Kalman Filter Estimation of Underwater Vehicle Position and Attitude Using a Doppler Velocity Aided Inertial Motion Unit

by

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Abstract

This Paper explores the use of an extended Kalman filter to provide real-time estimates of underwater vehicle position and attitude. The types of previously available sensors are detailed including strapdown accelerometers, roll and pitch sensors, gyro and magnetic compasses, depth sensor, and various types of acoustic positioning systems. A doppler velocimeter is added to this sensor suite to improve the performance of the filter. As an integral part of the filter, magnetic compass and gyrocompass biases are estimated to improve vehicle heading accuracy. The filter is designed to account for numerous real-life complications. These include varying rates of sensor output, lengthy gaps in reception of position information, presence of non-Gaussian position fix errors (flyers), and varying probability density functions for sensor errors. Simulated data are used to test the filter with varying availability of data and accuracy of initial conditions, along with actual data from a deployment of the towed DSL-120 vehicle. The increased accuracy obtained by using the doppler velocimeter is emphasized.

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Chapter 1

Introduction

1.1 Motivation

This thesis has two major goals. The first is to provide accurate estimates of underwater vehicle position and attitude and thereby improve the quality of sonar and video information collected. The second is to provide these estimates in real-time.

1.1.1 Improving Vehicle Position and Attitude Information

More than two thirds of the Earth is covered by water. Until very recently in history, the ocean depths were mysterious and inaccessible. However, in the past few decades new technologies have dramatically expanded man's abilities to explore the ocean bottom. Discoveries range from the remnants of human incursions, epitomized by the *Titanic*, to new life on the ocean floor gaining its sustenance from the earth's interior rather than the sun.

One of the primary tools for conducting underwater searches and surveys from unmanned vehicles is the sidescan sonar. The sonar emits a beam of relatively high-frequency sound on either side of the vehicle. When this sound beam hits the bottom or any objects within range, it is reflected and the return is received by transducers mounted on the vehicle. The characteristics of the received sound, primarily magnitude and phase, can then be analyzed to determine the characteristics and contours of the bottom as well as the location and general shape of any objects.

For this system to work at an optimum level, it is vital that the location and attitude of the vehicle be known as accurately as possible. Any position errors lead directly and obviously to an error in the assumed position of all objects mapped by the sonar. Equally important, however, is knowledge of the vehicle's roll, pitch, and heading. Due to the nature of sound propagation in water, a significant time lag occurs between the transmission of a sonar ping and the receipt of any returns. During this time, the vehicle will not only have changed position but may have changed its attitude as well. For proper interpretation of the sonar returns, the attitude of the vehicle at the time of sonar transmission must be known, because that determines the precise direction of the beam. This same information is also needed at the time of the sonar return, so the location of any objects found can be accurately determined.

1.1.2 Previous Work on Underwater Vehicle Navigation

The invention of feasible inertial navigation produced a great interest in combining inertial measurements with other fix sources to improve navigational accuracy. These early inertial navigation units required gimbal-stabilized platforms to achieve the desired accuracy, which added size and weight. Due to these restrictions, early work was confined to aircraft and ships, including submarines. In the early 1970s, the U.S. Air Force was one of the first to evaluate the use of the Kalman filter to integrate inertial measurements with external fix sources (*D'Appolito*, 1971).

Later, strapdown inertial systems permitted much smaller and lighter equipment, though at a cost in accuracy. Once again, the military provided a major impetus to developing these systems to their fullest potential. For example, the North Atlantic Treaty Organization's (NATO) Advisory Group for Aerospace Research and Development (AGARD) included much work on these strapdown systems, although still for use primarily in aircraft and spacecraft (*VanBronkhorst*, 1978; *Catford*, 1978).

Ever since remotely operated vehicles (ROVs) became feasible, there has been interest in improving their navigational accuracy as well. Early ROVs had only a few sensors available to provide navigational information, since inertial navigational systems were still too heavy and power-intensive to be usable. These included a magnetic compass to provide heading and inclinometers to measure pitch and roll. Additionally, an acoustic transponder network was often used to provide position information for operations in a small area. A later improvement was the gyrocompass, which provides a more consistent output than the magnetic compass but adds new errors caused by drift.

Improvements in the information provided by these acoustic transponder nets has been marked. In her 1992 thesis, Diane Di Massa provided one example with her exploration of the possibilities of hyperbolic navigation to permit long-range acoustic navigation by an Autonomous Underwater Vehicle (AUV) (*Di Massa*, 1992). Brian

Tracey contributed another with his improvements to a newer technique for ROV navigation, ultrashort-baseline navigation, in his 1992 thesis (*Tracey*, 1992).

