS thinking its walking a random walk.

This Dynamic bias error which we will claim for simplicity is our DVL standard deviation, when integrated once by the DVL would give a position error which would grow linearly with time:

s(t) = d_DVL . t

In comparison when integrated twice by the state machine using the internal accelerometers it would result in a position error which would grow as a second order random walk in time:

s(t) = b_INS . T^1.5.sqrt(dt/3).

And again here this position error would grow faster on the accelerometer than the DVL as depicted in the figure below:

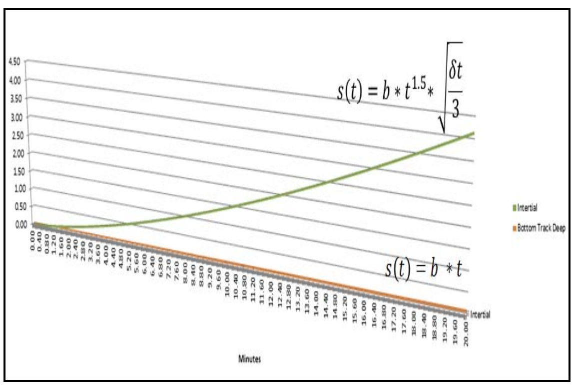

Figure 5. CPE Inertial vs. DVL Bottom Track Dynamic Bias Error

Now the Engineers at IXBlue and KEarfott have found some very efficient ways to reduce these biases. Please refer to them for more details.

But in any case the math still pertains here and the point is again:

By integrating a DVL to the INS, we have added the capability to compensate for these exponential-like errors from the accelerometer.

Schuler Error

As the earth is far from being flat, as we move, close to the surface, we need to keep tilting the platform (with respect to inertial space) to keep the axes of the North and East accelerometers horizontal.

To do this, we can use the gyro torquers for instance, and feed them with a signal proportional to the North and East velocity.

The angular torquing rate θ' that we apply is

equal to v/R, where v is the linear velocity from the first integrator, and R is the radius of the earth.

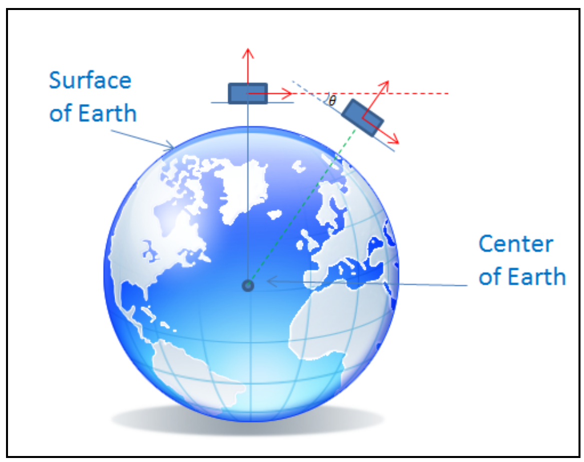

Figure 6. Schuler Error Inertial frame tilting

Hence $\theta' =$ a/R, where a is the acceleration

sensed by the accelerometer, which may be real acceleration, or a component of the gravitational field if the platform is not horizontal.

This is recognizable as the equation of motion of a simple undamped pendulum of length R, which has a period of oscillation of around 84 minutes, known as the Schuler period, after M. Schuler, who published a definitive text in 1923.

The result is a distance error and gyro drift both oscillating at the Schuler period.

The DVL does not feel this acceleration nor need to be compensated thereof for this tilting. Therefore its data can help reduce the Schuler effect. Overall, a DVL will provide independent measurements with uncorrelated errors which will improve the resulting navigation solution.

DVL specifications

When acquiring one of our DVLs whether it is as a stand-alone Navigation Remote Sensing system or to be integrated to a larger system such as an INS, we will be providing you with the performance card of each product.

