Autonomous Underwater Vehicle Motion Tracking using a Kalman Filter for Sensor Fusion

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Abstract - **AUVs are ideal platforms for search and rescue operations. They can also be used for inspection of underwater terrains. These vehicles need to be autonomous and robust to cope with unpredictable current and high pressures. In this paper it will be shown how a Kalman Filter is used to estimate the position of an autonomous vehicle in a three dimensional space. The Kalman filter is used to estimate movement and position using measurements from multiple sensors.**

I. INTRODUCTION

In the world of underwater vehicles one of the main obstacles to overcome is accurate vehicle motion tracking. This is needed so that the position of the vehicle can be known. In the case of an autonomous vehicle this information becomes vital as the vehicle must know its own position before it can know how to get to a new position. The accuracy of the vehicle position is directly connected to the vehicle performance in terms of autonomous operations. Normally, accurate vehicle position is determined by use of expensive sensors. The low cost sensors are not accurate enough to be used on their own in such a system.

For aerial and land autonomous mobile systems, a global positioning system (GPS) is normally used to determine the vehicle position and positioning measurement can be very accurate. In the case of an under water vehicle this system becomes unavailable due to the high level of attenuation of radio signals in water. This means that the vehicle position needs to be determined by other means.

Many systems are available that can track the motion of such a vehicle and if the starting position is known, the vehicle's current position can be determined. Some of these systems include inertial measurement units (IMU) or Doppler velocity log (DVL) systems. The problem with these systems is that small measurement errors can add up and in the end the resultant error can become huge, especially if the area to be covered is large. However these sensor systems may be combined to create a system where the measurement errors may be reduced. This is done by combining the data from two sensors that measure more or less the same thing and estimating the result.

A problem with using these sensors is that sensors that give accurate data are very expensive and low-cost sensors are not accurate enough to be used on their own in such a system.

In motion tracking of an underwater vehicle one has to track movement in six degrees of freedom (DOF). This includes linear movement along the three axes as well as rotation around the three axes, roll around the X axis, pitch around the Y axis and yaw around the Z axis. The six degrees of freedom is illustrated in Fig. 1.

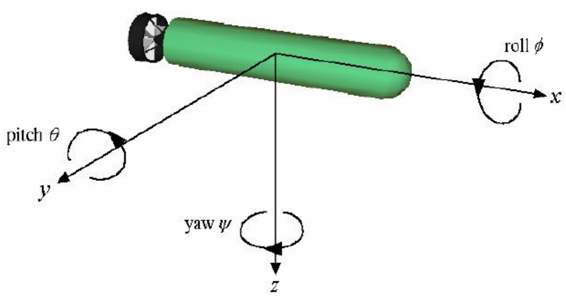

Figure 1 – Illustration of the 6 DOF of an AUV [3]

The vehicle used for the experiments performed in this paper is a simple rectangular vehicle with thrusters facing different directions for improved manoeuvrability. The vehicle is shown in figure 2.

II. SENSOR SYSTEM

Some of the most commonly used sensor systems to track vehicle motion will be discussed in this section. The first sensor system to be discussed is the IMU. This sensor system consists of three accelerometers and three gyros. The accelerometers are positioned on the X, Y and Z axes and measure acceleration in their respective directions.