In the past few years, a number of new devices have been developed to assist in solving this navigational problem. In his 1988 thesis, Gregory Vaughn discussed the use of a lightweight, strapdown inertial motion unit in conjunction with an external acoustic positioning net to improve closed-loop vehicle control (*Vaughn*, 1988). He concluded that by incorporating this new data into a Kalman filter to provide real-time optimal estimates of vehicle parameters, closed-loop control of ROVs, such as the Woods Hole Oceanographic Institution's *Jason*, could be improved. However, for his application vehicle attitude was unimportant and therefore was not incorporated into his simulations.

A fairly recent addition to the repertoire of instruments available to the oceanographic engineer is the doppler velocimeter, also known as the acoustic doppler current profiler (ADCP). For the first time, accurate real-time velocity measurements of a ROV could be made relatively cheaply and without exceeding the restrictive power and weight limits inherent in ROV operations. RD Instruments, a doppler velocimeter manufacturer, has been funded by the Office of Naval Research to explore the use of the instrument to provide an independent and accurate measurement of vehicle velocity within the context of a Kalman filter. Their initial work verifies the utility of the velocimeter, although so far their research has been confined to inertial navigation systems too large for ROV use (*Rowe and Brumley*, 1992).

These are but a few examples of the extensive work that has been published on improving underwater vehicle navigation. A search of the literature reveals diverse techniques for improving sensor information and integration, including several variations on Kalman filtering techniques.

1.1.3 Cost and Processing Time Reduction

In the real world, cost considerations are almost always important. Cruises are expensive and usually result in computer disks full of unprocessed, raw data, which are essentially worthless until processed. This processing can take many man hours, which translates into a considerable cost. Unfortunately, this sometimes means that processing is never completed, since either the time or the money runs out. Therefore, the more real-time processing that can be performed the better. Real-time processing means that the important data are immediately available. Also, since it is accomplished at sea while the cruise is in progress (and already paid for), additional expenses are minimized.

Another important application for this capability pertains to autonomous underwater vehicles (AUVs). Much research is being conducted currently on these vehicles, which should be capable of operating independently for days or even weeks. Real-time processing is essential to permit the vehicle to navigate successfully and is also vital in reducing the on-board data storage requirements of AUV deployments.

1.1.4 Resources Available

This thesis investigates how the navigational sensors currently available at the Deep Submergence Laboratory (DSL) can be used to improve the real-time position and attitude information available for the operation of a ROV. This summer, DSL personnel participated in a cruise aboard the R/V *Knorr*. A major purpose of the cruise was to obtain detailed sidescan sonar data from an area of the Mid-Atlantic Ridge where seafloor spreading is occurring. The DSL-120, a towed vehicle carrying a 120-kHz sidescan sonar system and multiple navigational sensors, was used for this survey. Data from these DSL-120 deployments are used to demonstrate the performance of the Kalman filter developed in this thesis. By integrating the velocity data provided by the doppler velocimeter into a Kalman filter algorithm, the vehicle's navigational accuracy can be greatly enhanced. This substantially improves the usefulness of the sonar data collected and demonstrates the feasibility of performing real-time navigation sensor processing.

1.2 Advantages and Limitations of the Kalman Filter

Sonar data collected by underwater vehicles has often been rendered nearly useless due to inaccurate navigation information and an overly simplistic approach to tracking vehicle parameters. For example, relying solely on a magnetic compass for heading information nearly guarantees that the measured heading will be inaccurate.

The Kalman filter uses a state space model to provide a well defined method for integrating the information obtained from different sensors into a coherent whole. Taking advantage of the a priori knowledge of the relative accuracies of these sensors as well as the dynamics of the system, the Kalman filter can provide real-time output without overstressing computer memory or computational limits.

The addition of the doppler velocimeter provides a marked improvement in the ability of a Kalman filter to provide valid position and attitude information. By providing accurate measurements of the magnitude of vehicle velocities in all three dimensions, a more precise, continuous estimate of vehicle position and attitude can be provided than would be available by the other sensors alone.

In this application, there are several obstacles to overcome in creating a usable Kalman filter. First, the system is nonlinear and cannot therefore use the simplest and most mathematically precise version of Kalman filter theory. Instead, an extended Kalman filter is required. Second, a method for ignoring obviously faulty measurements must be included. Finally, there are several practical problems involved in using the output of such a wide variety of sensors. These problems and their proposed solutions are discussed in detail later in this thesis.