Parameter	300KHz	600KHz	1200KHz
Velocity Range	±10m/s	±10m/s	±10m/s
Accuracy	±0.4% ± 0.2 cm/s	±0.3% ± 0.1 cm/s	±0.2% ± 0.1 cm/s
Horizontal Single Ping Precision at ½ Range & 1 m/s	±0.3cm/s	±0.3 cm/s	±0.3 cm/s
Horizontal Single Ping Precision at ½ Range & 3 m/s	±0.6 cm/s	±0.5 cm/s	±0.4 cm/s
Horizontal Single Ping Precision at ½ Range & 5 m/s	±0.8 cm/s	±0.6 cm/s	±0.5 cm/s
Minimum Altitude	1.0m	0.7m	0.5m (0.25m optional)
Maximum Altitude @ 24V, 5C, 35ppt Salinity	200m	90m	30m

Figure 7.a. DVL Specification sheet – WorkHorse

Parameter	PAVS DVL (PIONEER DVLs)			EXPLORER DVL 600KHz	
	38KHz	150KHz	300KHz	Phased Array	Piston
Velocity Range	± 9.5m/s	± 9.5m/s	± 9.5m/s	± 9.5 m/s	± 9.5 m/s
Accuracy	± 1%±0.5cm/s	± 0.6%±0.2cm/s	± 0.6%±0.2cm/s	± 0.4% ± 0.2 cm/s	± 0.4% ± 0.2 cm/s
Horizontal Single Ping Precision at ½ Range & 1 m/s	± 0.8cm/s	± 0.9cm/s	± 0.6cm/s	±1.2 cm/s	±1.2 cm/s
Horizontal Single Ping Precision at ½ Range & 3 m/s	± 2.1cm/s	± 2.3cm/s	± 1.7cm/s	±2.0 cm/s	±2.0 cm/s
Horizontal Single Ping Precision at ½ Range & 5 m/s	± 3.0cm/s	± 3.4cm/s	± 2.6cm/s	±2.4 cm/s	±2.4 cm/s
Minimum Altitude	12m	3m	1.1m	0.5m (0.31 m optional)	0.25 m
Maximum Altitude @ 24V, 5C, 35ppt Salinity	2500m	500m	275m	75 m	65 m

Figure 7.b. DVL Specification sheet – PIONEER

These specification sheets are available online and contained at a minimum these values here: Velocity Range, Accuracy, Single Ping STD, Min and Max altitude

The accuracy figures are all expressed as follow:

± X% ± Ycm/s

Note that the left part in percent is the dynamic bias on the DVL which will result in a linearly increasing random walk if integrated once for position.

The second part of the accuracy figure on the right is the static bias which will result in a linear drift if integrated once for position.

One can think of the Accuracy as the measurement noise at its minimum, and to be more specific: should you average a lot of measurements with each a specific short term error (ie the Single Ping Precision) together then the noise will decrease the more samples are used in the averaging and at some point will plateau to the long term error, here called ‘accuracy’.

Finally, the DVL Standard Deviation (ie short term accuracy) depends mostly on Velocity but also Altitude. In general short term error increases inversely to range, in other words the closer the DVL is to the seabed the greater the noise. Teledyne RD Instruments offers Bottom Track modes which uses advanced strategic sampling method to reduce this exponential-like increase.

As an example, the figure below compares the Bottom track modes available on a TRDI WorkHorse DVL 1200KHz.

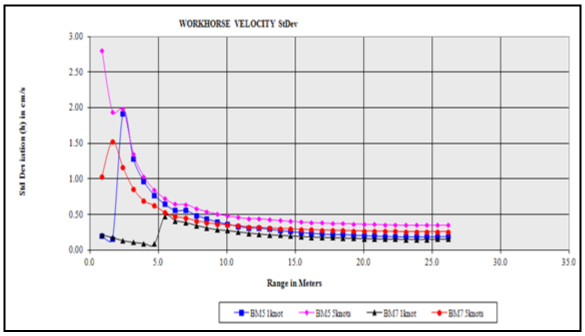

Figure 8. Bottom Track short term error comparison on a 1200KHz WorkHorse DVL.

Note that Bottom Track mode 4 is the simplest of all mode as it does not have any sampling strategy thus its short term error increases as the DVL is getting closer to the seabed.

Bottom Mode 5 and 7 both switch to an advanced sampling strategy at a frequency specific altitude thus drastically reducing the short term error in shallow environment.

Bottom Mode 8 was introduced with our new generation DVLs, called the Pioneers which includes ExplorerDVL 600KHz Piston and Phased Array as well as PAVS300, 150 and 38KHz DVLs.

