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OBSERVER DESIGN FOR CONTROL OF THE SPRAYFORMING OF TOOLING

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Abstract: This paper describes the design of an observer for use in a distributed parameter control system which is used to regulate the surface temperature profile of a tool or die being manufactured by sprayforming. The observer design is complicated by the time varying obscuration of the surface from the sensor caused by the equipment performing the spraying. Three potential observer designs are presented and compared.

Keywords: Manufacturing processes, observers, temperature control, distributed parameter systems

1. INTRODUCTION

Tools and dies are required for many manufacturing processes including the stamping of body panels in the automotive industry, the laying up of aerofoil sections in the aerospace industry and injection moulding in the plastics industry. The market for the supply of tools and dies is worth in excess of $10billion per annum. The conventional method for producing tooling is to use a CNC machine to mill out the required shape from a metal block, but this can be a lengthy process, particularly for large pieces where the metal block has to be cast before the milling can start. A recently developed alternative process involves creating a ceramic substrate whose shape is the inverse of the required tool. Molten metal is then sprayed onto the surface of the ceramic to build up a metal shell (referred to as the sprayform) that accurately reproduces the topography of the ceramic (Newbery *et al.*, 1998). Compared to the conventional “subtractive" process where metal is removed, the additive spray process has the potential to be much quicker, giving significant advantages for flexible manufacturing.

The main technical difficulty with the sprayforming process is that the sprayed molten metal contracts as it cools. In order for the sprayed shell to be used in tooling applications, it is essential that the sprayform satisfies strict tolerances on the dimensional accuracy of the shell. An important feature of the process is that it relies on the metal droplets undergoing prescribed phase transformations as they cool after being deposited on the surface of the sprayform (Jordan and Roche, 1999). Ensuring that the metal undergoes an expansive phase transformation from austenite, which has a face centered cubic structure, to martensite, which has a body centered tetragonal structure (Honeycombe and Bhadeshia, 1995), offsets the natural contraction of the metal as it cools. This allows the dimensional accuracy of the sprayform to be maintained. In order that the required transformations occur, accurate regulation of the thermal history of the sprayed material is necessary. One method of regulating the thermal history is to control the temperature of the surface, which ensures that the cooling curve for the deposited material passes through a given temperature at a specific time after deposition. This paper describes the design of a state observer used in the implementation of a system for regulating the temperature profile of the sprayform surface during spraying.

2. DESCRIPTION OF EQUIPMENT

A schematic of the sprayforming equipment is shown in figure 1.

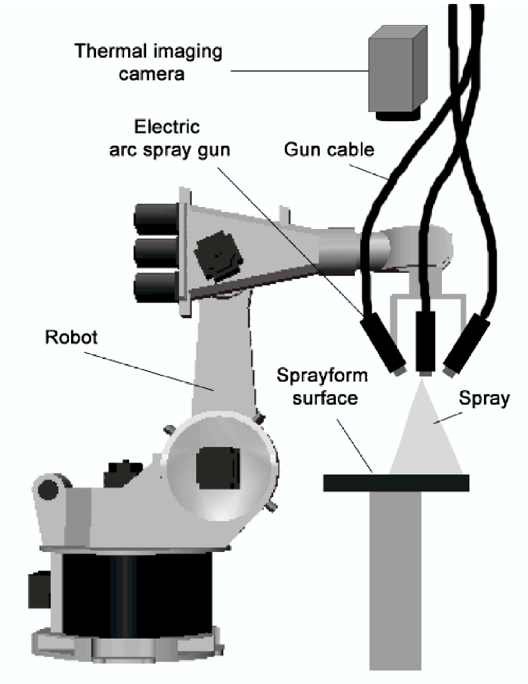

Fig. 1. Schematic of sprayform tooling equipment

The spray forming process deposits molten metal from a cluster of four Sulzer Metco SmartArc electric arc spray guns onto a ceramic substrate to form a metal shell that accurately reproduces the topography of the ceramic. The molten metal is produced by direct current arcing between two oppositely charged wires made of 0.8wt%C steel. The arcing causes the wire tips to melt and a high-pressure nitrogen gas stream continuously strips molten material from the arc, atomising it into a spray of droplets. The gas stream carries the droplets to the surface of the object where they are deposited. Wire is continuously fed to the arc guns to maintain the flow of sprayed metal and the amount of metal that is deposited can be adjusted by changing the feed rate of the wire.

