2008 American Control Conference
Westin Seattle Hotel, Seattle, Washington, USA
June 11-13, 2008

Event based Kalman filter observer for rotary high speed on/off valve

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***Abstract*— A novel hydraulic rotary self-spinning high speed on/off valve is being developed to enable hydraulic systems to be controlled in a more efficient throttle-less manner via pulse-width-modulation (PWM). The valve is designed to operate at a spool frequency of $20Hz$ to $40Hz$. A coarse non-contacting optical encoder is proposed to measure the angular position of the valve spool. Measurement events in the form of encoder count changes are obtained at irregular times and infrequently. An event-based Kalman filter is developed to improve on the resolution and to provide continuous estimation of the spool angular position and velocity. Simulation and experimental results show that the event based Kalman filter can provide accurate continuous estimation for both spool angular position and velocity.**

I. INTRODUCTION

A Kalman filter is an optimal recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. Discrete-time Kalman filters and continuous-time Kalman filters have been widely used as an estimating approach in the presence of model uncertainty and measurement noise. However, with irregular measurements, traditional Kalman filter structure must be adapted to operate as an event-based estimator. In this paper, such an alternative is developed for use with a novel type of hydraulic rotary high speed on/off valve.

Traditional method of controlling hydraulic systems makes use of a fixed displacement pump, a pressure regulating relief valve and a throttling valve. In this case, unneeded flow is bled off at high pressure resulting in high power loss, and significant energy is lost due to pressure drop across the throttling valve. As an alternative to throttling control, a high speed on/off valve can be pulse width modulated (PWM) to control the average flow. In either the on or the off state, the power loss of the valve is minimal, because either the pressure drop across the valve is very small, or the flow rate through the valve is zero. However, fast on/off transition is critical to minimize throttling loss during transition and high PWM frequency is needed to reduce flow or pressure ripple. To this end, a new type of rotary high speed self-spinning on/off valve has been proposed in [1]. The continuous unidirectional rotary motion overcomes the challenge of linear on/off valves which require significant power to repeatedly accelerate and decelerate the spool. In addition, the rotary motion is actuated by scavenging energy from the fluid flow directly. In one configuration, the rotary valve is used together with a small accumulator, which enables a fixed displacement pump to realize the function of a variable displacement pump [2] [3]. One key feature of the valve is that the spool rotates and travels axially inside a stationary sleeve, as shown in Fig.1. Knowledge of the axial and rotary states are useful for controlling the function of the valve effectively.

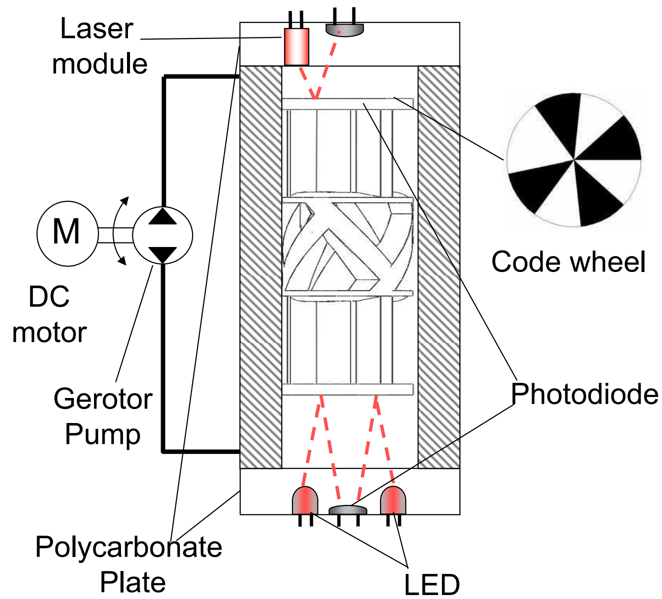

Fig. 1. System schematic

The axial motion of the spool is actuated hydrostatically using a small gerotor pump. Both axial and rotary sensing are achieved using non-contact methods, which simplify the spool structure and the sealing structure. The axial position is measured using an optical sensor consisting of LEDs and a photodiode [1]. The intensity of the LED light reflected back from the spool end is a monotonic function of the distance between the spool and the sensor, and can thus be used as an axial position sensor. The rotary states of the spool are also measured using a non-contacting optical sensor, which consists of a laser module, a photodiode and a rotary encoder code wheel. The light emitted from the laser is reflected from the code wheel. The photodiode response depends on whether the laser is reflected off of a black or white sector on the codewheel, and the changes can be used to sense the rotary position. Due to the small spool diameter (2.5cm)