This mode is a combination of years of experience with these modes and the advance in the new generation electronic which opened more opportunities for even more aggressive strategic sampling in shallow environment.

Bottom Mode 8 has been proven at low altitudes to better handle slopes/steep terrain; provide higher resolution bottom detection by use of feeler pings; have a smoother transition from deep to shallow sampling modes and provide a much improved standard deviation by sampling beams independently.

Speed Through Water aided

The following is a very simple method which consist in using Water Profile in conjunction with Water Track DVL features to aid the navigation from the surface down to the bottom when no GPS signal is present and the DVL is not yet at range of the seafloor.

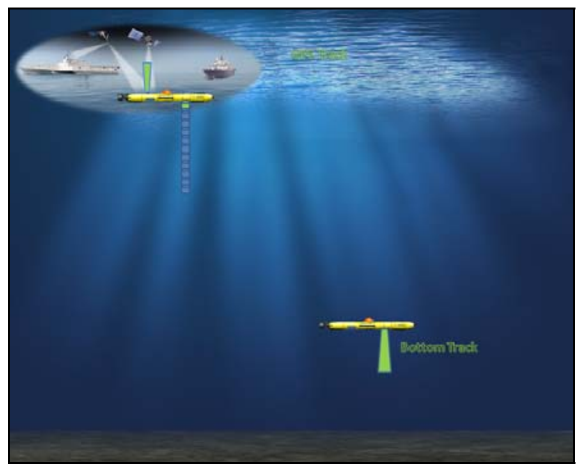

Figure 9. Speed Through Water Aided Navigation diagram.

The UUV would stay at the surface to keep an Earth Reference position using our GPS.

And while we it is at the surface, it would Water Profile the water column below its hull for as far as the DVL can Water Profile.

This way we obtain a partial view of the current –which we can reference to the GPS to remove the vehicle motion to get back to true current– into the water column and making the assumption that the current will not change as we fly through the water then we could then reference the Water Track Velocities to the profiled Water Current to remove any bias from the local current at profiled depth.

Limitations:

- Water Profile Acoustic Range
- Assumption that Ocean does not change that much during decent

Benefits:

- Simple method
- Provide backscattering information of the Water Colum

Water Column aided

The goal is for a UUV (Unmanned Underwater Vehicle) equipped with an ADCP (Acoustic Doppler Current Profiler) to descend to the bottom, and know its position at the bottom with as much accuracy as possible. The UUV can get a position/velocity fix at the surface using GPS. Once the UUV has descended to within tracking range of the bottom, the ADCP can provide bottom track for dead reckoning. The challenge is to determine the UUV's motion using current profiles as a reference, during the descent when GPS is unavailable and the bottom is not yet within range. This problem is slightly different from Lowered ADCP (LADCP) problem in that the end goal is to determine the velocity of the UUV, not the current profile. It is similar in that the each submerged observation (ADCP subsurface ping) is an unknown superposition of both water motion and vehicle motion. The observed vehicle relative water motion is nevertheless a valuable measurement. In order to determine the earth referenced water motion we must know the vehicle motion, but in order to determine the earth referenced vehicle motion we must know the water motion. We are inspired to try to unravel this chicken and egg problem, at least adequately enough to be useful.

The concept of isolating vehicle motion requires that we difference successive observed profiles leaving the change in vehicle velocity. Integrating these vehicle velocity changes to get vehicle motion introduces random walk. Random walk error is influenced strongly by the variance. In order to reduce the variance of this estimate as much as possible we would like to average current profiles in time, at common locations in space, and we would like to average vehicle motion in space at an instant in time. Based on these assumptions we can difference successive observed measurements in time at depths where they overlap. If the currents are unchanging then the remainder is a profile of estimates of vehicle motion and measurement noise. The contribution of the vehicle velocity is the same for all of the range cells so we can average the change in velocity (ΔV) over the bins.

Scenario Example: A UUV sits at the surface for several minutes collecting GPS position data. The UUV has a 300 kHz downward facing ADCP with a profile range of 80 meters. The ADCP collects 4m range cells (bins), approximately once per second. The total water depth is 400 meters. The UUV descends to that depth over 5-10 minutes, profiling 80 m observations as it goes. The submergence of each measurement is determined by pressure sensor. The single ping standard deviation of the horizontal current profile is about 3 cm/s or better. The single ping standard deviation of the horizontal bottom track velocity is approximately 9mm/s. The simulated ocean currents are mildly stratified and less than 0.5 m/s. The rate of descent can vary and the UUV might glide down in a straight line or gently spiral.