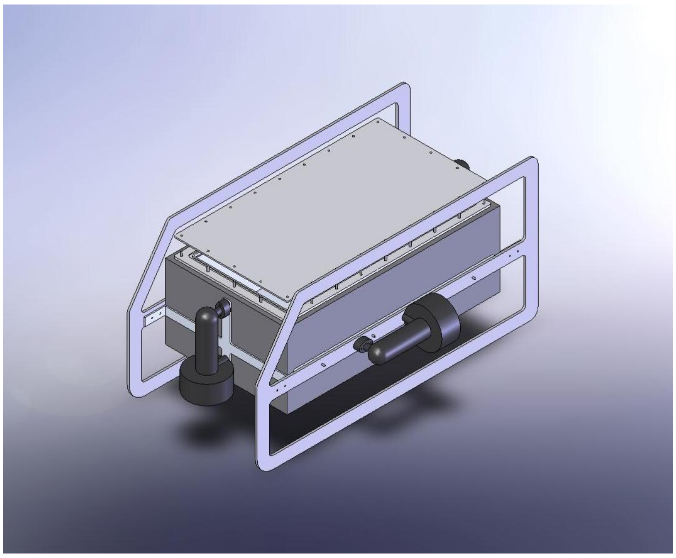

Figure 2 – Underwater vehicle design

The three gyros are then positioned to each measure rotational speed around each of the above mentioned axes.To determine vehicle motion from these sensors one can use the gyro data and determine the integral over time. This will reveal the total degrees rotated around the axis in question. This data can then be used to determine the orientation of the vehicle. The accelerometer data can be used to determine linear motion by calculating the double integral of the accelerometer data over time. This will give the calculated movement of the vehicle in the given direction. The accelerometer data can also be used to calculate pitch and roll of the vehicle since the 3 accelerometers will always measure a downwards vector force thanks to gravity. This vector can be used to determine the angles between the two horizontal axes which will then be the pitch and roll angles of the vehicle.

Another commonly used sensor to measure the movement of an underwater vehicle is a DVL. This type of sensor bounces acoustic pulses off the bottom and uses it to calculate the velocity and direction of the vehicle's movement. If the starting position of the vehicle is known one can easily use this information to calculate the current position of the vehicle. These sensors are described in more detail in [4].

Some systems have also been implemented where beacons with fixed positions have bean deployed. These beacons transmit their position and the vehicle calculates the distance to all beacons from which it received the position signals and thus determines its own position at the point where all these circles intersect i.e. triangulation.

Additional sensors that can be used are digital compasses, which can measure the yaw of a vehicle directly. One can include a pressure sensor to measure the water pressure outside the vehicle and use this information to calculate the depth of the vehicle. One can also include inclinometers or tilt sensors to measure the roll and pitch of the vehicle.

III. SENSOR FUSION USING A KALMAN FILTER

Once the data from all sensors have been collected they must be combined to determine the position of the vehicle in all six DOF. Since many sensors measure more or less the same thing or the same DOF, we use some form of sensor fusion to combine the data obtained from these sensors to calculate an estimate of the vehicles position or orientation. This paper proposes the use of a Kalman-Bucy filter to combine sensor data and estimate the vehicles current position. The prospect of sensor fusion also improves on the measurement of vehicle position by using data from more than one sensor to calculate a more exact estimate of the vehicle position than just with a single sensor. The Kalman filter can deliver the required estimates in an optimal way. The Kalman filter was develloped by Rudolph E. Kalman in 1960 [6] and the Kalman-Bucy filter which is implemented for a continuous time process in 1961 [7]. The filter was derived based on a stochastic noise model [8]. The filter uses differential equations to define the state estimates and filter gains. The Kalman-Bucy filter will be used for the purposes discussed in this paper.

To be able to use this filter one needs to have a system model in the form of differential equations as shown in equations (1) and (2) taken from [1].

$$\dot{\mathbf{x}} = \mathbf{A}(t)\, x + \mathbf{B}(t)\, \mathbf{u} + v \qquad (1)$$

$$\mathbf{y} = \mathbf{C}(t)\, x + \mathbf{D}(t)\, \mathbf{u} + w \qquad (2)$$

In these equations $\boldsymbol{x}$ represents the state vector to be estimated, $\boldsymbol{y}$ is the measured output for $\mathbf{u}$ the measured input. $\dot{\boldsymbol{x}}$ denotes to the derivative of $\boldsymbol{x}$. v and w denotes the state and measurement noises respectively and are both zero mean and white. To get the system model values for $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$, and $\boldsymbol{D}$ must to be chosen so that the model is complete. This will be shown in the following section.

The estimate will be calculated using the Kalman-Bucy filter as shown by Eitelberg [1], given in equations (3), (4) and (5).

$$\dot{\mathbf{P}}(t) = \mathbf{A}(t)\mathbf{P}(t)+\mathbf{P}(t)\mathbf{A}^{T}(t)-\mathbf{P}(t)\mathbf{C}^{T}(t)\mathbf{R}^{-1}(t)\mathbf{C}(t)\mathbf{P}(t)+\mathbf{Q}(t) \qquad (3)$$

$$\mathbf{K}(t) = \mathbf{P}(t)\mathbf{C}^{T}(t)\mathbf{R}^{-1}(t) \qquad (4)$$

$$\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t)+\mathbf{B}(t)\mathbf{u}(t)+\mathbf{K}(t)[\mathbf{y}(t)-\mathbf{D}(t)\mathbf{u}(t)-\mathbf{C}(t)\mathbf{x}(t)] \qquad (5)$$