1.3 Thesis Outline

Chapter Two describes the sensors used to provide information for the Kalman filter. Principles of operation for each sensor are discussed, as well as limitations and considerations for each when integrated into the overall system.

Chapter Three explains the development of the Kalman filter and its state space model for this application. A basic review of Kalman filter theory is included, with emphasis on the specifics of the extended Kalman filter required for nonlinear problems. This chapter also discusses the specific problems that were addressed for proper filter operation and how the filter was implemented.

Chapter Four shows the results of filter operation by using both simulated and actual data. The improvement in performance obtained by using the doppler velocimeter measurements of vehicle velocities is emphasized.

The results are summarized in Chapter Five, along with suggestions for further refinements to the filter. Finally, some possibilities for additional experiments are discussed.

Chapter 2

Sensor Information

2.1 Overview of Sensors

Like any mathematical abstraction of a real-world system, the Kalman filter is a simplified model of reality. For the filter to function optimally, the model must be as complete and as accurate as possible. For this application there are two major aspects of the filter that must be considered. The first concerns prediction: based on knowledge of present system parameters, what will happen to these parameters in the future? The second is more basic: how can knowledge of these system parameters be obtained?

In this chapter, the latter issue is addressed. Each sensor providing input to the filter is described in detail. Using our knowledge of the available sensors, the Kalman filter model can then be developed. Before proceeding further, however, a clarification of the coordinate systems used is required.

2.2 Coordinate Systems

Within the filter algorithm, two different coordinate systems are used. The first is earth-referenced, with positions measured relative to fixed reference points on the earth. The second is vehicle-referenced, also referred to as body-referenced. In this case, all measurements are made relative to a specific point on the ROV, usually the center of rotation of the vehicle. Table 2-1 and Figure 2-1 explain the differences in more detail.

An additional coordinate system is sensor-referenced, which depends on the location of the individual sensor. For linear acceleration and velocity measurements, a difference in measurement magnitudes between sensor-referenced and vehicle-referenced measurements exists due to the effects of angular velocities when the sensor is mounted away from the vehicle's center of rotation. The orientation of the axes is the same as vehicle-referenced coordinates since the instruments are mounted colinear with the vehicle axes. Compensation for this difference is discussed in Section 3.5.3.

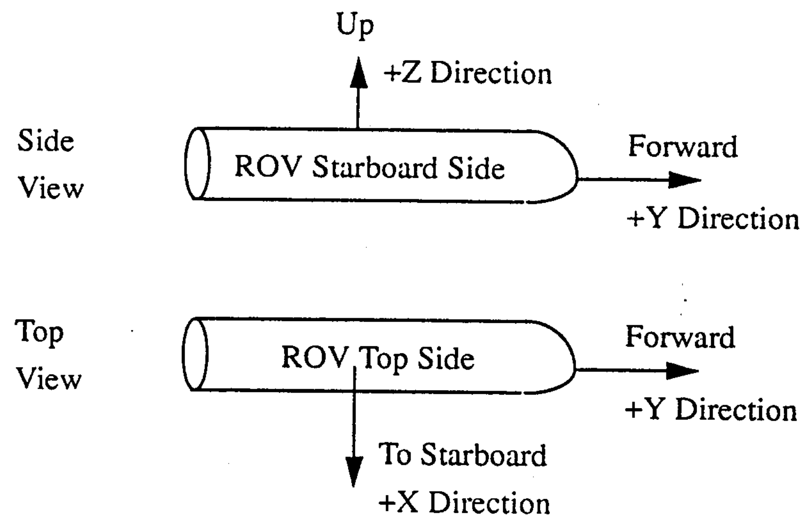

Figure 2-1. Vehicle-referenced coordinate system.

Table 2-1: Comparison of Coordinate Systems

Direction	Earth-Referenced	Vehicle-Referenced
X	Longitude (+X = east)	Perpendicular to side of vehicle (+X = to starboard)
Y	Latitude (+Y = north)	In direction of vehicle bow or stern (+Y = forward)
Z	Depth/Altitude (+Z = up)	Perpendicular to top or bottom of vehicle (+Z = up)

2.3 Doppler Velocimeter

The proper name for this instrument, used to provide vehicle velocities, is the Direct-Reading Broadband Acoustic Doppler Current Profiler (DR-BBADCP). Manufactured by RD Instruments (RDI), the DR-BBADCP is designed to measure current velocities at discrete points through the water column (see Fig. 2-2). Its alternate mode, which is the mode used to gather data for this application, is the bottom-track profiling mode. With the DR-BBADCP mounted on the vehicle looking downward, vehicle