Assumptions

Assumption 1: We know the depth of each measurement so we can spatially interpolate subsequent pings such that we have velocity observations referenced to a fixed spatial grid of depths.

Assumption 2: Vehicle motion is superimposed on the observed water profile so vehicle motion is the same spatially across all bins, at an instant in time.
Assumption 3: The vehicle velocity is changing with time in unknown fashion.
Assumption 4: The current profile is mostly static during the duration of the descent. The current profile is static from ping to ping.
Assumption 5: Non-static environmental effects (such as waves or internal waves) are zero mean processes that average out without special handling.
Assumption 6: There is opportunity to sit at the surface a few minutes prior to descending and refine the preliminary current profile estimate with averaging to lower variance using GPS as an unambiguous earth reference for vehicle position and motion.

Conceptual Overview

Unlike lowered ADCP techniques, we are interested in the vehicle motion not the current profiles. This approach to isolating vehicle motion requires that we difference successive observed profiles leaving the change in vehicle velocity. Integrating these vehicle velocity changes to get vehicle motion introduces random walk. Random walk error is influenced strongly by the variance. In order to reduce the variance of this estimate as much as possible we would like to average current profiles in time, at common locations in space, and we would like to average vehicle motion in space at an instant in time.

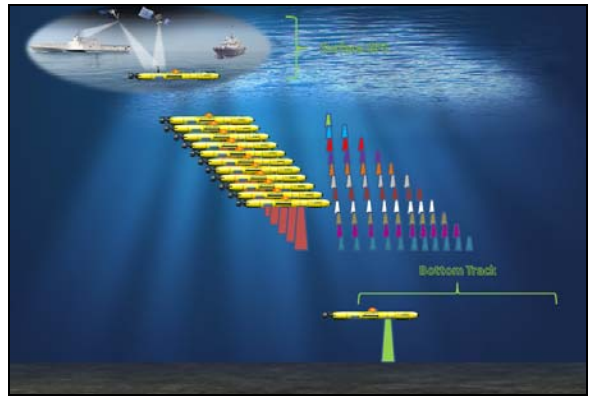

Figure 10. Water Column Aided Navigation diagram.

Differencing Profiles in Time

Based on these assumptions we can difference successive observed measurements in time at depths where they overlap. If the currents are unchanging then the remainder is a profile of estimates of vehicle motion and measurement noise. The contribution of the vehicle velocity is the same for all of the range cells so we can average the change in velocity (ΔV) over the bins.

Observed = Water + Vehicle + η

$O_2 - O_1 \quad = W_2 - W_1 + V_2 - V_1 + \eta_2 - \eta_1$
$W_1 \quad = W_2$
$\Delta O_2 \quad = O_2 - O_1 = \Delta V_2 + \eta_{12}$
Average $\Delta V_2 = (1/n_{bin}) \sum_{bin} (\Delta O_2)$
$V_2 \quad = V_1 +$ AverageΔV_2
var(Average ΔV_2) = 2 var(η)/n_{bin}

η is the single ping measurement noise.

Improving the Profile Estimate

The first strategy is to improve the estimate of the current profile. Single ping measurement of the observed profile can be noisy. If the water velocity is indeed relatively static then estimates of the current profile can be averaged in time to get a lower variance. This also becomes important as the descending UUV measures depths that have not had the benefit of GPS to isolate the current profile from the vehicle motion. Because the vehicle velocity is changing in time it cannot be averaged in time very much.

Averaging at the Surface.

By averaging a few hundred current profiles at the surface, we can begin the process with a very quiet estimate of the current, one in which the vehicle velocity was provided by GPS and could be removed from the observed profiles. As the vehicle descends we no longer have an independent source for vehicle motion and we must extend the range of the subsequent profiles.