Equation (3) first calculates the error covariance $\boldsymbol{P}(t)$ where $\boldsymbol{Q}(t)$ is the covariance of v given in equation (1) and $\boldsymbol{R}(t)$ is the covariance of the measurement noise given in equation (2). Equation (4) then calculates the filter gain given the new value for $\boldsymbol{P}(t)$. The next step is to calculate the estimate in equation (5), where $\boldsymbol{y}(t)$ is the measured output and $\boldsymbol{u}(t)$ is the measured input. One also needs to choose reasonable starting values for the state variable $\boldsymbol{x}(t)$ and for the error covariance $\boldsymbol{P}(t)$. All three these calculations need to be done for all iterations of the process. $\boldsymbol{x}(t)$ can be found from $\dot{\boldsymbol{x}}(t)$ by calculating the integral and the same goes for $\boldsymbol{P}(t)$. The values of $\boldsymbol{R}(t)$ and $\boldsymbol{Q}(t)$ can now be adjusted until suitable results are obtained.

IV. VEHICLE YAW ESTIMATION

In the case of yaw estimation an experiment was carried out to see how the use of a Kalman-Bucy filter and the use of two sensors measuring the same thing can improve on results taken using a single sensor.

A. Experimental setup

The sensors used in this experiment all needed to measure rotation around the Z axis or yaw. The sensors chosen were the Z gyro of a low-cost IMU and a digital compass. The IMU used in this case was the ADIS16350 from Analog Devices. The gyro gives a measurement of rotational velocity in degrees per second. The digital compass used was an HMC6352 from Honeywell and the data is in the format of degrees from magnetic north. Both these sensors have their drawbacks but by combining their data one can get the best from both. To see how accurate the estimation was another sensor was needed as reference. For this purpose the two sensors were mounted together onto a potentiometer so that the actual rotation could be measured here as well. Data from the three sensors was captured together with a timestamp for each measurement. The data was processed afterwards to determine the optimal estimation. The sensor pack was then rotated on top of the potentiometer while data was being collected. The data collected are thus from real sensors and not only simulated data

B. System model

As seen in equation (1) and (2) a system model in the form of differential equations is needed. The model is chosen to estimate the rotational position, so $\dot{\boldsymbol{x}}$ is chosen as shown below.

$$\dot{x} = \begin{bmatrix} velocity \\ position \end{bmatrix} \quad (6)$$

The values chosen for ***A***, ***B***, ***C*** and ***D*** is shown in equations (7) to (10).

$$A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \quad (7)$$

$$B = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad (8)$$

$$C = \begin{bmatrix} 1 & 0 \end{bmatrix} \quad (9)$$

$$D = 0 \quad (10)$$

The starting value for $\dot{x}$ was taken as 0 for velocity and the first compass reading for position. The starting value for ***P*** is shown in equation (11).

$$P = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix} \quad (11)$$

After running the estimation steps a substantial amount of times it was determined that the following values for ***R*** and ***Q*** delivered good results.

$$R = \begin{bmatrix} 100 \end{bmatrix} \quad (12)$$

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (13)$$

All these values were then used in equations (3), (4) and (5) to calculate the estimate for the yaw of the vehicle iteratively as new data was collected from the sensors.

C. Results

The experimentation results can be seen in Fig. 2. In this figure the Y axis shows the rotational position or yaw in degrees and the X axis shows the time in seconds. The green line shows the measurements taken from the potentiometer. In other words this is then the actual rotational position of the unit. The black line shows the compass data with its low update rate. The blue line shows the gyro data which was integrated over time, with the first compass measurement taken as the starting value.

One can see the sensor drift after about 30 seconds. The red line is the estimation using the Kalman-Bucy filter described above. One can now see the improvement from using only gyro data to calculate yaw. In this case the gyro data at a higher frequency is used to give the finer detail where the lower frequency data of the compass is used to align the result. This is seen in the last few seconds of the graph where the estimate tends back towards the actual position where significant movement in gyro data has stopped.