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and the relatively large beam size, the encoder resolution is relatively poor (about 8 sectors per revolution). Improving the quality of the laser source and improving the resolution of the code wheel may improve the sensor resolution, however, they are not easy or costly to realize.

Because of the coarse encoder resolution, it is beneficial to estimate the angular position and velocity between transitions of the encoder counts. Since the measurement of black-white transition events can occur at irregular time, we propose an event based Kalman filter observer for this purpose. The transition events are subject to uncertainty due to finite sampling interval, and the fact that optical signal changes gradually and the threshold for distinguishing a white or black sector is uncertain. Continuous time varying Kalman filter theory is adapted to accommodate the uncertain event based measurements. The resulting algorithm is such that between events, the Kalman filter operates in an open loop manner; when a transition occurs, both the Kalman filter gain and the state estimate are updated discretely.

Two approaches are frequently used to estimate angular velocity from encoder measurement: finite-difference and inverse-time. In finite difference method, angular velocity is calculated by counting the number of pulses within a fixed time interval, converting the counts to angle, and dividing the angle by the time interval. In inverse-time method, angular velocity is calculated by dividing the sector angle by the time between successive pulses. In both cases, measurement precision relies heavily on the codewheel resolution. Glad and Ljung [6] presented a Kalman filter to do velocity estimation based on position measurements obtained at irregular time instants. Measurement noise due to occurrence time uncertainty was considered, and simulation results showed that in the presence of high noise this Kalman filter is superior to the previous two methods. Position estimation was not discussed is the methods above.

In the next section, the position measurement approach and the dynamic model of the system will be presented. In section III, the design of the event-based Kalman filter will be described. Simulation results and experimental results will be presented in section IV. Concluding remarks and future research plans will be discussed in section V.

II. SYSTEM DESCRIPTION AND MODELING

A. Rotary On/off Valve Working Principle

The high speed rotary on/off valve consists of a spool that rotates inside a stationary sleeve (Fig. 2). The spool has a center PWM section and two outlet turbines. The center section is composed of helical barriers, which act as turbine blades, so that when high velocity fluid is transferred from the inlet nozzles to the valve spool, the fluid momentum is captured and transferred into the angular momentum of the spool. When the flow leaves the spool to either application or tank, the outlet turbines reverse the direction of the flow relative to the inlet, and a reaction force is generated on the spool. As the spool rotates, flow is apportioned to application (on) or tank (off) by the helical barriers. The duty ratio, which is defined as the ratio of valve on-time to the PWM period, is controlled by controlling the axial position of the center part relative to the rhombus inlet nozzle [1]. Flow is continuously fed into the spool regardless of the duty ratio, and the valve is designed to rotate at between 20Hz to 40Hz. Since three PWM cycles occur per revolution of the spool, this corresponds to a PWM frequency of 60Hz-120Hz,