Successive Weighted Averages

As the vehicle descends we no longer have an independent source for vehicle motion and we must extend the range of the subsequent profiles. One way of combining the data is a weighted average. Current profiles can be accumulated in both space and time. While descending, successive pings can be accumulated. The difference approach (above) can be used to remove the rough estimate of the vehicle velocity, then profile data can be weighted and averaged. The initial profile estimate is weighted heavily because many pings occurred at the surface. New data is lightly weighted because it has fewer overlapping samples. As the UUV descends previously measured depths overlap with the new profiles and new depths are measured. The new bins at the end of the profile have the smallest N but successive overlapping profiles progressively increase the number of independent samples till the UUV descends below that depth. By keeping track of exactly how many observations have occurred for a given depth cell, each cell can be appropriately weighted.

The averaged (quieted) current profile can then be subtracted from the instantaneous observation in an attempt to isolate a better estimate of vehicle velocity than a single ping could provide.

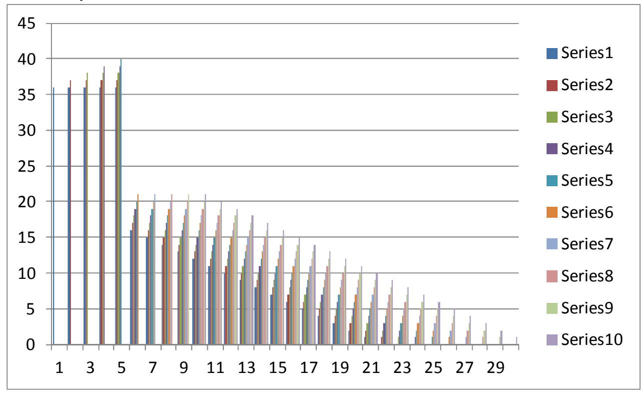

Figure 11. Weighting of bins.

Weighting of bins with successive pings. Initial values have large weight from preliminary averaging at the surface. Subsequent bins accumulate more samples as overlapping depths are measured in the ADCPs profile window. Bins at the end of the profile range have very few independent measures because they have just come into the profile window. The preliminary approach (weighted averaging) is intended to provide intuition about the problem. This is essentially a problem of optimally combining different kinds of data with different or changing variances. This type of problem is well suited to a Kalman filter.

Model Results

Modeling this process is intended to provide some big picture insight into the most significant error sources and operational bounds of the approach. For simplicity the model has been reduced to one dimension and we presume that the profiles have been interpolated to a fixed grid of range cells.

Synthesized data

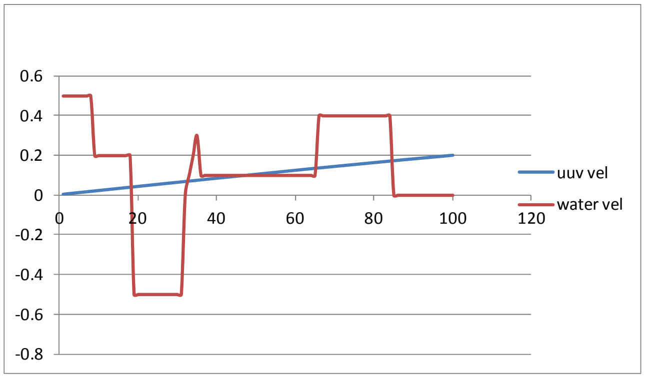

Figure 12. Synthesized Vehicle velocity in blue and current profile in red.

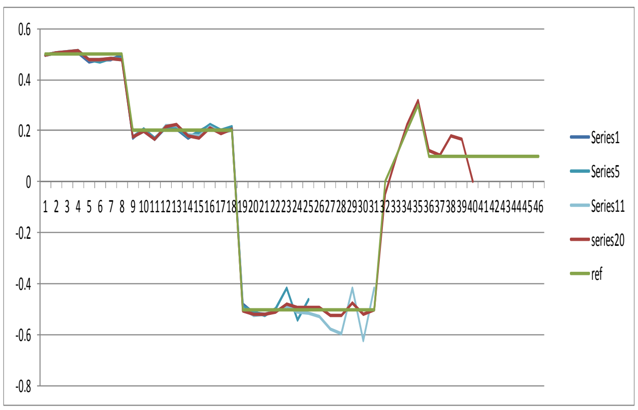

Figure 13. Successively refined estimates of the profile.

Ongoing averaging quiets the estimates of the average current profile. At any instant in time the bins at the end of the profile have the fewest samples included in their average.

