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Generalized Likelihood Ratio Detector for Aluminum Alloy Defect Detection

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Abstract: This study investigates the issue of automated defect inspection for aluminum alloy and proposes a new defect detection method based on a maneuver detector, i.e., the Generalized Likelihood Ratio (GLR) detector. In this method, the intensity of the defect-free aluminum alloy image is supposed to be Gaussian distributed, while the defect intensity usually follows other statistical distributions. In terms of this different statistic property between the normal and abnormal area in an aluminum alloy image, an unknown input is employed to model the change of intensity distribution. Under the assumptions, defect inspection problem is approximated as the detection of abrupt changes in stochastic dynamical system. Kalman filters are used to filter the image and the measurement residuals are estimated. Defects are located by statistical tests on measurement innovations using the Generalized Likelihood Ratio (GLR) test based maneuver detector. Experimental results exhibit effective defect detection for aluminum alloy with low false alarm.

Key words: Kalman filter;generalized likelihood ratio test, maximum likelihood estimation, defect detection

INTRODUCTION

The intelligent visual inspection systems have been widely employed to ensure the high quality of products over the past decades. Automated visual defect detection in many product lines, such as web materials and metal artifacts, are in increasing demand. The objective of defect detection is to separate its inspection image into regions of distinct statistical behavior. Defect detection in the web materials, such as in metals and textured materials, usually relies upon identification of regions that differ from the normal background and classify the image into defect and defect-free areas.

According to the characteristics of defects in web materials, numerous visual approaches have been proposed to address the problem of defect detection. Defect detection using gray level thresholding like bi-level thresholding (Macaire and Postaire, 1993) is one of the simplest methods. These detection techniques are easy to be implemented and able to detect high contrast defects, failing to locate defects without altering the mean gray level in defect-free areas. Defect detection techniques using edge detection such as Sobel edge (Conci and Proenca, 2000) take advantage of gray level transitions in an image to detect failures, which can represent lines, edges, point defects etc. Another defect detection method is using the templates or models of defect, which measures the similarity between images and multiple templates for defect declaration. This method is difficult to select correct templates and window sizes (Amano, 2006). The earlier mentioned low-level statistical approaches will be invalid in some conditions, for instance, edge detection will break down when defects appear as subtle intensity transitions. Defect detection using frequency and spatial-frequency domain features in uniform materials have been reported in the literature.

Gabor filter Bodnarova *et al.* (2002) and Wavelet transform (Tsai and Hsiao, 2001) based detection approaches are efficient to find detects for web fabrics with stable repetition of textures, since it is easier to find defects in frequency domain. In addition, a novel method is proposed in (Zhai *et al.*, 2009) that applying the target maneuver onset detection algorithms to defect inspection of aluminum foil. This detection approach assumed that the intensity of normal aluminum foil images is Gaussian distributed and defects make the intensity taking on a distribution other than Gaussian. Defects can be determined, once the probability distribution changes are detected by chi-square test based maneuver onset detector.

In this study, we focus on defect detection for Aluminum Alloy sometimes ruined by scratch. Intensity of the aluminum alloy image is assumed as 1-D random variable, which normally obeys Gaussian distribution, namely, intensity of the defect-free pixels is Gaussian distributed different from the defect pixels with other distributions. According to this statistical feature, we employ the Kalman filter with random walk model to estimate the measure innovations (Bar-Shalom *et al.*, 2001; Li, Jilkov, 2002). Abrupt changes in the measure innovations can be used to locate defects in the inspection image, which constitute a measure of the

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maneuver's effect on the system residuals. In real time, the measure innovations are monitored and estimate the maneuver onset time and magnitude using the maximum likelihood. Finally, a binary decision that whether there is a defect or not is made by the GLR detector (Willsky and Jones, 1974, 1976) .