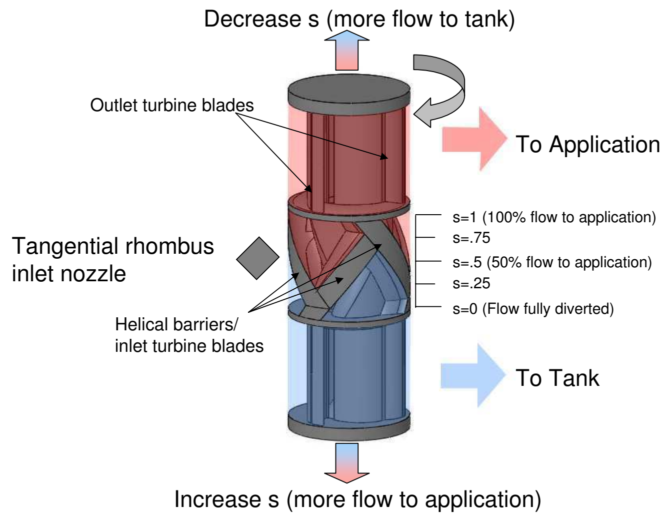

Fig. 2. Rotary on/off valve principle

B. Non-contact Rotary Sensing

A sensing system for the rotating spool is shown in Fig. 1. The rotary optical sensor consists of a laser diode module light source, a photodiode and a code wheel printed on a piece of transparent media. The code wheel is attached to one end of the spool. A low power laser module and a photodiode are mounted next to each other on one end of the sleeve. The code wheel is designed to include a small number of sectors and an index. As the spool rotates, the laser beam reflects off of either a black or a white (metal) sector, causing a measurable alternating signal from the photodiode. The index is found by calculating the light responses each sector receives, and calculating which sector has a longer duration than the previous one.

The output voltage from the photodiode is amplified using an op-amp. The reading is discretized by comparing with a threshold value (Fig. 3). We are interested in the response of the photodiode when the center of the light spot is at the boundary between the white and black sectors, Fig.4). That threshold value is calculated by averaging the transition response of the photodiode over one revolution.

After discretizing the photodiode response, a counter is used to detect the index and the edges of each sector on the code wheel, which represent the spool position. For example, as shown in Fig.5, the edge between the index and the sector next to it is assigned to be zero. Following the index, each edge represents another 42°. The counter value is incremented whenever a discretized signal changes values.

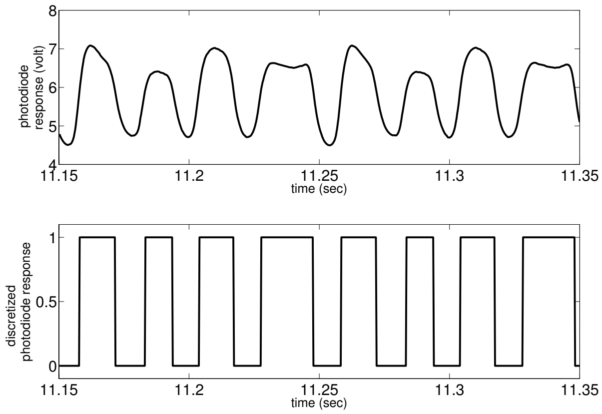

Fig. 3. Raw (top) and discretized (bottom) signal from the photodiode.