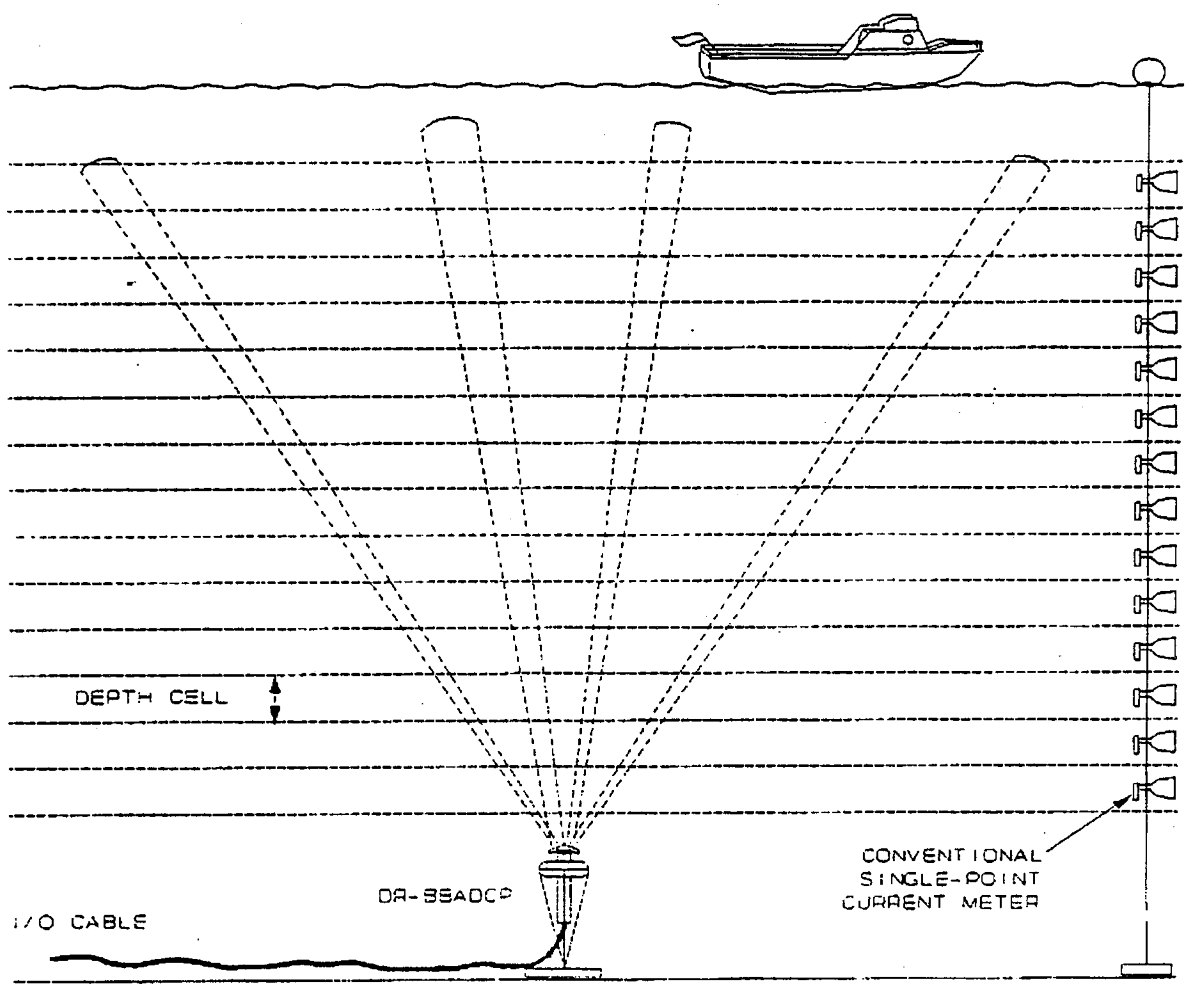

Figure 2-2. Broadband ADCP setup for current profiling (*RDI*, 1993).

instrument in this application, the more descriptive name of "doppler velocimeter" is used in the remainder of this thesis.