FORMULATIONS OF THE DEFECT DETECTION PROBLEM

Firstly, we consider the following discrete-time linear dynamical system. The dynamical model and measurement model are linear Gaussian, i.e.:

$$x_{k+1} = F_k x_k + u_k + w_k \tag{1}$$

$$z_k = H_k x_k + v_k \tag{2}$$

$$x_{k+1} = F_k x_k + w_k \tag{3}$$

where x_k, u_k, z_k are the target state (i.e., the intensity estimate of a pixel in the inspection image), maneuver control input and the measurement (i.e., the observed intensity of a pixel in the inspection image) at time k, respectively. w_k and v_k are zero-mean, independent, white Gaussian sequences with covariances Q_k and R_k, respectively and the initial state x_0 is independent of w_k and v_k. (1) and (3) are maneuvering model and nonmaneuvering model without input respectively. Since the intensity of the defect-free pixels in aluminum alloy image is Gaussian distributed, we use a random walk model $x_{k+1} \sim N(x_k, \Sigma)$ with fixed Gaussian white noise variance in the one-dimensional state space to describe the dynamic model in this study.

It is assumed that system component failures or abrupt dynamical changes will lead to jumps in some state derivatives. Thus by monitoring jumps in state variables and some of their derivatives, we should be able to detect a dynamics change such as a maneuver control input, measurement residuals and increase in the noise covariance. In this formulation, the maneuver control input u_k is used to model abrupt dynamical changes. If the target is not maneuvering at time k then $u_k = 0$, while $u_k \neq 0$ if the target is maneuvering. In terms of the principles, we can also apply the maneuver detection method to detect defects in an image. The defect causing distribution change in the image intensity can be modeled to be target maneuver and be detected by the maneuver onset detector.

GLR TEST BASED MANEUVER DETECTOR

Denote u as the input responsible for maneuver and denote θ as the maneuver onset time. Such that $u_k = 0$ for $\kappa<\theta$ and $u_\kappa \neq 0$ for $\kappa \geq \theta$ over the time window [k-s, k), where k is the current time step and s is the time window width. Two different hypotheses are designed as follow:

$$H_0: u_\kappa = 0 \text{ for all } \kappa \in [k-s, k) \tag{4}$$

$$H_1(u,n): u_\theta = u_{\theta+1} = \cdots = u_{k-1} = u \neq 0 \text{ for some } \theta \in [k-s, k) \tag{5}$$

where, the input level u and the maneuver onset time θ are regarded as unknown parameters.

Estimate the measurement residuals and input using kalman filters (KFS): Two Kfs are considered (Bar-Shalom *et al.*, 2001), namely actual one based on nonmaneuvering model (3) under H_0 and a hypothetical one based on maneuvering model (1) under H_1. Assume that a KF based on H_0 has been implemented (for all k):

$$\hat{x}_{k+1|k} = F_k \hat{x}_{k|k} \tag{6}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + W_k \nu_k^* \tag{7}$$

where, ν_k^* is the measurement residual with covariance:

$$S_k = R_k + H_k P_{k|k-1} H_k^T \tag{8}$$

Here $\hat{x}_{j+1|j}$ is the predicted state at time j+1, $\hat{x}_{j|j}$ is the updated state at time j, W_k is the filter gain and $P_{i|j}$ is the associated state covariance. They can be computed from the following equations:

$$W_k = P_{k|k-1} H_k' S_k^{-1} \tag{9}$$

$$P_{k+1|k} = F_k P_{k|k} F_k' + Q_k \tag{10}$$

$$P_{k|k} = P_{k|k-1} - W_k S_k W_k' \tag{11}$$

Similarly, the hypothetical KF is implemented under H_1. Then an expression for the measurement residual ν_k involving θ and u can be derived. Under the assumptions of linearity, the previous hypotheses can be equivalently written as:

$$H_0: \nu_k = \nu_k^* \tag{12}$$

$$H_1(u,\theta):\ \nu_k = \tilde{G}_{k,\theta}u + \nu_k^* \tag{13}$$

where, $\tilde{G}_{k,\theta}u = G_{k,\theta}u$ with:

$$G_{k,\theta} = \sum_{i=\theta}^{k-1} L_{k,i+1}$$

if k>0 and $\tilde{G}_{k,\theta}u = 0$ otherwise. If k>i, then $L_{k,\,i+1}$ satisfies:

$$L_{k,i} = L_{k-1}L_{k-2}\cdots L_i \tag{14}$$

$$L_{j,j} = I \tag{15}$$

$$L_j = F_j(I - W_jH_j) \tag{16}$$

and if k>i, $L_{k\,i} = 0$.