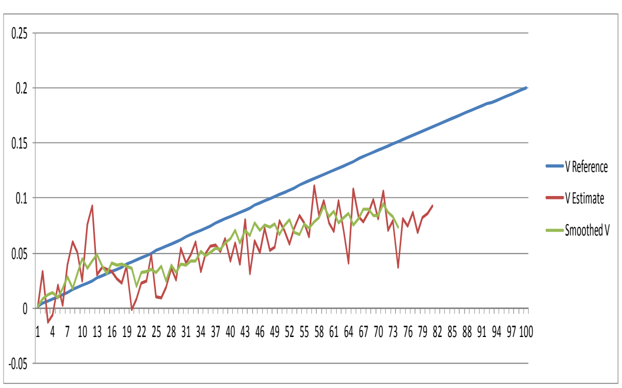

Figure 14. Velocity estimates show random walk. Sigma =0 .3m/s.

In figure 4 we show a rough (30 cm/s standard deviation) velocity estimate derived from our current profiles, compared to the synthesized data in blue.

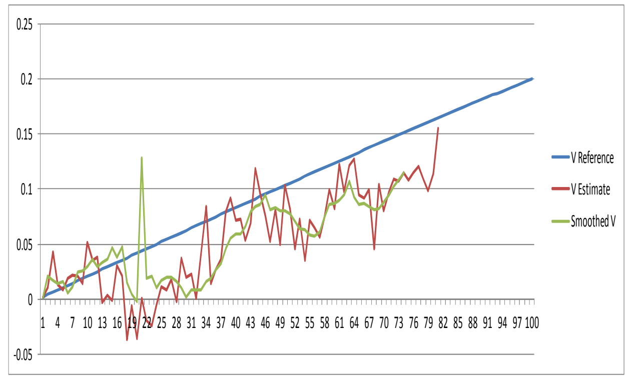

Figure 15. Surface averaging helps initially bound the first velocities (1-20).

Subsequent profile averaging is limited in its benefit, because even if we had a perfect estimate of the current profile we are still subtracting the currents from our observation ping to get instantaneous vehicle velocity. Our observation ping still has single ping variance, so 50% of the measurement still has single ping variance. Taking this cue we can attempt to average observation pings in a narrow window in time, before differencing to get our change in velocity. This works as long as the change in vehicle velocity is small during the averaging time. We are essentially filtering out high frequency noise from the estimate using the bandwidth of a small boxcar average.

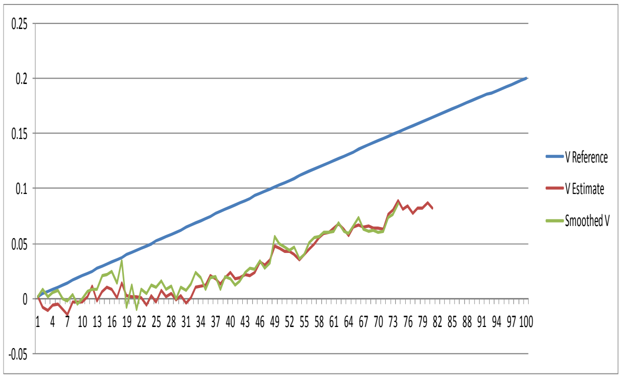

Figure 16. Averaging observations in a time in a narrow window (3-5 samples) reduces variance of the core measurement, however this does not prevent random walk.

By averaging in a narrow window we have selectively removed noise at higher frequencies. While the velocity looks quieter, longer period variability still produces random walk when we accumulate velocity differences into velocity.

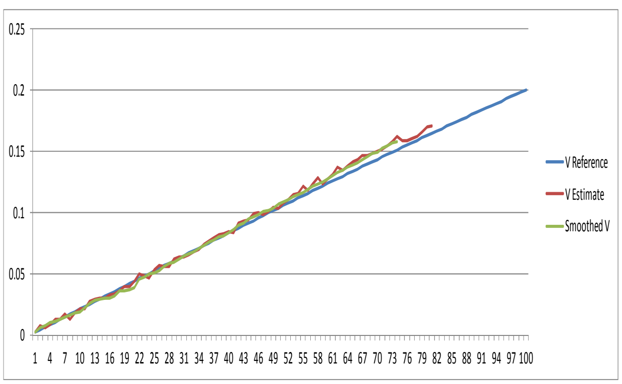

Figure 17. Low single ping standard deviation of the observations is the most important factor to limiting random walk and producing a usable estimate. (3cm/s Std.).