The droplet spray from the guns is scanned over the surface of the ceramic substrate by a 6-axis industrial robot in a pre-determined, repetitive manner, referred to as the “path plan". The temperature profile on the surface is recorded by a thermal imaging camera, positioned directly above the sprayform.

The equipment is housed in a booth and a fan blows a stream of air (at a velocity of $4ms^{-1}$) across the surface of the sprayform to remove dust, fumes and splashed material from the spray that does not adhere to the surface.

3. DESCRIPTION OF CONTROL SYSTEM

The surface temperature profile of the sprayform is controlled using a distributed parameter control system (Jones *et al.*, 2002). There is only a single actuation variable, the wire feed rate of the arc spray guns, but the location of the actuator changes as the robot moves the guns over the surface. This is an example of mobile control (Butkovskiy and Pustylnikov, 1987). The sensor for the control system is the thermal imaging camera which provides information about the surface temperature profile during the spraying process.

The control design is based upon a partial differential equation (PDE) model of the heating effect of the spray guns as they are tracked across the surface of the sprayform. An additional complication is that the nitrogen gas used to propel the molten droplets acts as a source of cooling which must be included in the thermal model. The resulting PDE is

$$\begin{aligned}\rho c z(t)\frac{\partial\theta(x,y,t)}{\partial t} &= \\ &Kz(t)\nabla^2\theta(x,y,t) - H_a\theta(x,y,t) \\ &+f(x,y,t)u(t)[\theta_g-\theta] + g(x,y,t)[\theta_n-\theta]\end{aligned} \tag{1}$$

where,

ρ = density of sprayform (Kg m^{-3})
c = specific heat capacity of sprayform (J Kg^{-1} K^{-1})
$z(t)$ = thickness of sprayform (m)
$\theta(x,y,t)$ = temperature of sprayform surface (K)
H_a = heat transfer coefficient from sprayform to air (W m^{-2} K^{-1})
$f(x,y,t)$ = heat flux footprint of guns (J kg m^{-2})
$u(t)$ = wire feed rate to guns (kg s^{-1})
θ_g = temperature of sprayed droplets from guns (K)
$g(x,y,t)$ = nitrogen cooling footprint from guns (J kg m^{-2})
θ_n = temperature of nitrogen from guns (K)

A discrete time finite dimensional state space model can be derived from the PDE (Pathirana *et al.*, 2002)

$$\mathbf{q_{k+1}} = \mathbf{A}\mathbf{q_k} + \mathbf{B_k}u_k + \mathbf{D_k} + \mathbf{W_k} \tag{2}$$
$$\mathbf{y_k} = \mathbf{C_k}\mathbf{q_k} + \mathbf{V_k} \tag{3}$$

where $\mathbf{B_k}$ represents the time varying heat input from guns, u_k is the wire feed rate to the guns, $\mathbf{D_k}$ represents the time varying cooling from the guns, $\mathbf{W_k}$ is the state noise and $\mathbf{V_k}$ is the measurement noise.

An optimal time varying control law can be designed for this state space system (Pathirana *et al.*, 2002) which takes the general form,

$$u_k = -\mathbf{K_k}\mathbf{q_k} \tag{4}$$

where $\mathbf{K_k}$ is the optimal controller gain matrix.

The control law is implemented in C++ on a PC. The thermal data from the camera enters the PC through a framegrabber card. The actuation signals are sent to the arc spray gun controllers via a digital to analogue converter card in the PC.