Under the linear-Gaussian assumption of the KF, the input levels and maneuver onset time can be estimated by the Maximum Likelihood Estimator (MLE) or Least Square Estimator (LSE) (Bar-Shalom *et al*., 2001):

$$\hat{u}_k = \Sigma_k e_k \tag{17}$$

$$\Sigma_k^{-1} = \sum_{i=\theta+1}^{k} (H_iG_{i,\theta})'S_i^{-1}(H_iG_{i,\theta}) \tag{18}$$

$$e_k = \sum_{i=\theta+1}^{k} (H_iG_{i,\theta})'S_i^{-1}\nu_i \tag{19}$$

Maneuver detection using generalized likelihood ratio (GLR) test: If a threshold value λ and the maximum likelihood estimates:

$$(\hat{u},\hat{\theta}) = \arg\max_{(u,\theta)} f(\nu_{k-s},\cdots,\nu_k \mid H_1,u,\theta) \tag{20}$$

are given, the generalized likelihood ratio(GLR) is defined by:

$$\Lambda(\hat{u},\hat{\theta}) = \frac{f(\nu_{k-s},\cdots,\nu_k \mid H_1,\hat{\theta},\hat{u})}{f(\nu_{k-s},\cdots,\nu_k \mid H_0)} \tag{21}$$

Since the conditional densities are Gaussian, (21) can be simplified as:

$$J(\hat{u},\hat{\theta}) = 2\ln\Lambda(\hat{u},\hat{\theta}) = \sum_{\kappa=k-s}^{k} \nu_\kappa{}'S^{-1}\nu_\kappa - \sum_{\kappa=k-s}^{k} [\nu_\kappa - G_{\kappa,\hat{\theta}}\hat{u}_\kappa]'S_\kappa^{-1}[\nu_\kappa - G_{\kappa,\hat{\theta}}\hat{u}_\kappa] \tag{22}$$

To select either H_0 or H_1, the decision rule is as follow:

$$J(\hat{u},\hat{\theta}) \underset{H_0}{\overset{H_1}{\gtrless}} \lambda \tag{23}$$

where, the preset threshold λ is determined by the desired decision error rates. If the GLR test statistic $J(\hat{u},\hat{\theta})$ exceeds the preset threshold, a maneuver is declared. According to the above principles, maneuver detection technique based on GLR test is summarized as follow (Willsky and Jones, 1974, 1976):

Step 1: Input estimation. Under the linear-Gaussian assumption, for each $\theta = k-s,\cdots,k-1$, compute $\hat{u}_k$ according to (17)~(19)

Step 2: Onset time estimation. According to formulas (17)~(19) and step1, compute by the MLE method:

$$\hat{\theta} = \underset{k-s\le\Theta<k}{\arg\operatorname{mex}}\, \hat{u}(\theta)'[\Sigma(\theta)]^{-1}\hat{u}(\theta) = \underset{k-s\le\Theta<k}{\arg\operatorname{mex}}\, e(\theta)'\Sigma(\theta)e(\theta)$$

Step 3: Maneuver detection. A maneuver is declared if .

IMPLEMENTATION OF GLR DETECTOR BASED DEFECT DETECTION

Implement details: In our product line, the aluminum alloy passes the camera at 1 meter per second or so. The gray level image of aluminum alloy with M rows and N columns is obtained after each equal time span. Statistics from a large number of aluminum alloy images indicate that intensity of defect-free areas defined by 1-D random variable normally obeys Gaussian distribution, which is different from the defects of other distributions. In terms of this statistical property, we take detecting defects for maneuver onset detection. Here the intensity of each column (row) constitutes a time sequence which is Gaussian distributed and its temporal evolution is molded by random walk model. The Kalman filter (KF) with random walk model is used to filter the column from up to down, where measurement matrix is H = 1, the state matrix is F = 1 and the covariance R should be set a bit larger than the variance of the intensity of the image. Each column is filtered by one KF filter. The maneuver position, i.e., the defect position, is detected by the GLR based maneuver detector. The detecting result is stored in the