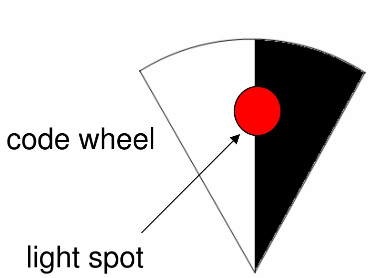

Fig. 4. Finding threshold value

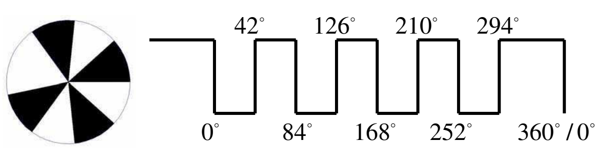

Fig. 5. Code wheel interpretation

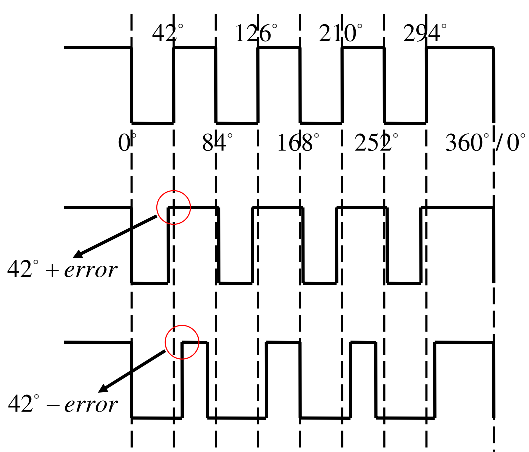

Fig. 6. Effect of threshold value setting error on measurement

As shown in Fig.6, error in the threshold value setting will introduce measurement noise. The second line shows the case when the threshold value is lower than the true value, while the third line showed the case when the threshold value is higher than the true value. At a given time, the error in the measured position due to error in the threshold value will be biased; negative if the threshold is too high, and positive if it is too low. However, since the error in the threshold value is assumed to have zero mean, and the shape of the black to white and the white to black transitions are assumed to be the same, the position error should be a zero-mean.

C. System Modeling

The angular velocity of the spool is mainly a function of the inlet flow rate [1] which should be a constant. Thus, we model the angular velocity to be constant except for random effects due to secondary fluid flow forces. Since the effect of the fluid on the angular velocity of the spool is difficult to predict, a process noise term d is added to the spool dynamic model:

$$\begin{aligned} \dot{\theta}(t) &= \omega(t) \\ \dot{\omega}(t) &= d(t) \end{aligned} \tag{1}$$

where θ is the angular position of the spool, ω is the angular velocity of the spool, and d is the angular acceleration of the spool which is assumed to be random.

Let the transition counter output at time t be $\texttt{count}(t)$. Let the sampling period be ΔT and the sampling times be $t_k = k \cdot \Delta T$. A change in the counter value signifies that either a rising or a falling transition edge has occurred between the current sampling instant and the previous one. We say that an transition event is detected at t_k if:

$$\texttt{count}(t_k) - \texttt{count}(t_{k-1}) \geq 1. \tag{2}$$

Because the code wheel has a limited number of sectors (≈ 8), for the range of angular velocities (20-40Hz) under consideration, the sampling rate is sufficiently fast to safely assume that at most one transition edge has occurred between time samples. Here we have assumed that counter overflow has been properly adjusted.

The counter readings can provide position measurement which is accurate up to the resolution of the encoder. For example, with an 8 sector encoder, the accuracy is $2\pi/8 = 0.73rad$. Our goal is to derive a Kalman filter so that it can utilize the transition event signal to increase the resolution of the sensing system.

III. Event-based Kalman Filter

A. Kalman filter problem

Consider the timing diagram in Fig. Fig.7. Angular position information is provided when the light spot transitions from a black to a white sector and vice versa. The time when the $j-th$, $j = 1, 2, \ldots,$ transition of this type happens is denoted by τ_j^* and the corresponding spool's angular position be denoted by $x_p(count)$. Notice that τ_j^* occur irregularly depending on the spool angular velocity. On the other hand,

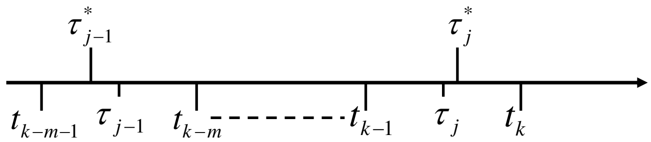

Fig. 7. Time denotations

the computational sampling times, $t_k = k\Delta T$, $k = 0, 1, \ldots$, do occur regularly. A transition is detected at t_k if $\texttt{count}(t_k) - \texttt{count}(t_{k-1}) = 1$. Then, τ_j^* would be uniformly distributed on $(t_{k-1}, t_k]$. Therefore if we estimate the transition event to happen at $\tau_j := (t_k + t_{k-1})/2$, the uncertainty on transition event occurrence time can be converted to a zero mean random measurement noise on rotary position. We use n_1 to represent this measurement noise, which is uniformly distributed, and is bounded as $|n_1| \leq 0.5\omega\Delta T$; the variance of this variable is $(0.5\omega\Delta T)^2/3$. This measurement noise is linearly affected by the sampling time ΔT.