V. VEHICLE PITCH AND ROLL ESTIMATION

In the case of estimating roll and pitch of the vehicle the following experiment was performed to show how a Kalman-Bucy filter can be used to estimate this.

A. Experimental setup

In the case of measuring pitch and roll, tilt sensors or inclinometers are used. Most of these sensors measure tilt by utilising some form of accelerometers and measuring the downward vector from gravity. Since the IMU already contains three accelerometers it was decided to use these instead of acquiring a new sensor. The measurements of the three accelerometers will always yield a downward vector due to gravity. The pitch and roll angles can then be calculated by calculating the angles between the Z axis and the gravity vector in the X and Y directions respectively. These are calculated using standard trigonometric functions.

A problem with using only these sensors for pitch and roll calculation is that the measurements will be affected by linear movement of the vehicle. As it accelerates in a given direction another acceleration vector will be added to the gravity vector.

Another sensor that may be used to calculate pitch and roll is the gyros also found in the IMU. To find pitch and roll movement from the gyro measurement one needs to find the integral over time of the gyro data as the measurements gives rotational velocity.

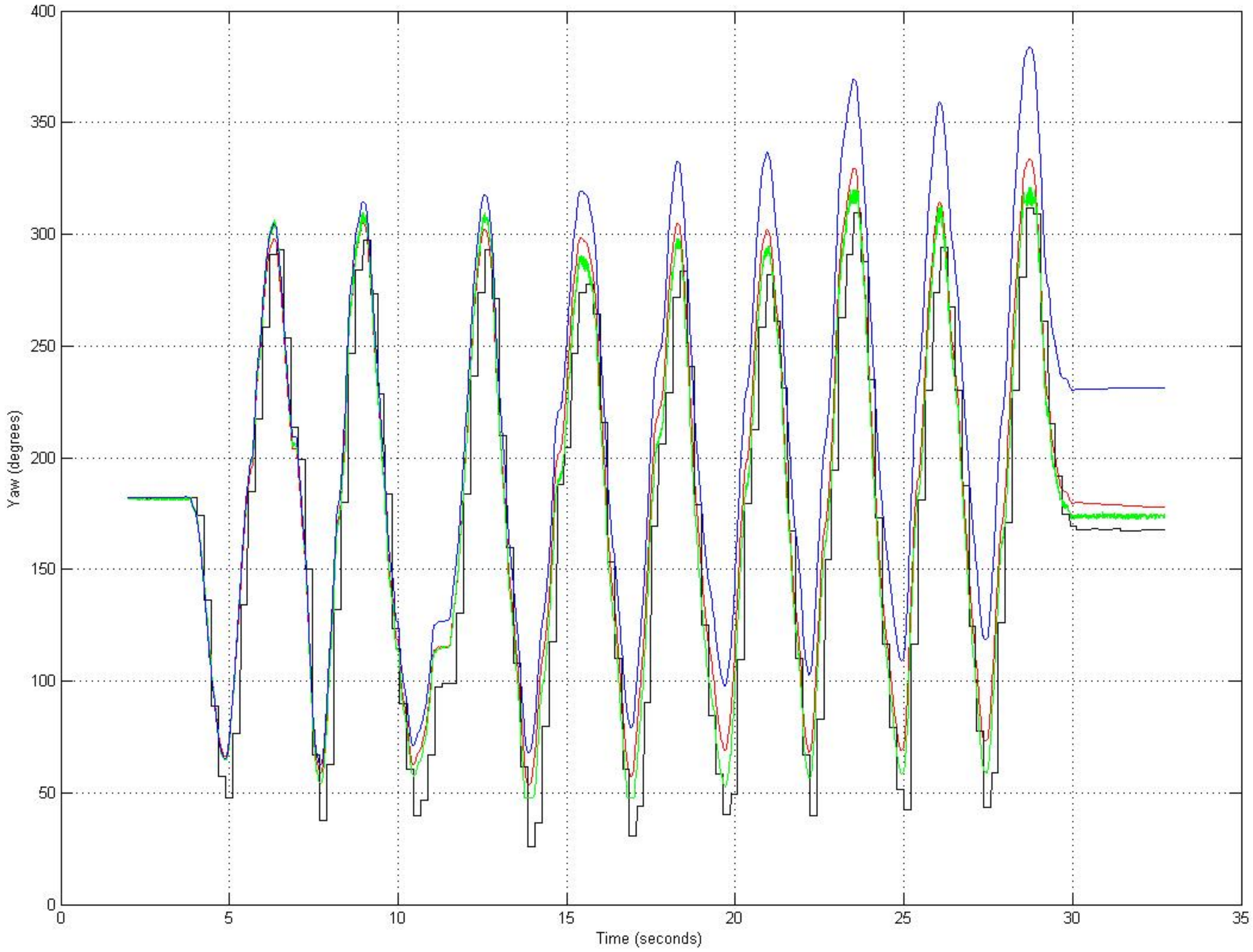

Figure 2 - Yaw estimation results using a Kalman-Bucy filter

The same IMU was used as in the previous experiment. The sensor pack was tilted in both pitch and roll directions and real sensor data was recorded in the experiment.

B. System model

For the system model in the case of both pitch and roll, the same values for ***A***, ***B***, ***C*** and ***D*** are being used as in the case of estimating vehicle yaw. The starting value for ***P*** is also similar. However for $\dot{x}$ we can take starting values of 0 as it is likely that the vehicle may start at the position for pitch and roll very close to 0. The values for ***R*** and ***Q*** which yields the best result are shown below.

$$R = [100] \tag{14}$$

$$Q = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \tag{15}$$

C. Results

