Hardware Implementation Optimization of Extended Kalman Filter for the Estimation of State of Charge of Li-ion Battery

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Abstract.
Extended Kalman Filter (EKF) is widely studied in the field of State of Charge (SOC) estimation of Li-ion batteries, however, in practical applications like Electric Vehicles (EV), there are usually a large number of individual battery cells. In order to meet the demand of real-time computation, a high performance MCU is essential. In this paper, we propose a hardware structure to implement EKF which is economical in area and power consumption and could be easily integrated in a larger design and at the same time is capable of satisfying the real-time restriction.

Introduction

As the development of electrical vehicles and new energy system, there are more and more occasions where a large number of batteries are applied for energy storage. When compared to some other types of electrochemical batteries, Li-ion battery shows its merits in higher energy density, higher power density, higher cell voltage and lower self-discharge rate and it is free from the memory effect [1]. However, it also suffers from disadvantages in the aspect of uniformity and reliability which might limit the widespread application. Therefore, it is very essential to monitor the state of Li-ion battery, including the State of Health (SOH), the State of Life (SOL), as well as the State of Charge (SOC), which we will emphasize in this paper.

The State of Charge is defined as the ratio of remaining capacity to the rated capacity, which is unable to measure directly. Methods of estimation typically include electrochemical approaches, Ah counting, Open Circuit Voltage measurement and Extended Kalman filter [2]. Electrochemical approaches, for example the measurement of electrochemical impedance spectroscopy, is accurate however at the same time hard to be implemented in application system. Ah counting, also known as Coulomb counting, on the other hand is relatively easier to implement and is widely used. But its accuracy mostly depends on initial SOC and the parameters of charge and discharge efficiency. The Extended Kalman Filter, tries to remove the noise components and produces a statistically optimal estimation of latent system state. It is widely discussed as one accurate method and is capable of dealing with white noise. However, when applied to practice, problems of large computational time and complex algorithm begin to emerge. The large number of individual battery cells in applications seem to deteriorate this problem. Therefore, it is vital to conciliate the contradiction of accuracy and complexity. In this paper, we present one optimization for the implementation of Extended Kalman Filter according to the specificity of Li-ion battery model.

The Extended Kalman Filter

The Kalman Filter gives the optimum state estimation of a linear system under the circumstance of Gaussian noise. When dealing with nonlinear system, a linearization process is performed, and this results in the Extended Kalman Filter. Assuming the state equation of one non-linear system follows the form below,

$$\begin{cases} \mathrm{x}_{\mathrm{k+1}} = f(x_k, u_k) + w_k \\ \mathrm{y}_{\mathrm{k}} = g(x_k, u_k) + v_k \end{cases}, \tag{1}$$

Where vector $\mathbf{x}$ stands for state vector, u represents controlled variable and $\mathbf{y}$ means the observation vector. We linearize the equations with,

$$\begin{cases} \mathrm{A}_{\mathrm{k}} = \left.\frac{\partial f(x_k, u_k)}{\partial x_k}\right|_{x_k = \hat{x}_k} \\ \mathrm{B}_{\mathrm{k}} = \left.\frac{\partial f(x_k, u_k)}{\partial u_k}\right|_{x_k = \hat{x}_k} \\ \mathrm{C}_{\mathrm{k}} = \left.\frac{\partial g(x_k, u_k)}{\partial x_k}\right|_{x_k = \hat{x}_k} \end{cases}. \tag{2}$$

Then, the computation step follows the equations [3].

$$\hat{\mathrm{x}}_k^- = A_{k-1}\hat{x}_{k-1}^+ + B_{k-1}u_{k-1}, \tag{3}$$

$$\Sigma_{\mathrm{x_k}}^- = A_{k-1}\Sigma_{\mathrm{x_k}}^+ A_{k-1}^T + \Sigma_{\mathrm{w}}, \tag{4}$$

$$\mathrm{L}_{\mathrm{k}} = \Sigma_{\mathrm{x_k}}^- C_k^T \left[C_k \Sigma_{\mathrm{x_k}}^- C_k^T + \Sigma_v\right]^{-1}, \tag{5}$$

$$\hat{\mathrm{x}}_k^+ = \hat{\mathrm{x}}_k^- + L_k[y_k - C_k\hat{\mathrm{x}}_k^-], \tag{6}$$

$$\Sigma_{\mathrm{x_k}}^+ = (I - L_k C_k)\Sigma_{\mathrm{x_k}}^-. \tag{7}$$

The Extended Kalman Filter works in an iteration of two steps. First, it calculates prediction of output and error covariance of next step, and then, it utilizes the observations of system output to calibrate the present state estimation. The predicted state and error covariance are denoted by $\hat{\mathrm{x}}_k^-$ and $\Sigma_{\mathrm{x_k}}^-$ in Eq. 3-7 and the corrected ones are denoted as $\hat{\mathrm{x}}_k^+$ and $\Sigma_{\mathrm{x_k}}^+$.

