The Set-Valued Run-to-Run Controller With Ellipsoid Approximation

Chang Zhang, Hao Deng and John S. Baras

Department of Electrical and Computer Engineering, University of Maryland at College Park, College Park, MD, 20742

Motivations

• Robustness. Traditional run-to-run (RtR) control methods neglect the importance of robustness due to the estimation methods they use. We want to find a new RtR controller which can identify the process model in the feasible parameter set which is insensitive to noises, therefore the controller can be robust.
• Fast convergence. The new RtR controller should be able to track the changing process quickly.
• Noises discerning ability. It can discern different noises such as shifts (step disturbances) or drifts.
Introduction of the Set-valued Method

• Due to the existence of noises, it is difficult to accurately estimate the process models, what we can be sure is a set that the model parameters reside in.
• We want to find a “good” and “safe” estimate of the process model within this set.
  – “Good” means that the estimated model is close to the underlying real model in mean square sense;
  – “Safe” means that the estimated model is insensitive to noises.
• Applications: Optimal control, image processing, system identification, and spectral estimation, etc.

Why Ellipsoid

• The main difficulties of the set-valued method lie in:
  – The excessive computational time required to calculate the feasible sets. It is hard to describe these sets with explicit formulas, because they can be very irregular.
  – Solving the optimization problem within these sets.
• It is nature to use ellipsoids to approximate these sets.
• Advantages of the ellipsoid approximation:
  – An ellipsoid is characterized by a vector center and a matrix, which is easy to calculate;
  – For convex or almost convex regions, ellipsoids can be used to obtain a satisfactory approximation;
  – Linear transformations map ellipsoids into ellipsoids.
Find the Minimum Ellipsoid

- The minimum ellipsoid bounding the feasible parameter sets is desired.
- Two main ellipsoid schemes available:
  - The Optimal Volume Ellipsoid (OVE) algorithm by M. F. Cheung, etc in 1991 [1].
  - The Optimal Bounding Ellipsoid (OBE) algorithm by Fogel and Huang in 1982 [2].
- Differences between the two ellipsoid schemes:
  - The derivation of the OVE algorithm is based on a geometrical point of view.
  - The OBE algorithm uses a recursive least square type scheme to update the ellipsoid.

Estimate the Model within the Ellipsoid

- The center of the ellipsoid is a good and safe estimate of the process model in general (Shown in the figure).
- Point B is not a good estimate, since it can easily fall out of the feasible parameter set.
- There are some other schemes to estimate the process model parameters like the worst-case approach [3].
Modify the OVE Algorithm

- The OVE algorithm can not track fast changing processes.
- The Modified OVE (MOVE) algorithm works for fast changing processes. The procedure is shown by the following figure.
- The MOVE algorithm can deal with various disturbances including large step disturbance, drifts, etc.
- We will focus on the MOVE algorithm later on.

![Bounding ellipsoid](image)

Changing process

![Estimate of the model at run k+2](image)

Run k  Run k+1  Run k+2  ...

Formulation of the MOVE Algorithm

- Given a linear-in-parameter system, we can rewrite it as:
  \[ y_k = X_k^T \theta_k + \eta_k \]  \hspace{1cm} (1)

- For example:
  \[ y_k = c_{1,k} + c_{2,k} u_{1,k} + c_{3,k} u_{2,k} + c_{4,k} u_{3,k} + c_{5,k} u_{4,k} u_{2,k} + c_{6,k} u_{3,k}^2 + \eta_k \]
  can be rewritten as the form of equation (1), with

  \[ X_k = [1, u_{1,k}, u_{2,k}, u_{3,k}, u_{1,k} u_{2,k}, u_{3,k}^2]^T, \quad \theta_k = [c_{1,k}, c_{2,k}, c_{3,k}, c_{4,k}, c_{5,k}, c_{6,k}]^T \]

- Let the noise bound be \( \gamma \), the feasible parameter set is:
  \[ F_k = \{ \theta_k : |y_k - X_k^T \theta_k| < \gamma \} \]

170
The MOVE Algorithm

- The MOVE algorithm calculates the ellipsoid $E_k$:
  \[ E_k = \min\{\text{vol}(E)\}, \text{s.t.} \; E \supseteq F_k \]
- If the disturbance exceeds certain threshold, then the ellipsoid center $\theta_k$ and size $P_k$ are updated.
- For detail of the MOVE algorithm, please refer to [4].
- An expanding matrix $F$ is added in the MOVE algorithm. It is used to track fast changing processes.

\[ P_k := P_k + F = P_k + \begin{bmatrix}
0 & 0 & \cdots & 0 \\
0 & F(2,2) & 0 & \cdots & 0 \\
0 & 0 & \ddots & 0 & \vdots \\
\vdots & \vdots & 0 & \ddots & 0 \\
0 & \cdots & \cdots & 0 & F(n,n)
\end{bmatrix} \]

Structure of a Set-valued RTR Controller with Ellipsoid Approximation
Procedures of the SVR-MOVE Controller

- The set-valued RtR controller using the MOVE algorithm will be called the SVR-MOVE controller.
- Procedures:
  - Step 1: Initialize model, cost function & recipes;
  - Step 2: Setting targets & constraints;
  - Step 3: Setting the controller parameters;
  - Step 4: Generating recipes by the process model to minimize the cost function;
  - Step 5: Measure outputs, update process model if necessary;
  - Step 6: Go to Step 4.