The results of this experiment are shown in Fig. 3 and Fig. 4 for pitch and roll respectively. In both figures the black line is the calculation of tilt using the accelerometer data as explained above. The blue line shows the gyro data which is again integrated over time. Once again the drift in the gyro data in both figures can be seen. The red line shows the estimation using a Kalman-Bucy filter. By playing around with the values of ***Q*** and ***R***, one can move the estimate closer to either the gyro data or the accelerometer calculation.

VI. PROPOSED VEHICLE MOTION ESTIMATION

For estimation of the linear movement of the vehicle, the main sensors to be used will be the accelerometers contained in the IMU. To determine the actual movement of the vehicle, a double integral of the data obtained needs to be calculated over time. This will then yield the movement along the given axis.

An important aspect that needs to be taken into account is the fact that as the orientation of the vehicle changes the axis of the IMU changes in respect to the global axes of movement. This introduces the use of two reference frames. One is in respect to the world around the vehicle, for example the X axis may be from North to South, Y axis from East to West and the Z axis would be vertical. The second reference frame would always turn with the vehicle so the X axis would always go from the front of the vehicle to the rear, the Y axis always from the left of the vehicle to the right and the Z axis from the bottom of the vehicle to the top. These reference frames can be referred to as the global and the local reference frames according to [2].

To be able to track the vehicles movement one needs to keep track of the differences between these reference frames.

In the case of estimating the vehicles linear movement one will again need multiple sensors for measurement, so that the resultant estimate can be an improvement on using just a single sensor. As stated previously, the main sensor to be used in this case will be the accelerometers included in the IMU. Other sensors that may be used to track linear movement may be DVL for forward or sideways movement, or pressure sensors for vertical movement.