Another measurement noise comes from the threshold value setting, as shown in section II-B. This kind of noise is denoted by n_2. The transition time from black to white or from white to black is denoted by t_{tran}. We assume this variable is a normal distributed variable with $2\sigma = 0.5\omega t_{tran}$, and therefore, the variance of n_1 is $((0.5\omega t_{tran})/2)^2$.

Since n_1 and n_2 are independent, we define the measurement noise term $n := n_1 + n_2$, which can be expressed as:

$$\begin{aligned} y(\tau_j) &= x_p(\texttt{count}(t_k)) + n \\ E[n(t)n'(t)] &= R(t)\delta(t-\tau) \quad E[w(t)] \equiv 0 \\ R(t) &= \frac{1}{3}(0.5\omega\Delta T)^2 + (\frac{1}{2}(0.5\omega t_{tran}))^2 \end{aligned} \tag{3}$$

Define system states as $X = (\theta \quad \omega)^T$, the system model is represented as:

$$\begin{aligned} \frac{d}{dt}X(t) &= \underbrace{\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}}_{F} X(t) + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \cdot d(t) \\ y(t) &= \begin{cases} (\ 1 \quad 0\ ) \cdot X(t) + n & \text{if } t = \tau_j \\ \text{not avaliable} & \text{if } t \neq \tau_j \end{cases} \\ E[d(t)d'(t)] &= q(t)\delta(t-\tau) \quad E[d(t)] \equiv 0 \end{aligned}$$

Where $q(t)$ is assumed to be a Gaussian distributed noise with zero mean and standard deviation σ.

B. Event based Kalman Filter algorithm

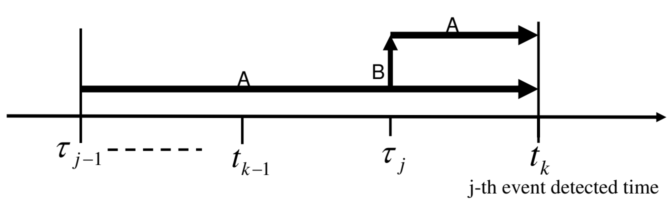

Fig. 8. Event-based Kalman filter time line

Based on the model discussed in the previous section, An event-based Kalman filter was designed to continuously estimate the angular position and velocity of the spool. Time flow is shown in Fig. 8. t_k is the sampling time. τ_j is the transition event time. Open loop manner estimation is denoted by A, and measurement update action is denoted by B. The algorithm is explained along the time line. We use the notation $\hat{X}(t|j)$ to denote the estimate of $X(t)$ if the first j events have been detected, and $P(t|j)$ being the covariance of the estimate.

The algorithm is initialized with $\hat{X}(t = t_0|j = 0)$ being the initial a-priori estimate of the the state; and $P(t = t_0|j = 0)$ being the corresponding estimation error covariance.

In section A, no measurement is detected. The Kalman filter works in an open loop manner. Estimate of the states is calculated based on the knowledge of the system model and the most recent measurement. The estimate of the states is denoted by $\hat{X} := (\hat{\theta} \quad \hat{\omega})$:

$$\frac{d}{dt}\hat{X}(t|j-1) = F\hat{X}(t|j-1) \tag{4}$$

Since no measurement is available in this period of time, continuous-time Kalman filter is adapted to update the covariance of the estimation error only with the knowledge of system model. Under this condition, the Riccati equation for calculating the corresponding covariance of the estimation error $P(t|j-1)$ is simplified into the form:

$$\begin{aligned} \frac{d}{dt}P(t|j-1) &= P(t|j-1)F^T + FP(t|j-1) + Q(t) \\ Q(t) &= \begin{pmatrix} 0 & 0 \\ 0 & q(t) \end{pmatrix} \end{aligned} \tag{5}$$