For a sprayform of dimension $300mm$ by $300mm$ and thickness $5mm$ the time constant of the fastest controllable mode is of the order 60s. However, the robot typically moves at $0.2ms^{-1}$, so it will move from one side of the sprayform to the other in $1.5s$. This means that the sample time is chosen not because of the constraint of the thermal dynamics of the system, but instead by the rate of change of the B_k and D_k terms. For this reason the sample time for the system is chosen to be 0.1s.

4. MOTIVATION FOR STATE OBSERVER

The controller relies on knowledge of the current system states, $\mathbf{q_k}$. The system states cannot be measured directly so an observer is required to provide an estimate of the state vector, $\hat{\mathbf{q}}_\mathbf{k}$. The observer uses the information from the thermal images together with the state space model of the system to generate the state estimate.

The design of the observer is complicated by the fact that the camera cannot see all of the surface. Areas of each image contain varying amounts of invalid data because the robot, guns and gun cables obscure the camera's view of the surface (Jones and Duncan, 2001). The obscured areas in the image cannot be predicted because although the robot and guns follow a predetermined path, the cables connected to the guns are free to lie in any orientation. There are further invalid regions around these obscured areas caused by out of focus blurring as the objects causing the obscuration are outside the focal plane of the camera. The obscured and blurred pixels can be removed using a pruning filter algorithm (Jones and Duncan, 2001) to leave a valid measurement vector, $\mathbf{y_k^v}$. This valid measurement vector has variable and unpredictable length dependent on the number of valid pixels in a given image. The measurement equation, (3), becomes time varying

$$\mathbf{y_k^v} = \mathbf{C_k^v q_k} + \mathbf{V_k^v} \tag{5}$$

where $\mathbf{C_k^v}$ and $\mathbf{V_k^v}$ are formed by extracting the rows from $\mathbf{C_k}$ and $\mathbf{V_k}$ which correspond to the valid pixels remaining in $\mathbf{y_k^v}$.

5. STATE OBSERVER DESIGN

Assuming the state and measurement noise models to be independent zero mean white sequences with known, constant covariance matrices then $E[\mathbf{W_k W_{k'}^T}] = \mathbf{Q}\delta(k-k')$ and $E[\mathbf{V_k V_{k'}^T}] = \mathbf{R}\delta(k-k')$.

Although the full measurement noise covariance matrix is constant, the actual measurement noise covariance matrix varies with the number and position of the valid pixels in the measurement vector. The result is a time varying covariance matrix, $\mathbf{R_k^v}$.

The linear minimum variance of error sequential state estimation algorithm with these noise models is the Kalman filter (Sage and Melsa, 1971).

Three potential designs for Kalman filter based observers were investigated.

5.1 *Design 1*

The first method examined is the use of the full optimal time varying Kalman filter. Using the standard equations from (Gelb, 1974) or (Gustafsson, 2000) for the system described gives the algorithm,

Online computation per sample time

$$\mathbf{L_k} = \mathbf{P_{k|k-1} C_k^{v^T}}[\mathbf{C_k^v P_{k|k-1} C_k^{v^T}} + \mathbf{R_k^v}]^{-1} \tag{6}$$

$$\hat{\mathbf{q}}_\mathbf{k|k} = \hat{\mathbf{q}}_\mathbf{k|k-1} + \mathbf{L_k}[\mathbf{y_k^v} - \mathbf{C_k^v}\hat{\mathbf{q}}_\mathbf{k|k-1}] \tag{7}$$

$$\mathbf{P_{k|k}} = [\mathbf{I} - \mathbf{L_k C_k^v}]\mathbf{P_{k|k-1}} \tag{8}$$

$$\hat{\mathbf{q}}_\mathbf{k+1|k} = \mathbf{A}\hat{\mathbf{q}}_\mathbf{k|k} + \mathbf{B_k}u_k + \mathbf{D_k} \tag{9}$$

$$\mathbf{P_{k+1|k}} = \mathbf{A P_{k|k} A^T} + \mathbf{Q} \tag{10}$$

where $\mathbf{L_k}$ is the Kalman gain matrix.