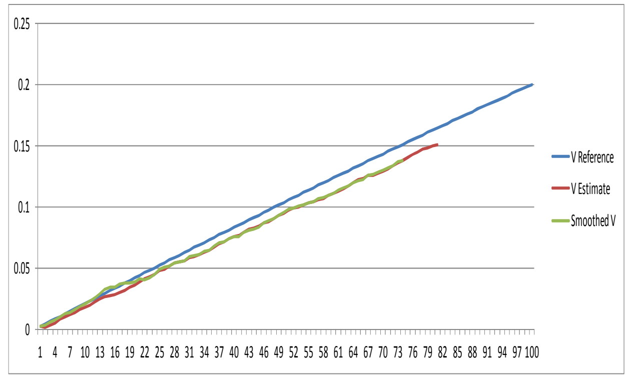

Figure 18. The bandwidth of time averaging can bias the result even in a noiseless measurement. The bias is a result of the bandwidth of the time average relative to the non-linearity of the rate of change of velocity.

Bounding the Estimate with Bottom track

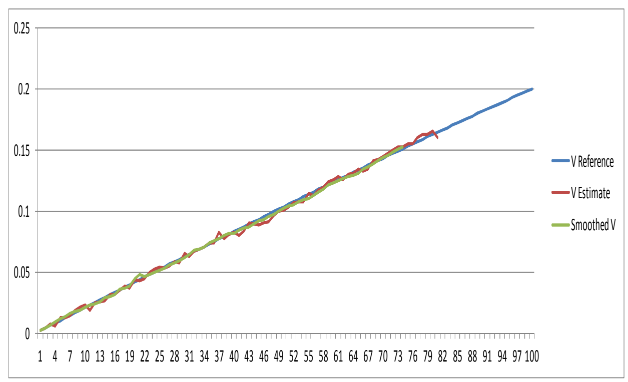

Figure 19. Velocity Estimate is bounded on the far end by high accuracy bottom track.

The addition of bottom track velocity at the end of the descent provides a means to correct the estimates moving backward in time. This is of limited value if random walk is large. When the measurement noise is small, however, it does an excellent job of restoring the whole velocity time series.

From the above data, it can be seen that proper averaging methods and reduction of noise from the initial and subsequent measurements, error sources can be mitigated to avoid cumulative (random walk) errors, and can result in a very accurate estimate of the actual vehicle velocity and thus it actual position. In the final variation, calculated velocity and position was near that of the input actual value in the simulation model.

The following conclusions were drawn from this model:

- Single ping standard deviation is the dominant source of error.
- Averaging of profiles with time is helpful but limited because the raw observation still contains measurement noise.
- The error shows up as random walk. Random walk is a consequence of accumulating measurement noise. Random walk is characteristic of navigation problems where an accumulation is performed to get velocity from acceleration, or distance from velocity.
- Averaging at the surface, and bottom track at the bottom, help to bound the solution at the end points.
- Averaging estimates over the whole profile, at a single instant in time, is beneficial to the problem.
- Averaging observations in a narrow window around the time of interest is beneficial but does not solve the problem of random walk. The width of the window relative to the rate of change of velocity is important.

Next Steps

Teledyne RD Instruments is working to perfect the models and algorithms for use of its Water column navigation algorithms. Next steps will include broader ranges of simulation with different error sources, understanding the effects of other bias errors present in acoustic measurements due to environmental conditions and measurement error, and ultimately sea trials.

We intend to partner with vehicle manufacturers to perfect these methods in the hopes of achieving a navigation algorithm that can allow for accurate movement through the water column.

Summary

Challenges in navigation were described and methods and sensors for use in understanding position and velocity were reviewed. The advantages and limitations of those sensors were clarified. Doppler sonar was introduced and its capabilities described. Finally, combining these with 2 conceptual models for navigation based on relative velocity measurements within the water column were shown as relevant and capable methods to successfully navigate through the water column away from GPS signal and not at acoustical range of the seabed.