An analytical solution is developed for the equation as:

$$\begin{aligned} P_{11}(t|j-1) &= \frac{1}{3} \cdot q \cdot (t-\tau_{j-1})^3 + P_{22}(\tau_{j-1}|j-1) \cdot (t-\tau_{j-1})^2 \\ &\quad + P_{12}(\tau_{j-1}|j-1) \cdot (t-\tau_{j-1}) \\ &\quad + P_{21}(\tau_{j-1}|j-1) \cdot (t-\tau_{j-1}) + P_{11}(\tau_{j-1}|j-1) \\ P_{12}(t|j-1) &= P_{21}(t|j-1) \\ &= \frac{1}{2} \cdot q \cdot (t-\tau_{j-1})^2 + P_{22}(\tau_{j-1}|j-1) \cdot (t-\tau_{j-1}) \\ &\quad + P_{12}(\tau_{j-1}|j-1) \\ P_{22}(t|j-1) &= q \cdot (t-\tau_{j-1}) + P_{22}(\tau_{j-1}|j-1) \end{aligned} \tag{6}$$

Open loop manner estimation continues until a measurement is detected at $t = t_k$, and this information is used to update the estimation of the states and the covariance of the estimation error at $t = \tau_j$. This is step B in Fig. 8. The posteriori state estimate is denoted as $\hat{X}(\tau_j|j)$, which is calculated as:

$$\begin{aligned} \hat{X}(\tau_j|j) &= \hat{X}(\tau_j|j-1) + K(\tau_j)(y(\tau_j) - H^T\hat{X}(\tau_j|j-1)) \\ H &= (\ 1 \quad 0\ )^T \\ K(\tau_j) &= P(\tau_j|j-1)H \end{aligned} \tag{7}$$

Similarly for estimation error covariance matrix at this instant, we denote a priori estimate by $P(\tau_j|j-1)$ and a

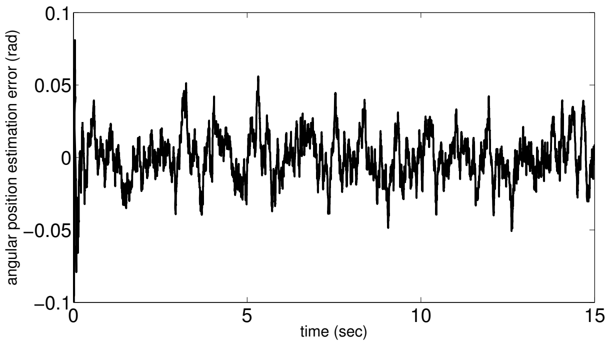

Fig. 9. Angular position estimatoin error when $\Delta t = 1ms$

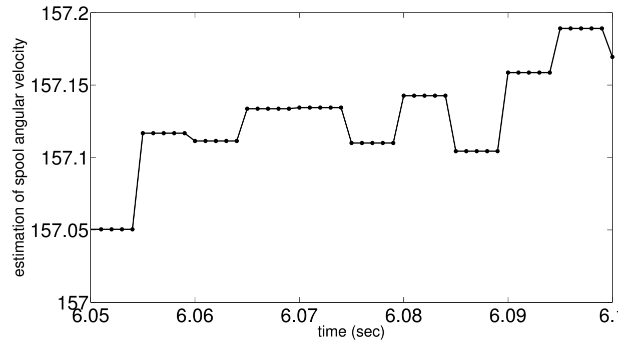

Fig. 11. Angular velocity estimation when $\Delta t = 1ms$

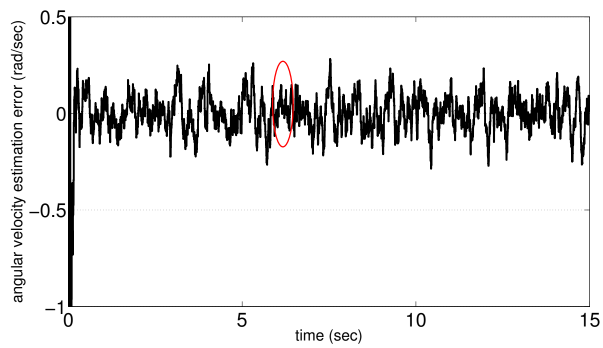

Fig. 10. Angular velocity estimation error when $\Delta t = 1ms$

posteriori estimate by $P(\tau_j|j)$

$$P(\tau_j|j) = [(P(\tau_j|j-1))^{-1} + H^T(\tau_j)R^{-1}(\tau_j)H]^{-1} \qquad (8)$$