Li-ion Battery Model

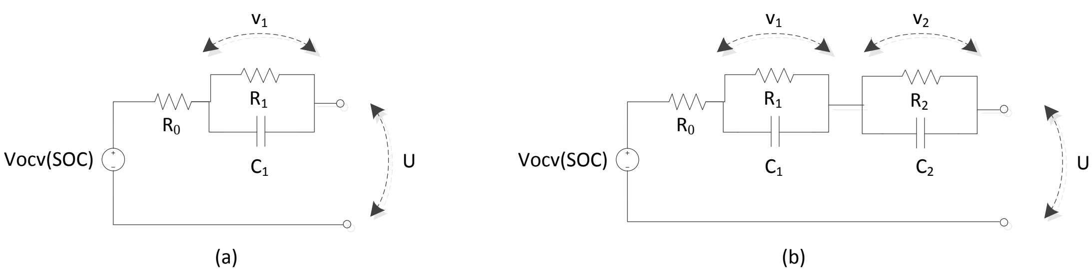

Fig.1 (a) Thevenin equivalent model and (b) Randle equivalent model

The Extended Kalman Filter requires the knowledge of Li-ion battery model, such as electrochemistry model or equivalent circuit model. As we are interested in the implementation of Extended Kalman Filter in an embedded system which usually could only perform non-destructive site test on the batteries, we prefer the latter one. Among those equivalent circuit models, Thevenin model and Randle model are mostly under discussion. The first one is a one order equivalence of the battery, with RC circuit to depict the polarization effect and the second 2nd model details that description with two RC loop circuits. In this paper we mainly focus on the latter model. From the models show in Fig. 1, Spagnol, Rossi and Savaresi [4] deduce the state space expression as Eq. 8.

$$\begin{cases} \begin{pmatrix} \dot{v}_1 \\ \dot{v}_2 \\ S\dot{O}C \end{pmatrix} = \begin{pmatrix} -\frac{1}{R_1C_1} & 0 & 0 \\ 0 & -\frac{1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \\ SOC \end{pmatrix} + \begin{pmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ -\frac{\eta}{C_{rated}} \end{pmatrix} \mathrm{i} \\ U = -v_1 - v_2 + v_{OCV}(SOC) - R_0 i \end{cases} . \tag{8}$$

And after discretization, we get the matrices used in Extended Kalman Filter,

$$\begin{cases} A = \begin{bmatrix} e^{-\frac{T}{R_1C_1}} & 0 & 0 \\ 0 & e^{-\frac{T}{R_2C_2}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ B = \begin{bmatrix} R_1\left(1 - e^{-\frac{T}{R_1C_1}}\right) \\ R_2\left(1 - e^{-\frac{T}{R_2C_2}}\right) \\ -\frac{\eta T}{C_{rated}} \end{bmatrix} \\ C = \begin{bmatrix} \frac{dSOC}{dOCV} & -1 & -1 \end{bmatrix} \end{cases} . \tag{9}$$

More in general, when using equivalent circuit model, matrix B usually becomes column vector and C turns out to be row vector. This is because in the model, output end-to-end voltage is treated as the only observation variable in those equivalent circuit models and the current of the battery is considered to be the control vector.