2.3.1 Principles of Operation

The doppler velocimeter uses four downward-looking acoustic beams operating at high frequency. Figure 2-3 shows the beam pattern of two of these beams in an upward-looking mode. RDI manufactures these instruments with six different transmit frequencies: 75, 150, 300, 600, 1200, and 2400 kHz. As with any sonar, increasing frequency improves the accuracy but reduces the effective range. Therefore, the frequency

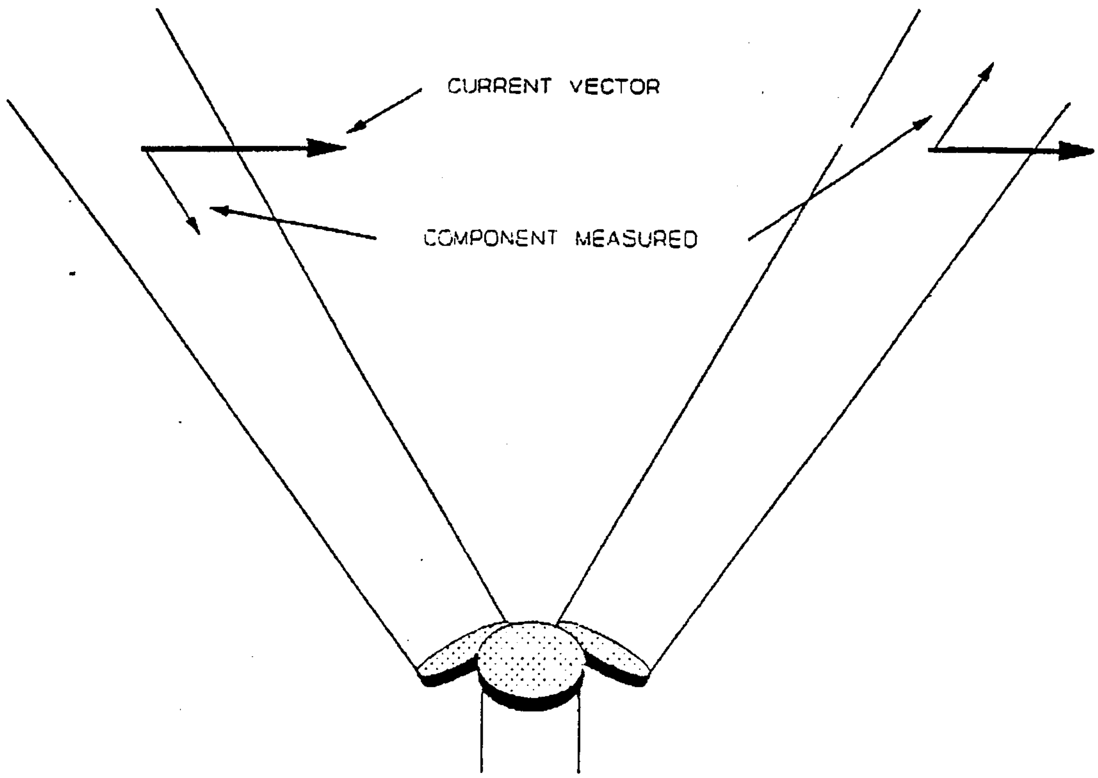

Fig. 2-3. ADCP beam geometry (*RDI*, 1993).

for a given operation is chosen to be as high as possible while still providing sufficient range to ensonify the bottom based on the expected altitude of the vehicle.

As evidenced by its name, the instrument operates on the doppler principle. Vehicle velocity in the direction of a beam increases the frequency of the returned signal, while velocity away from the beam decreases it. Specifically, the vehicle velocity in the direction of the beam is calculated by (*RDI*, 1993).

$$\text{Relative Flow Velocity (m/s)} = F_D \times \frac{c}{2F_S} \quad ,$$

where

F_D is the measured doppler frequency shift in kHz,
c is the speed of sound in water at the transducer face in m/s,
F_S is the transmitted acoustic frequency in kHz.