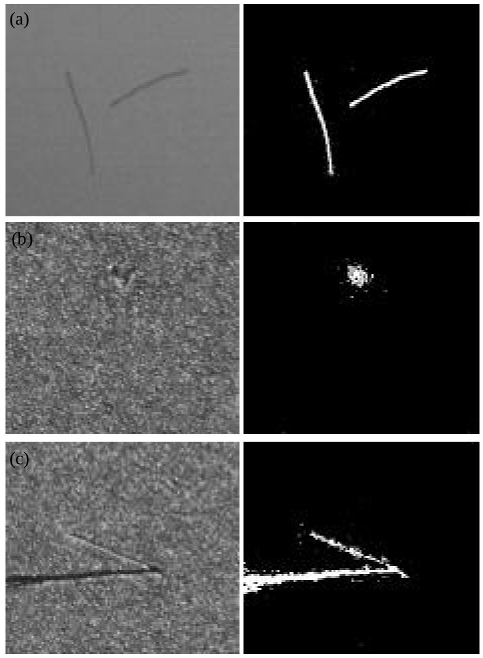

Fig. 1(a-b): Sample defect images and their detection results

defect mask Θ, which is a M×N matrix. If the pixel (I, j) in an image is a defect point by GLR detector, then update the corresponding element of Θ with value 1 otherwise with value 0.

The Kalman filter can be initialized as follows. Set initial state vector x (0) = x_0, where x_0 is the average intensity of the image. An alternative is to set x_0 as the intensity of the pixel where the filter starts to perform. Set the initial state covariance $P_{0|0}$ = R.

CHOOSING METHOD FOR DECISION THRESHOLD

In order to obtain an accurate decision threshold λ making the performance of defect detection better, we design a selection method for decision threshold λ in terms of a theoretical value and a heuristic choosing computation. Firstly, the theoretical value $\bar{\lambda}$, as shown in (Willsky and Jones, 1974), $\bar{\lambda}$ can be determined by the probability of false alarms P_F and the probability of miss alarms P_D. Then compare the performance of the GLR defect detector using n threshold value candidates:

$$\{\lambda'_i\}_{i=1}^{n}$$

which are generated by changing $\bar{\lambda}$ with a small scale. At last, choose the candidate λ'_i making the performance score highest as the final threshold value λ.

EXPERIMENTAL RESULTS

The proposed approach is tested using the defect image database, which contains multiple kinds of defects in aluminum alloy with or without plastic film cover. Some results using this defect detection method are shown in Fig. 1. The left images of Fig.1 show original images, while the right images show detection results of GLR detector with white pixels indicating their position estimates. It is shown that the proposed GLR detector based defect detection method is able to accurately locate defect position for aluminum alloy images with much less false alarms.

To evaluate the change in performance when applying GLR maneuver detector to defect detection, we compare defect detection approach based on GLR detector (DET_GLR) with defect detectors using chi-square maneuver detector (DET_CHI) and thresholding (DET_THR). Figure 2 shows comparison result of the three methods with Fig. 2a exhibiting the original inspection images and Fig .2b, c, d exhibiting detects of different defect detection methods. Comparing defect detects in Fig. 2b, c, d, the proposed method is more effective than the other ones in the scenario with complicated gray level, which could be attributed to employing more advanced maneuver detector (i.e., GLR detector) and a choosing method for more precise decision threshold.