Systolic Structure and Its Improvement

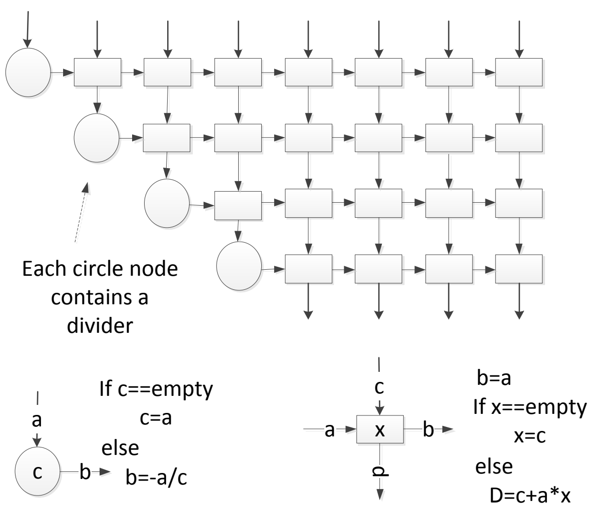

Fig. 2 Trapezoid systolic structure

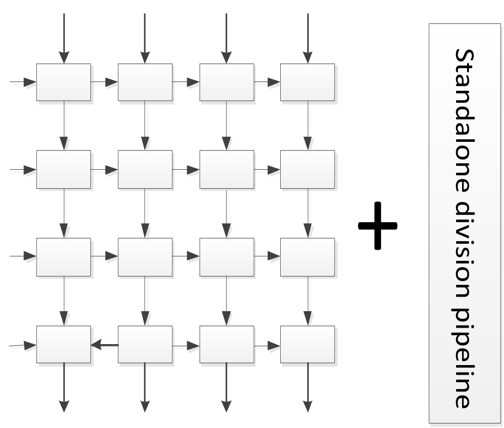

Fig. 3 Our Proposed structure

From the Eq. 3-7, we could find that the operations related to Extended Kalman Filter are mainly matrix addition, multiplication and inversion. A general-purpose matrix operation unit is proposed by Hen-Geul Yeh [5] as a trapezoid structure. It employs the Faddeev's algorithm and is capable of performing matrix multiplication, subtraction and inversion at the same time. Each circular node in Fig.2 contains one division module, and the square node contains one multiplication model and one subtraction module. However, given the practical implementation of those submodules, the optimal level of pipeline assigned to division and multiplication may differ, and not all input elements go through the same number of these element nodes. As a result, to synchronize the input data, careful consideration of delay insertion is necessary, which would lead to a higher design complexity.

On the other hand, as mentioned above, when dealing with equivalent circuit models, matrix B and C in Eq. 9 become column vector and row vector respectively, resulting in the simplicity of the matrix operation. As the matter of fact, the matrix to be inversed becomes a single element matrix and the inversion could be performed by division. Therefore, there is no need to maintain the circular node in the systolic and the extra square node could be omitted as well. A simplified structure is shown in Fig. 3 and the top module of Extended Kalman Filter is shown in Fig. 4.

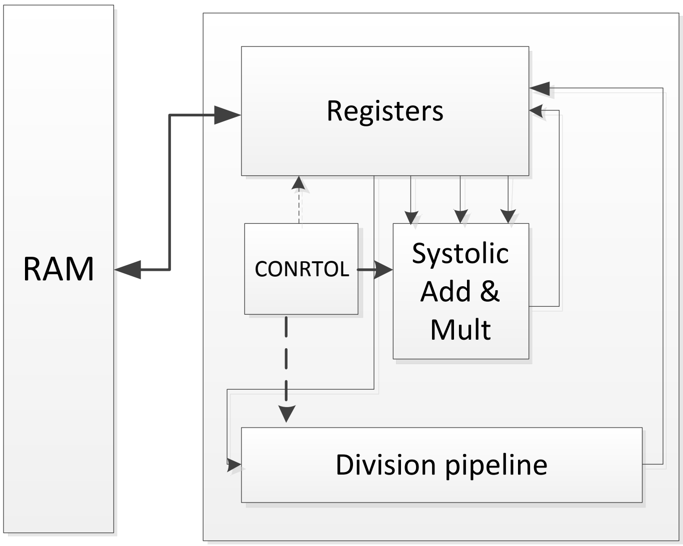

Fig. 4 Architecture of Extended Kalman Filter Module

Latency Concealing

When implementing arithmetic in fix-point, division usually takes more time to complete and is of long latency when implemented as pipeline structure. Due to the dependency of prior division results, matrix addition and multiplication unit has to stall. However, operations of different battery cells have no such dependency relationships, and could be arranged to fill the idle cycles as shown in Fig. 5.

Fig. 5 Illustration of latency concealing of matrix operation

Assessment

We implemented the Extended Kalman Filter on both Xilinx Virtex5 XC5VLX50T and Broadcom BCM2835 with ARM1176JZ-F. A comparison is listed in Table 1.

Table 1 Comparison of Performance

Platform	Broadcom BCM2835	Xilinx Virtex5
Frequency	700MHz	200Mhz
Arithmetic	Fix-point	Fix-point
Non-linear function	Lookup table	Lookup table
Compiler & compile options	GCC 4.6.3 with optimization level O3	N/A
Throughput	2.18MPoint/s	2MPoint/s

In practical applications, such as Tesla Model S, which employs 85 kW•h battery pack of 7,104 Li-ion battery cells in 16 modules, and if we are going to monitor all the cells in the pack and set a sample rate of 100Hz, the real-time requirement would be 0.71MPoint/s, so the two platform could both satisfy that demand. When integrated in a larger chip design and fabricated, our proposed structure would be of greater competitiveness, since implementation on FPGA is usually slower than ASIC. The extra gain in performance could be used to trade for power consumption.

To give an estimation of area occupied, we also synthesized our design in Design Compiler using SMIC 0.18 process. After place and route in IC compiler, the area it takes is approximately 4.1mm^2 (Pads are not included since this process unit acquires data from memory and does not directly talk to devices), and an estimated dynamic power of 85.4mW, which are usually smaller than a microprocessor would take.

Conclusion

In this paper, we discussed the equivalent circuit models of Li-ion battery and its specificity which could lead to the simplicity of systolic structure previously used, and in order to conceal the latency of division operation, rearrangement of time sequence was performed. We finally made a comparison between ARM11 platform and our design with a result of similar throughput and the estimation of area and power consumption showed an advantage.

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