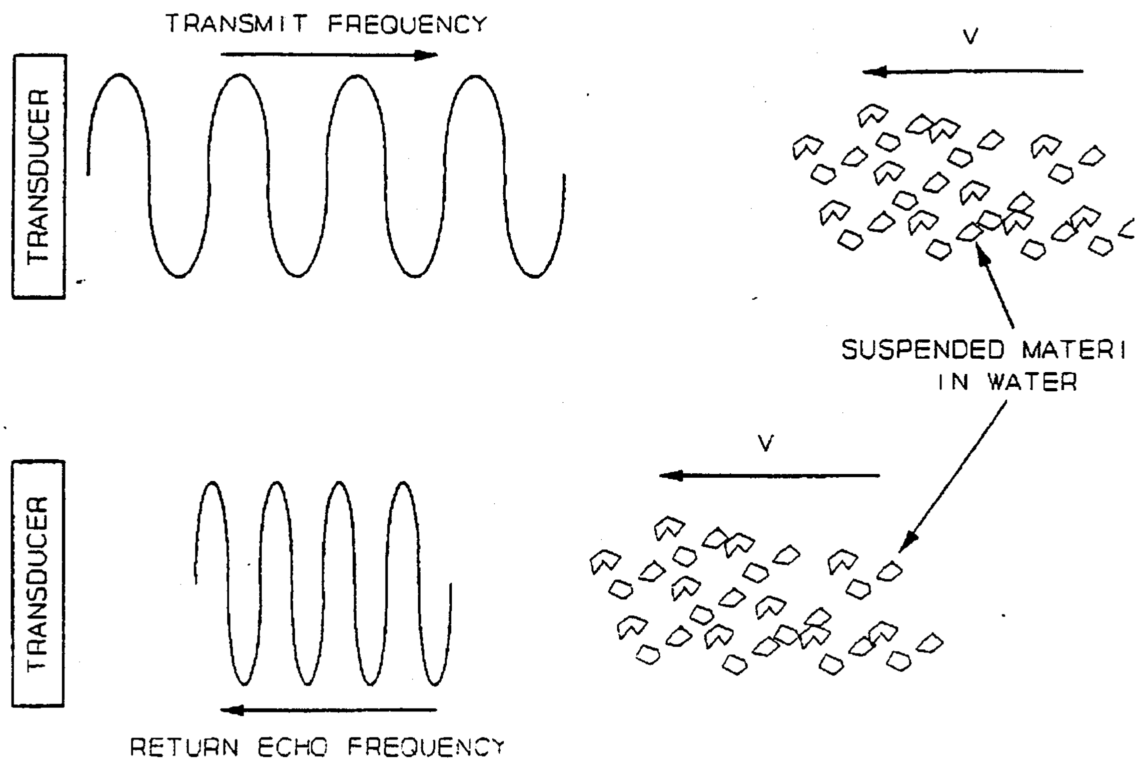

Fig. 2-4. Frequency change caused by doppler effect (*RDI*, 1993).

Figure 2-4 shows this effect with a fixed transducer and moving material in the water. The effect is the same with the transducer mounted on a moving vehicle over the fixed bottom. The four beams transmit at different angles so the velocities in each direction can be resolved. Three are needed to solve for velocities in all three directions and the fourth provides redundancy to ensure accuracy.

To interpret the received sonar data, the doppler velocimeter uses an autocorrelation processor. A series of short pulses is transmitted, each with a pulse length of T_P, with a known lag T_L between pulses. When the returns are received, the processor compares the phase change between two distinct pulses, accounting for the difference in time between their respective transmissions. As shown in Fig. 2-5, a zero phase change implies zero velocity. Likewise, a phase change equates to a velocity with magnitude determined by the amount of phase change. Phase changes with a magnitude greater than 2π are resolved using a proprietary RDI algorithm using different subsets of the