This method uses all of the available measurement data optimally to create an estimate of the state vector.

The Kalman gain update equation involves the inversion of a $N_k \times N_k$ matrix, where N_k is the number of valid pixels at sample time k. In this implementation the thermal images contain 17689 pixels, so $0 \leq N_k \leq 17689$. Unless the number of valid pixels is very small for all sample times, this computationally intensive task is infeasible given the constraint of the desired sample time, 0.1s.

5.2 *Design 2*

One method of reducing the computational burden of the Kalman filter algorithm is to settle for a sub-optimal time invariant Kalman gain obtained from,

$$\mathbf{L} = \mathbf{P C^T}[\mathbf{C P C^T} + \mathbf{R}]^{-1} \tag{11}$$

where $\mathbf{P}$ is the state error covariance given by the solution to the discrete algebraic Ricatti equation (Middleton and Goodwin, 1990)

$$\begin{aligned}&\mathbf{A P A^T} - \mathbf{P} - \\ &\quad \mathbf{A P C^T}(\mathbf{C P C^T} + \mathbf{R})^{-1}\mathbf{C P A^T} + \mathbf{Q} = \mathbf{0}\end{aligned} \tag{12}$$

Online computation per sample time

$$\hat{\mathbf{q}}_\mathbf{k|k} = \hat{\mathbf{q}}_\mathbf{k|k-1} + \mathbf{L_k^v}[\mathbf{y_k^v} - \mathbf{C_k^v}\hat{\mathbf{q}}_\mathbf{k|k-1}] \tag{13}$$

$$\hat{\mathbf{q}}_\mathbf{k+1|k} = \mathbf{A}\hat{\mathbf{q}}_\mathbf{k|k} + \mathbf{B_k}u_k + \mathbf{D_k} \tag{14}$$

A significant amount of the online computation has been taken offline at the expense of the loss of optimality. This allows the implementation to be run within the constraint of the 0.1s sample time. The Kalman gain is now optimal only for instances where the measurement vector is complete. If the measurement vector is incomplete, as is nearly always the case, then the Kalman gain will not be optimal, causing inaccurate state estimation.

5.3 *Design 3*

A further method of reducing the computational burden, without sacrificing optimality, is to use sequential processing of the pixel information in the valid measurement vector (Gustafsson, 2000). If all of the pixels in the valid measurement vector are used then this method is equivalent to design 1, but with a superior computational efficiency. A further advantage is that if not all of the valid measurement vector can be used in the sample time then the iteration can be stopped with only a partial loss of information. The equations are,

Online computation repeated for each pixel used from measurement vector each sample time

$$\mathbf{L_p} = \mathbf{P_{p|p-1}} \mathbf{C_p^T} [\mathbf{C_p} \mathbf{P_{p|p-1}} \mathbf{C_p^T} + R_p]^{-1} \quad (15)$$

$$\hat{\mathbf{q}}_{\mathbf{p|p}} = \hat{\mathbf{q}}_{\mathbf{p|p-1}} + \mathbf{L_p}[y_p - \mathbf{C_p} \hat{\mathbf{q}}_{\mathbf{p|p-1}}] \quad (16)$$

$$\mathbf{P_{p|p}} = [\mathbf{I} - \mathbf{L_p} \mathbf{C_p}] \mathbf{P_{p|p-1}} \quad (17)$$

where y_p denotes a single pixel measurement at a location in the image determined by p, $\mathbf{C_p}$ is the row of $\mathbf{C}$ corresponding to p.

Online computation performed once per sample time

$$\hat{\mathbf{q}}_{\mathbf{k+1|k}} = \mathbf{A} \hat{\mathbf{q}}_{\mathbf{k|k}} + \mathbf{B_k} u_k + \mathbf{D_k} \quad (18)$$

$$\mathbf{P_{k+1|k}} = \mathbf{A} \mathbf{P_{k|k}} \mathbf{A^T} + \mathbf{Q} \quad (19)$$

If all of the valid measurement vector is used then the $N_k \times N_k$ matrix inversion of design 1 has been replaced with N_k scalar inversions.