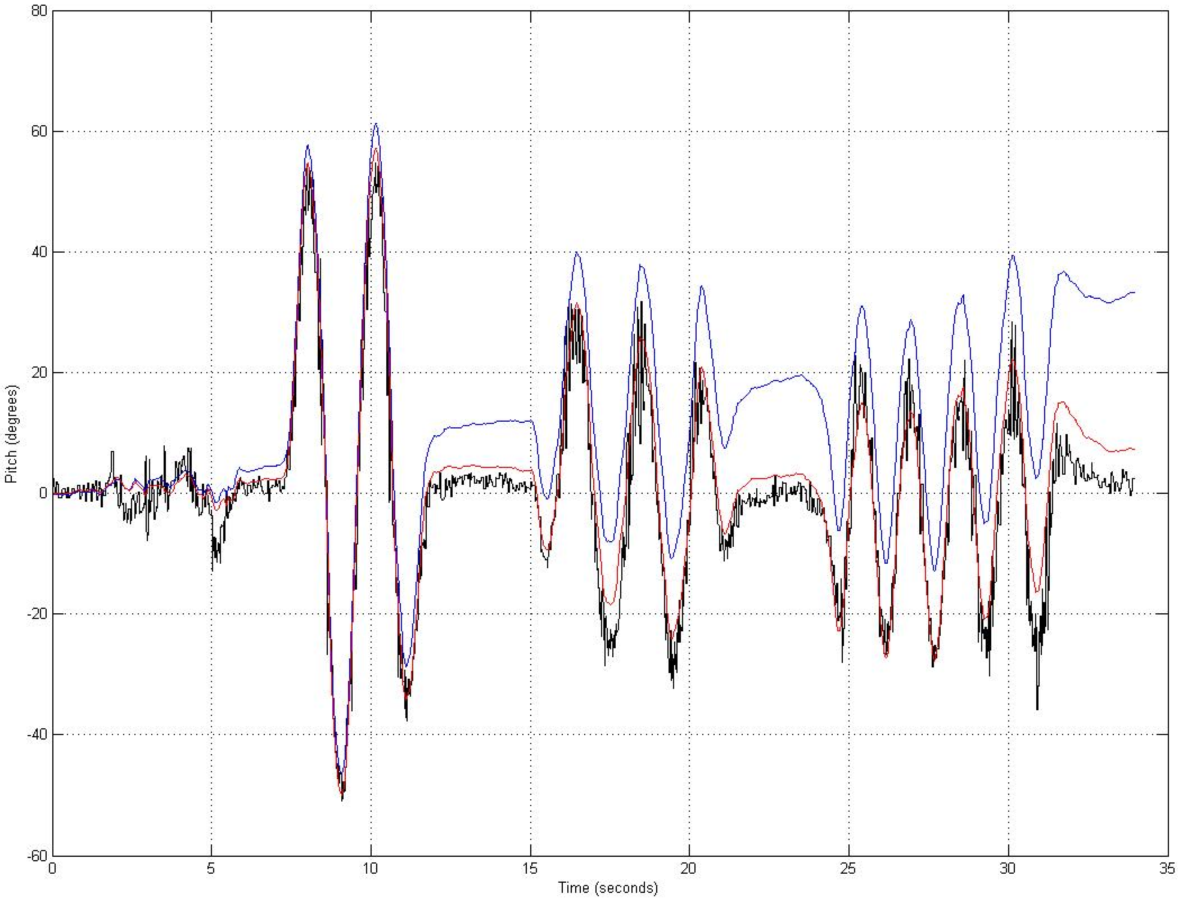

Figure 3 – Pitch estimation results using a Kalman-Bucy filter.