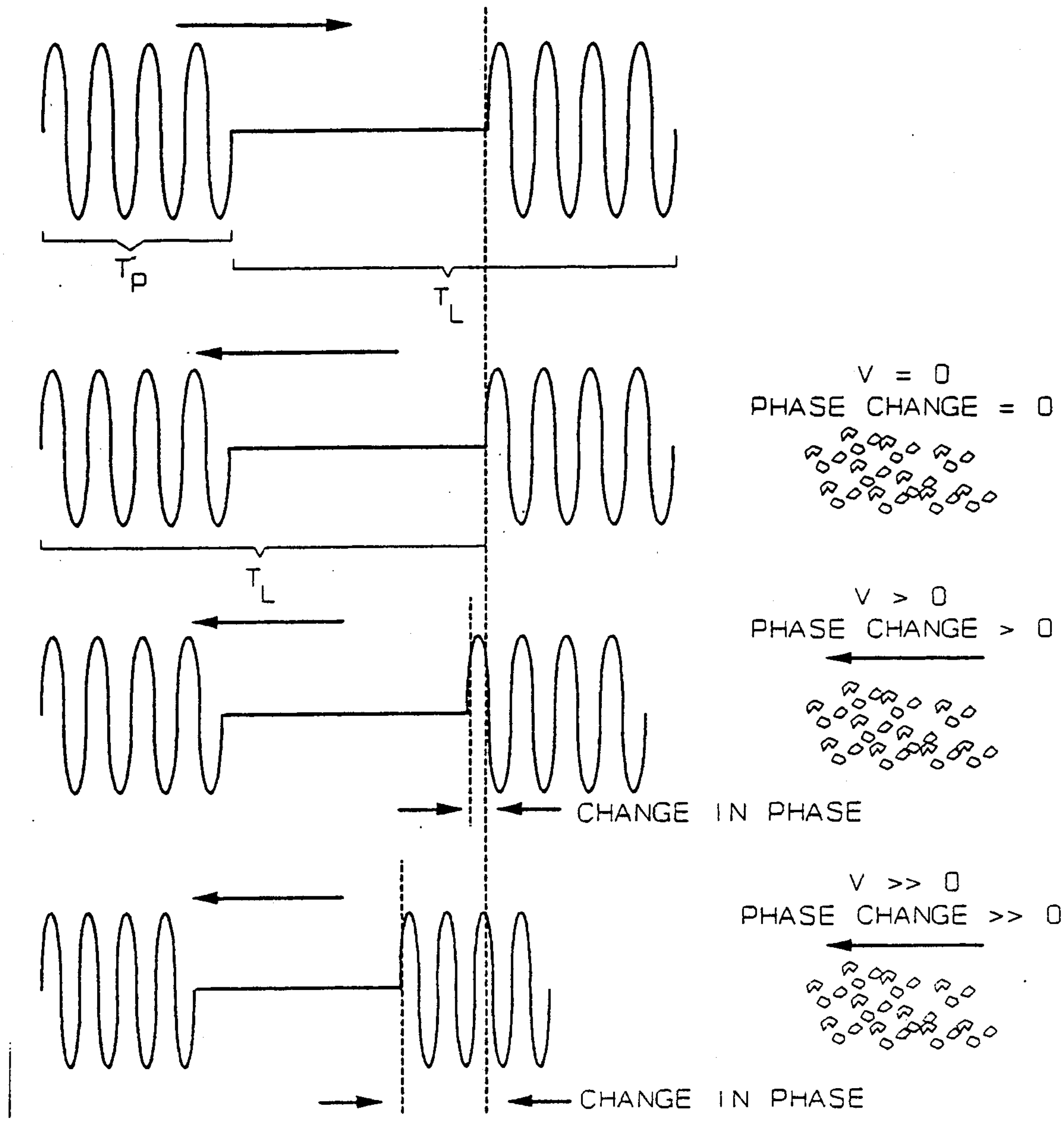

Fig. 2-5. Phase change seen by the broadband system (*RDI*, 1993).

transmitted pulses. If any datum is below the operator-selector minimum for correlation magnitude, that datum is rejected by the doppler velocimeter's processor.

The output of the velocimeter can be referenced four different ways. The most basic provides measurements of the velocities relative to each of the four beams. Alternatively, the velocimeter's internal processor can resolve the components of the four beams to provide velocity fore or aft, velocity left or right, and velocity up or down relative to the instrument. Third, if the instrument is not mounted on a ship or ROV with the same orientation as the platform's reference axes, the velocities can be converted to any desired direction relative to the platform using knowledge of the difference between the instrument axes and platform axes. Finally, the doppler velocimeter can use its internal flux-gate sensor, which uses heading and pendulum sensors to provide pitch and roll. The internal processor can use this roll, pitch, and heading information or similar data from external sensors to convert from vehicle-referenced to earth-referenced velocities.

For this Kalman filter the velocimeter is mounted with axes oriented the same as the vehicle axes described in Section 2.2. Therefore, a coordinate transformation to the platform axes is unnecessary except for any correction due to angular velocities. Instead of allowing the velocimeter's internal processor to convert velocities to earth-referenced coordinates, which would use the current output of the appropriate sensor for attitude measurements, the filter uses the vehicle-referenced values. Using vehicle-referenced velocities allows the filtered estimates of roll, pitch, and heading to be used to make the conversion to earth-referenced coordinates. This improves overall filter performance since the filtered estimates are less noisy than the instantaneous sensor outputs.

2.3.2 Inputs to Velocimeter

To provide the desired output, the doppler velocimeter uses the speed of sound in its calculations of vehicle velocity. As is the case for data used in this thesis, this speed of sound is typically entered manually by the operator to permit easier post-processing of the data. However, for more accurate calculations the doppler velocimeter can calculate the current speed of sound using three inputs: salinity, depth, and temperature.

For most open-ocean operations salinity is constant. Therefore, salinity can be manually inserted prior to operations. If operations are to be conducted in an area of varying salinity, such as near a river mouth, then an external conductivity sensor can be used to provide salinity information to the velocimeter.