Parameter Selection of the SVR-MOVE Controller

- The threshold for judging drifts and shifts. It is usually equal to 3 times of the estimate of the noise variance.
- The expanding matrix $F$. The most important parameter of $F$ is $F(1, 1)$. It is related to the drift disturbance directly.
- The noise bound $\gamma$. It should be set a small value. Usually the range $[0.01-0.05]$ is good.
Mean Square Errors (MSEs) with Respect to F(1,1)s

- The figures are based on simulation of low pressure chemical vapor deposition (LPCVD) furnace process.
- Two targets $R_1$ and $R_2$ are controlled.
- No other noises.
- Small F(1,1)s will have large MSEs.

MSEs When F(1,1)s are Fixed, White Noises are Added

$F_{1(1,1)}=F_{2(1,1)}=10^{-6}$  $F_{1(1,1)}=F_{2(1,1)}=0.05$
Comments about Value Selection of the Expanding Matrix F

- Trade-off in the selection of values of $F(1,1)$.
  - The larger the $F(1,1)$, the stronger the ability to compensate the drift disturbance.
  - However, since $F$ expands the ellipsoid at each run, it increases the size of the ellipsoid, which affects the estimation quality.
- It is safe to let the other parameters $F(i,i)$, $i=2,\ldots$, in $F$ to be infinite small compared to $F(1,1)$, since they are related to higher order terms.
- When no drifts exist, it is nature to let $F=0$.

Simulation 1. An Almost Linear Photoresist Process I

The process model [5] is:

$$T = -13814 + \frac{2.54 \cdot 10^6}{\sqrt{SPS}} + \frac{1.95 \cdot 10^7}{BTE \sqrt{SPS}} - 3.78 BTI - 0.28 SPT - \frac{6.16 \cdot 10^7}{SPS} + d \cdot k + w$$

- Inputs: SPS is the spin speed, SPT the spin time, BTI the baking time, and BTE the baking temperature. They are constrained to: $4500 < SPS < 4700$; $15 < SPT < 90$; $105 < BTE < 135$; $20 < BTI < 100$ respectively.
- Output: $T$, the resist thickness.
- Noises: $d$ is equal to -0.3, $w$ is Gaussian with variance 9.
- $K$: Run number
Photoresist Process I Controlled by the SVR-MOVE Controller

- The target is 12373.621.
- The three straight dashed lines in the figure are the +3σ, target and -3σ lines respectively.
- The uncontrolled process diverges
- The controlled process stays in the 3σ region satisfactorily.

Photoresist Process I without White Noises

- Only drift noise exists.
- The uncontrolled process diverges as a straight line.
- The controlled stays very close to the target.
- It proves the effectiveness of the controller to deal with drift.
Simulation 2. A full Second-order Nonlinear Photoresist Process II

The process model [5] is:

\[
R = 1344 - 0.046SPS + 0.32SPT - 0.17BTE + 0.023BIT - 4.34 \times 10^3 \cdot SPS \cdot SPT
+ 5.19 \times 10^4 \cdot SPS \cdot BTE - 1.07 \times 10^5 \cdot SPT \cdot BTE + 5.15 \times 10^4 \cdot (SPS)^2
- 4.11 \times 10^4 \cdot SPT \cdot BIT + d \cdot k + w
\]

- Inputs: Same as in photoresist process I.
- Output: R, the reflectance in percentage.
- Noises: Same as in photoresist process I.
- The target is fixed at 39.4967%.

Photoresist Process II Controlled by the SVR-MOVE Controller

- The uncontrolled process diverges.
- Most of the time the controlled process stays in the ±3σ area.
- It shows the ability of the SVR-MOVE controller to control non-linear processes.
Simulation 3. Photoresist Process I with Large Model Error

- The process model is:

\[ y_k = -13814 + \frac{2.54 \cdot 10^4}{\sqrt{SPS}} + \frac{1.95 \cdot 10^7}{BTE \sqrt{SPS}} - 3.78 BTI - 0.28 SPT - \frac{6.16 \cdot 10^7}{SPS} + d \cdot k + v_2 + v_3 + v_4 \times v_4 \]

- Inputs: Same as before.
- Output: \( y_k \).
- Noises.
  - \( d \) is defined the same as before.
  - \( v_2 \) is the product of two Gaussian random variables.
  - \( v_3 \) is a random variable with uniform distribution.
  - \( v_4 \) is a Gaussian variable too.

Photoresist Process I with Large Model Error

- There is a large model error at the beginning.
- A large step disturbance occurs at run 30.
- The output still stays close to the target.
- It shows the ability of the controller to deal with large model errors, large disturbance and multiple noises.
Summary

- The set-valued RtR controller with ellipsoid approximation gives a safe and good estimate of the process model in a minimum volume ellipsoid, which bounds the feasible parameter set.
- The SVR-MOVE controller is easily applicable to various semiconductor processes.
- The SVR-MOVE controller is robust, and it can deal with large model errors, large disturbance and multiple noises.
- In the parameter selection of the SVR-MOVE controller, further theoretical analysis is still needed.

References