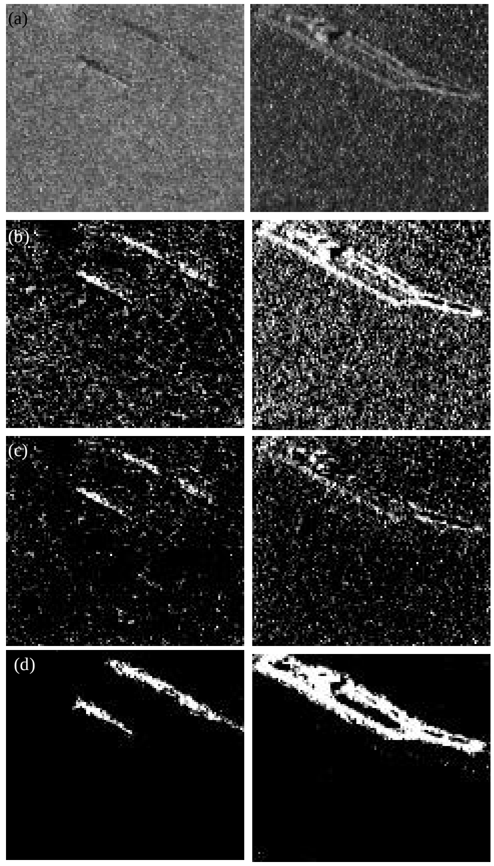

Fig. 2(a-d): Sample comparison detection results of three detection methods, (a) original inspection images, (b) detection results of DET _THR, (c) detection results of DET _CHI and (d) detection results of DET _GLR

CONCLUSION

In this study, the generalized likelihood ratio test based maneuver detector is applied to defect detection for aluminum alloy. In the proposed method, the intensity of the inspection image is formulated as 1-D random variable and its evolution in the spatial and temporal space is modeled by a random walk model. Defect is formulated as abrupt changes in the stochastic dynamical system and is located by GLR maneuver detector. To obtain an accurate decision threshold for a batch of aluminum alloy, we design a new threshold choosing method in terms of a theoretical value and a heuristic searching process. Experiments demonstrate that this proposed method can detect most defects efficiently for inspection images of aluminum alloy. To improve its performance, issues such as reducing false alarms and choosing the window length s etc, should be covered in the future work.

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REFERENCES

Amano, T., 2006. Correlation based image defect detection. Proceedings of the 18th International Conference on IEEE Pattern Recognition, August 20-24, 2006, Hong Kong, China, pp: 163-166.

Bar-Shalom, Y., X.R. Li and T. Kirubarajan, 2001. Estimation with Applications to Tracking and Navigation. John Wiley and Sons, New York, USA., ISBN-13: 9780471416555, Pages 558.

Bodnarova, A., M. Bennamoun and S. Latham, 2002. Optimal Gabor filters for textile flaw detection. Pattern Recog., 35: 2973-2991.

Conci, A. and C.B. Proenca, 2000. A computer vision approach for textile inspection. Text. Res. J., 70: 347-350.

Li, X.R. and V.P. Jilkov, 2002. A survey of maneuvering target tracking-part IV: Decision-based methods. Proceeding of the 2002 SPIE Conference Signal and Data Processing of Small Targets. April 26, 2002, Orlando, FL., pp: 1333-1364.

Macaire, L. and J.G. Postaire, 1993. Flaw detection on galvanized metallic strips in real time by adaptive thresholding. Proc. Spie Int. Soc. Optical Eng., 2183: 14-23.

Tsai, D.M. and B. Hsiao, 2001. Automatic surface inspection using wavelet reconstruction. Pattern Recognit., 34: 1285-1305.

Willsky, A.S. and H.L. Jones, 1974. A generalized likelihood ratio approach to state estimation in linear systems subjects to abrupt changes. Proceedings of the 13th Symposium on Adaptive Processes IEEE Conference on Decision and Control including, Vol. 13, November 20-22, 1974, Del Webb's Towne, pp: 846-853.

Willsky, A.S. and H.L. Jones, 1976. A generalized likelihood ratio approach to the detection and estimation of jumps in linear systems. IEEE Trans. Autom. Control, 21: 108-112.

Zhai, M., Z.L. Jing, S. Fu and X.B. Luo, 2009. Defect detection in aluminum foil by input-estimate-based chi-square detector. Opt. Eng., Vol. 48. 10.1117/1.3258433