Since the majority of vehicle operations occur within a relatively narrow depth band, making speed of sound changes due to depth change negligible, depth is also normally manually inserted. If operations involving large depth changes are expected, consideration should be given to providing depth estimates to the velocimeter to calculate a variable speed of sound.

Finally, the doppler velocimeter has an internal temperature sensor. Manual input can be used in this case as well. For operations near the bottom in deep water, where thermal gradients are negligible, manually inputting temperature permits more precise post-processing of the data without introducing significant errors. In areas with larger gradients, using the installed temperature sensor is necessary.

2.3.3 Doppler Velocimeter Outputs

Obviously, the primary output desired from the doppler velocimeter is vehicle-referenced velocity. However, there are several operator-selected options that affect the accuracy and the frequency of these measurements.

Frequency of output is determined by three factors: the speed of sound in the water, the range to the bottom (vehicle altitude), and the number of pings per ensemble. The doppler velocimeter averages the results from the pings in each ensemble to improve accuracy. The technical manual recommends four pings per ensemble. A larger number of pings per ensemble results in better quality measurements but at the cost of a lower update rate. Using the recommended four pings per ensemble, an average altitude of 100m, and the nominal speed of sound in seawater of 1500 m/s, the time between velocity measurements can be calculated as

$$4 \text{ pings} \times 200 \text{ m/ping} \times 1 \text{ s/1500 m} = 0.53 \text{ s/ensemble}.$$

The standard deviation for velocity measurements is computed by the velocimeter's processor based on the BBADCP frequency (for the model in use), the range to the bottom, the number of pings per ensemble, and the size of the depth cells selected prior to operation. The size of the depth cell is important for precision when operating in the water column profiling mode. For bottom tracking, however, the largest depth cell should always be used since this gives the lowest standard deviation for vehicle velocity measurements. For vehicle operations treated in this thesis, the standard deviation is on the order of 1-2 cm/s. Figure 2-6 shows how accuracy varies with range for a single ping using the 150-kHz model. This high accuracy enables precise measurement of

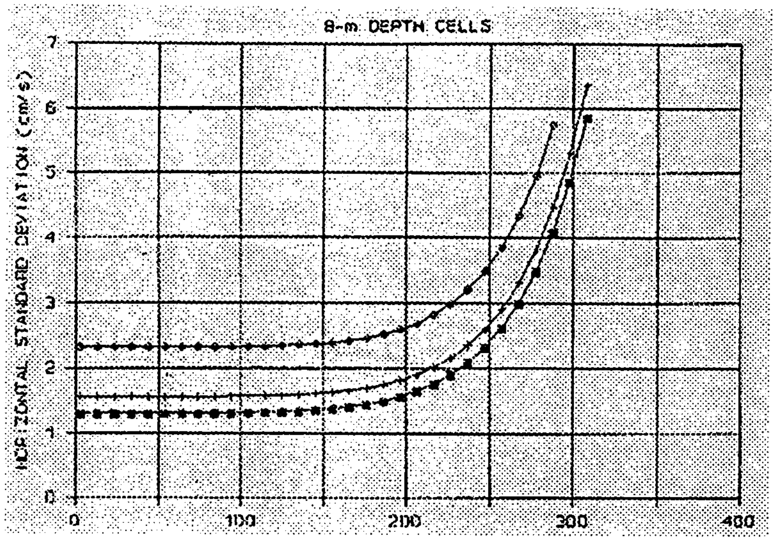

Fig. 2-6. Standard deviation for a single ping using the 150-kHz system (with ADCP velocity, from top to bottom, of 20 knots, 10 knots, and 0 knots) (*RDI*, 1993).

velocity magnitude. However, overall system accuracy is limited by how well heading, pitch, and roll can be estimated. Since standard deviation is constantly updated by the doppler velocimeter's software, that information can be included in the Kalman filter algorithm. Specifics of this implementation are discussed in Chapter 3.

2.4 Depth Sensor

The depth sensor used for this work is manufactured by Paroscientific, Inc. and consists of a quartz-crystal resonator whose frequency of oscillation varies with pressure-induced stress. The sensor also includes thermal compensation using a quartz-crystal temperature signal. Nominal accuracy of the sensor is 0.02%, and a reading can be obtained approximately every 0.25s. (*Paroscientific*, 1987).

For the purposes of achieving the best overall estimates of vehicle position and velocity, the absolute error of this sensor is less important than its stability. Previous experience indicates that the depth sensor should be very consistent in its outputs. Therefore, the output of the sensor is a vital element in increasing the accuracy of the