If all of the pixels used in the measurement update are positioned near to the node of a given state, then that state is estimated poorly. Therefore, if the sample time constraint dictates that only part of the measurement vector can be processed, the pixels should be used in a random order for the iterative measurement update. This increases the accuracy of the state vector estimate.

This observer design is the optimal use of the measurement information given the processing time constraint.

6. TESTING AND RESULTS

To test the observer designs Matlab simulations of them were developed. The simulation for design 1 could not be used because the size of the matrices caused Matlab to run out of memory. The other two designs were simulated with one complete measurement update cycle. The state estimate and state error covariance extrapolations were not performed as they are equivalent for all the methods. Both observers used a 25 element state vector and defined the noise covariance matrices as,

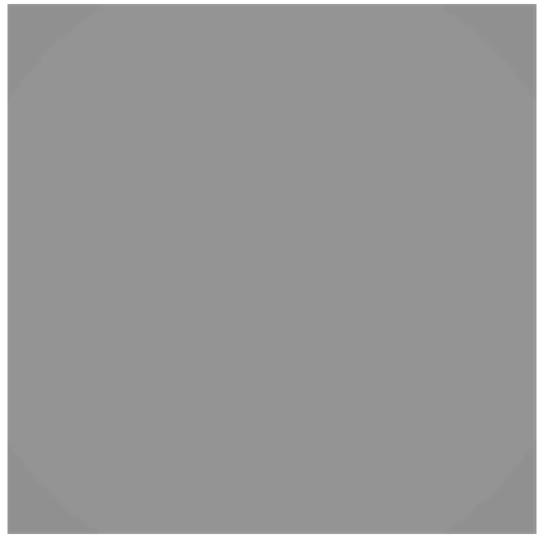

Fig. 2. Image representing initial state vector, a constant temperature surface at 240^oC

Fig. 3. Measurement image, left half at 215^oC and right half at 265^oC

$$\mathbf{Q} = 100\mathbf{I}$$

$$\mathbf{R} = \mathbf{I}$$

For the first test the observers were started with an initial state vector that described a flat temperature profile at 240^oC (figure 2) and were then used to update the state vector using a full measurement image which had the left half at 215^oC and the right half at 265^oC (figure 3). Both design 2 and design 3 matched the final state estimate to the measurement state with this much information. This was expected because designs 2 and 3 are equivalent when the measurement vector is full.

Fig. 4. Obscured measurement image with only 7% of pixels valid, left half at 215^oC and right half at 265^oC

Fig. 5. Image representing the result of the obscured measurement update for observer design 2

For the second test the observers were started with the same initial state vector (figure 2) but were used to update the state vector using only 7% of the pixels from the previous full measurement image (figure 4). This was done to model the effect of invalid pixels in the measurement vector. The results in figures 5 and 6 show that the optimal observer (design 3) gave better matching of the final state estimate to the measurement state than the sub-optimal observer (design 2).

7. CONCLUSION

This paper has described the sprayforming process used for manufacturing tools and dies. For the process to create dimensionally accurate parts the temperature of the surface during spraying must be controlled. This is done using a distributed parameter control system which uses a thermal imaging camera as its sensor and

Fig. 6. Image representing the result of the obscured measurement update for observer design 3

actuates the rate at which wire is fed to the arc spray guns.

The system's state vector cannot be measured directly so an observer is required. The observer design is complicated by the fact that the movement of the robot, spray guns and cables between the camera and the surface of the sprayform causes the thermal images to contain variable amounts and positions of invalid pixels. The observer is further constrained by the sample time. When the valid pixels are extracted the result is a time varying measurement equation. Three observer designs were investigated to solve the problem, an optimal time varying Kalman filter, a sub-optimal fixed gain Kalman filter and an optimal sequential measurement update Kalman filter. The observer designs were tested and it was found that the sequential measurement update method was the best given the constraints of accuracy and computation time.

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