After the discrete update, open loop estimation is used again to estimate the spool states and estimation error covariace from $t = \tau_j$ to $t = t_k$. But now it is estimated with the information up to j:

$$\begin{aligned} \frac{d}{dt}\hat{X}(t|j) &= F\hat{X}(t|j) \\ \frac{d}{dt}P(t|j) &= P(t|j)F^T + FP(t|j) + Q(t) \qquad (9) \end{aligned}$$

This j information is used with step A method until the next measurement is obtained, and the the above process is repeated.

IV. SIMULATION AND EXPERIMENTAL RESULTS

The system described in section II-C was simulated using Simulink with certain parameters selected based on an experimental setup. In the simulation model, the angular velocity of the spool was assumed to be $25Hz$, or $\omega = 157.1 rad/s$. The encoder is assumed to have the resolution of $0.785 rad$. p was set to be 1000. Assume the black-white transition time is smaller than $1.5ms$, set $R = 5.53 \times 10^{-3} rad^2/s^4$, $q = 0.25 rad^2$. Initial conditions for the states are selected to be $[\theta \quad \omega]^T = [0 \quad 50]^T$:

The sampling time was selected to be $1ms$. As shown in Fig.9 and Fig.10, it takes the estimation error of angular position less than $0.1sec$ to converge to less than $0.06rad$; and it takes the estimation error of angular velocity the same amount of time to converge to less than $0.3rad/sec$. Compared with the measurement noise bound of $0.36rad$, the event based Kalman filter significantly improves the estimation precision. A zoom in look on the spool angular velocity estimation on the period circled in Fig.10 is shown in Fig.11. The estimation of angular velocity will not change between measurements were detected, and will change when an transition event is detected. Initially, the estimation relies only on model dynamics and the initial condition of the current open loop period. This can explain the huge estimation error on rotary position for the first $0.1sec$, where the estimation is running with a poor initial condition, i.e: $50rad/sec$ compared with the true value of $157.1rad/sec$.

The experimental set up ran at a sampling time of $0.25ms$ in order to capture the valve pressure profile during transition, and the model was simulated at a sampling time of $0.25ms$ as well. Since the data aquasition time is lower, measurement noise n_1 is significantly smaller, while the noise due to threshold value setting shoud be almost the same. It takes the angular position estimation error less than $0.11sec$ to converge to around $0.04rad$, and the angular velocity estimation error to converge to less than $0.08rad/sec$ within the same amount of time. Compared with the simulation results with a sampling time of $1ms$, estimation precision is improved at the cost of a higher computation cost.

This Kalman filter is used to estimate the rotary position and angular velocity of the spool experimentally. The codewheel has a diameter of $3.22 \times 10^{-2}m$. As shown in Fig.1, including the index, the code wheel has 8 sectors. The system is operated so that the spool rotates at two different angular velocities.

At each angular velocity, the system was undergoing external adjustment during the initial phase. When no external adjustment was applied (last $10sec$ of each section, the estimations of angular velocities were at around $114.5rad/sec$ and $173.5rad/sec$ with a variation less than $1rad/sec$. Fig.12 and Fig.13 both show a fast transition response. In both the starting section and the step section, the transition period are less than $0.1sec$. The Kalman filter reflects the dynamical change on angular velocity as well.

Inlet pressure is ploted with the rotary position estimation.