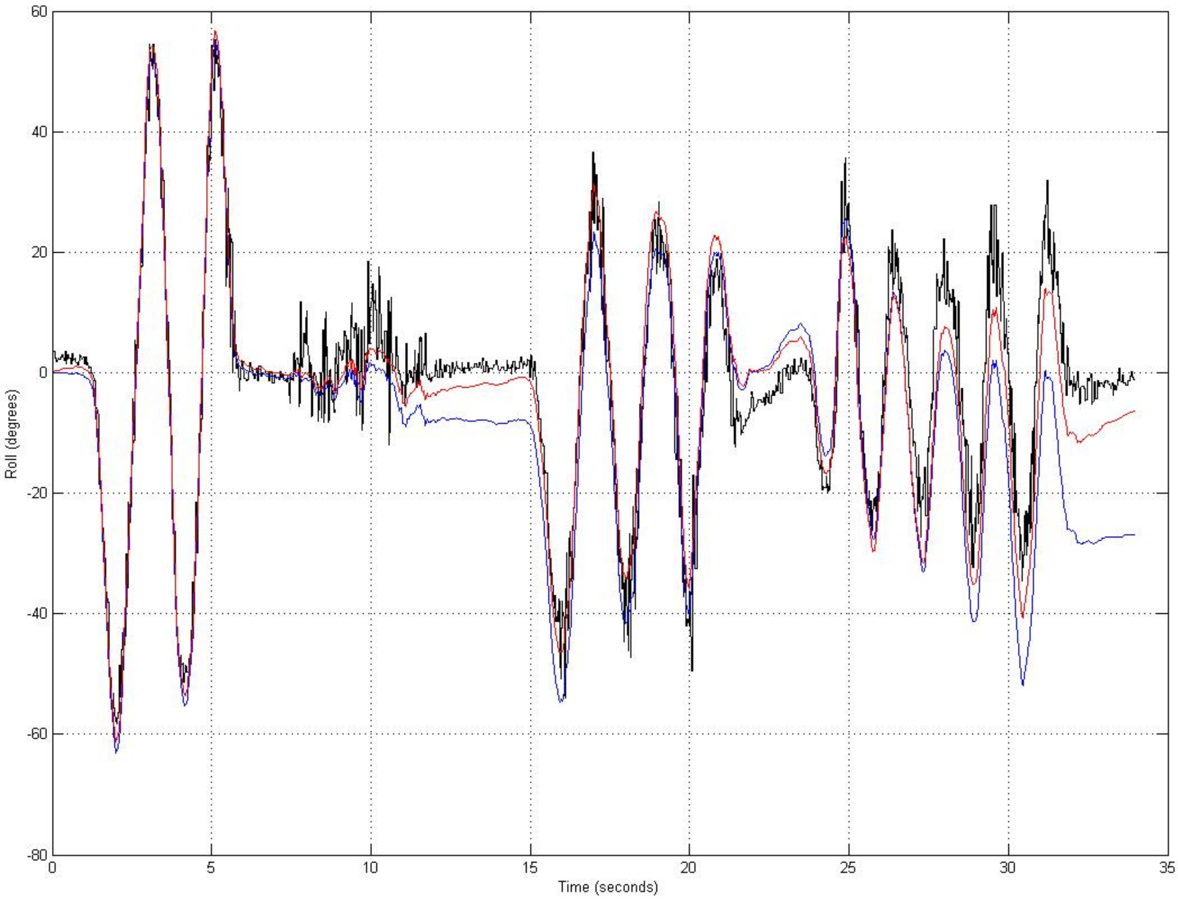

Figure 4 – Roll estimation results using a Kalman-Bucy filter.

The system model for using a Kalman-Bucy filter can now be derived. The model is chosen so that $\dot{x}$ is give as in equation (16).

$$\dot{x} = \begin{bmatrix} acceleration \\ velocity \end{bmatrix} \quad (16)$$

This means that the position will be contained in $\boldsymbol{x}$ as $\dot{\boldsymbol{x}}$ is simply the derivative of $\boldsymbol{x}$. The values for $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are shown below.

$$A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \quad (17)$$

$$B = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad (18)$$

$$C = \begin{bmatrix} 0 & 1 \end{bmatrix} \quad (19)$$

$$D = 0 \quad (20)$$

These values may be used in equations (3), (4) and (5) iteratively as new sensor data are obtained. In equations (3), (4) and (5), $\boldsymbol{u}(t)$ will be taken as the accelerometer reading and $\boldsymbol{y}(t)$ as the positional reading from whatever extra sensor is implemented. The system should now be simulated using different values for $\boldsymbol{P}$, $\boldsymbol{Q}$ and $\boldsymbol{R}$ to find the values that will yield optimal results for the estimation.

VII. CONCLUSION

In this paper it has been shown how the Kalman-Bucy filter can be used to find an estimate of an AUV's position. This can in fact be used for position estimation of any type of vehicle where one wants to use multiple sensors that measure the same thing, to improve on measurements from a single sensor. In many cases, acquiring sensors with a high enough level of accuracy can be very costly. Instead the designer can rather obtain multiple low cost sensors and improve on the measurements by implementing the algorithm for this filter. In other words the filter is being used for sensor fusion. The Kalman-Bucy filter can be optimised so that the estimate tends more towards the measurements of one sensor than the other. This may be useful in cases where the designer knows the characteristics of the sensors being used.

VIII. FUTURE WORK

The next step would be to acquire sensors to measure linear movement. The filters must then be implemented and similar experiments as shown in sections IV and V must be carried out. After this has been done the estimation of all six DOF has been achieved. The filter then needs to be implemented on an AUV and all six DOF put together.

The estimation results can also be improved once the mechanical dynamics of the system is known and has been modelled. The motion of an underwater vehicle, for example, is different to that of a wheeled land vehicle. The knowledge of this motion can be used to improve on the estimation process.

The six calculations can then also be combined into a single model where the estimation result will be a 12x1 vector and all other matrices needs to be adjusted accordingly. This will result in all six DOF estimated in a single calculation.

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