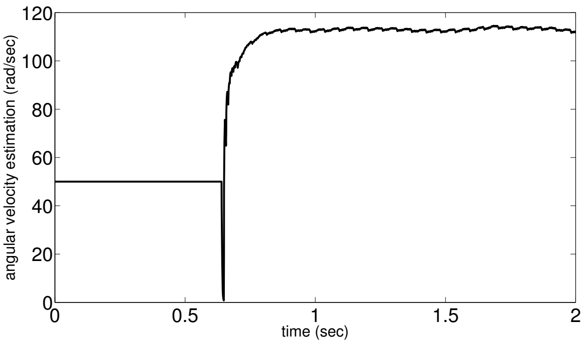

Fig. 12. Transition response when Kalman filter starts

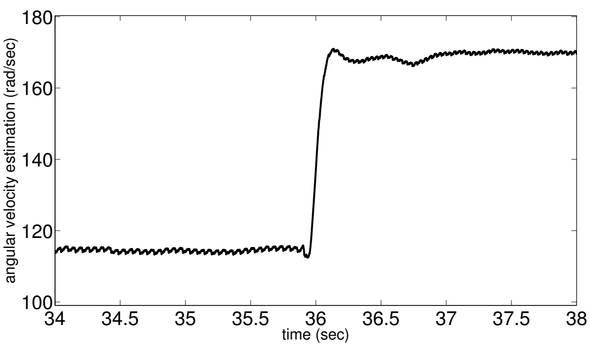

Fig. 13. Transition response to step change in angular velocity

As described in section II-A, during one revolution, the pressure shows three repetitive pattern. Since the pressure at a fixed angular position should be more or less the same, if the angular position estimation is correct, the pressure v.s. estimation position over one revolution should be repetitive as well. As shown in Fig.14, the first line showed the pressure profile for three successive revolutions. The second line showed data for $t = 29$sec to $t = 30$sec, which includes about 18 groups of data piled together; A similar pressure profile as shown in the first line is reflected in this plot, and the estimation variation (peak to peak) for a same pressure is smaller than $0.3rad$. Since pressure profile varies from revolution to revolution, which will cause the profile unable to overlap with one another, we believe the Kalman filter offers a satisfactory angular positon estimation.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a non-contacting optical sensing method was described to measure the rotary position of a valve spool. Based on the measurement and spool dynamics, an event based Kalman filter was developed to estimate both the spool rotary position and angular velocity.

A system model and an event based Kalman filter have been simulated with promising results in Matlab. The simulation results show that the modified Kalman filter can provide continuous estimation of the rotary position and the angular velocity of the spool. Sampling time is a key factor in minimizing the estimation error. However, decreasing sampling time will lead to a higher computational cost.

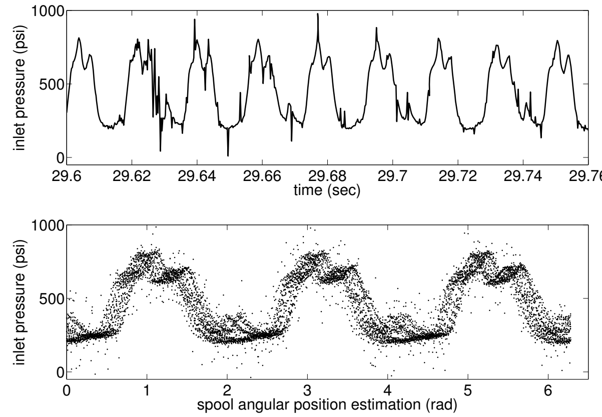

Fig. 14. presure profile v.s. time and angular position estimation

Increasing the code wheel resolution can also decease the estimation error; however, it is physically limited by the spool diameter and the laser spolt size. This Kalman filter works well experimentally, and it can reflect the dynamical change on spool states.

New experimental set up is being built to test the estimation accuracy instead of the pressure profile as a robust reference. Contamination, air entrainment and oil temperature may change the optical properties of the oil. These issues will be investigated more in the future.

VI. ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation under grant numbers ENG/CMS-0409832 and EEC-0540834. We thank Mike Rannow and Haink Tu from the University of Minnesota for their helpful comments and discussion.

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