Multiple Fault Diagnosis for Sheet Metal Fixtures Using Designated Component Analysis

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This paper presents a new approach to multiple fault diagnosis for sheet metal fixtures using designated component analysis (DCA). DCA first defines a set of patterns based on product/process information, then finds the significance of these patterns from the measurement data and maps them to a particular set of faults. Existing diagnostics methods has been mainly developed for rigid-body-based 3-2-1 locating scheme. Here an N-2-1 locating scheme is considered since sheet metal parts are compliant. The proposed methodology integrates on-line measurement data, part geometry, fixture layout and sensor layout in detecting simultaneous multiple fixture faults. A diagnosability discussion for the different type of faults is presented. Finally, an application of the proposed method is presented through a computer simulation. [DOI: 10.1115/1.1643076]

1 Introduction

Fixtures are used to locate and hold workpiece in manufacturing. In general, fixture elements can be classified by their functionality into locators and clamps. Locators establish the datum reference frame and provide kinematic restraint. Clamps provide additional restraint by holding the part in position under the application of external forces during the manufacturing process. A *3-2-1* locating scheme is used to uniquely locate a rigid body, constraining the six degrees of freedom of the part. According to this principle, three locators are placed in the primary plane, two in the secondary plane and one in the tertiary plane. However, for compliant sheet metal parts, Cai et al. [1] showed that an *N-2-1* principle is more adequate and is widely used in industry. The *N-2-1* fixture principle establishes that to locate and support compliant sheet metal parts, it is necessary to provide more than 3 locators in the primary plane due to part flexibility.

In general, fixture failure directly affects part location and assembly dimensional quality. Ceglarek and Shi [2] found that during the launch of a new vehicle, fixture faults represent around 70% of all dimensional faults. Consequently, adequate fixture failure diagnosis can positively impact dimensional quality.

Due to existence of new measurement systems, such as optical coordinate measurement machine (OCMM), a large amount of dimensional data can be obtained from manufacturing processes. Therefore, new opportunities for process diagnosis are available. Several authors have studied fixture diagnosis in the last few years. In general, past research in fixture diagnosis is based on three major approaches: principal component analysis, correlation clustering and least square regression.

In 1992, Hu and Wu [3] introduced the principal component analysis (PCA) to identify sources of dimensional variation in automotive body assembly. They used PCA to extract variation patterns from dimensional data. Later, Ceglarek and Shi [4] proposed a fixture fault diagnosis method combining PCA with pattern recognition. They developed variation patterns for each hypothetical fault based on the fixture and measurement sensor layout. Then, they used principal component analysis to extract variation modes from production data and map the modes with the hypothetical variation patterns. This method focused on single assembly fixture failure. Ding et al. [5] developed a diagnosis method based on a state space dimensional variation model for multistage manufacturing processes using PCA. In addition, Ceglarek and Shi [6] include considerations of measurement noise in fixture failure diagnosis.

Correlation clustering is able to detect multiple dimensional faults by matching a model behavior with the measured behavior. Shiu et al. [7] developed a multi-station assembly modeling for diagnostics in automotive body assembly process. The model is based on critical characteristics such as the locating mechanism (fixture to part interactions) and the joining conditions (part to part interactions). The variation patterns are expressed by a correlation matrix. Then, the correlation matrix from measurement data is compared with the different simulated correlated matrices associated with the faults.

Multivariate process diagnosis has also been studied using a least squares approach. The approach consists of relating the measurement variation patterns to potential causes. The least squares method is used to identify the significance of each of these potential causes [8–12]. Apley and Shi [9] used least squares algorithm to identify the significance or severity of multiple fixture faults. Fault severity was measured as the variance of the decomposition of the data for each variation pattern. The variation patterns where determined as the effect a fixture element fault over the measurement points.

Finally, Carlson et al. [13] proposed a multi-fixture assembly diagnosis model for rigid part assembly for single fault diagnosis. The methodology combines statistical multivariate data analysis with a fixture fault model. A fault is diagnosed if the measurement data varies significantly in correspondence with a fixture fault model. They use maximum likelihood estimators to calculate a variation vector from the data.

PCA based methods are generally not adequate for pattern recognition in the presence of multiple fixture element faults. In addition, least squares methods are sensitive to the pattern definition. Any change in one of the variation patterns will produce a change in the data decomposition and consequently in the severity measurement of different faults. Since multiple faults are not uncommon in real applications, it is necessary to develop a diagnostic methodology that works for simultaneous multiple fault cases as well as for single fault cases. Liu and Hu [14] proposed a new method called designated component analysis (DCA) for process diagnosis. This methodology enables to successfully identify multiple fixture failures occurring simultaneously for sheet metal parts in a *3-2-1* locating scheme.

An *N-2-1* fixture layout is used to locate compliant sheet metal parts [1]. However, there is a lack of tools for multiple fault diagnosis in *N-2-1* locating schemes. Thus, the objective of this

Contributed by the Manufacturing Engineering Division for publication in the JOURNAL OF MANUFACTURING SCIENCE AND ENGINEERING. Manuscript received June 2003. Associate Editor: E. C. DeMeter.

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research is to develop a multiple fixture fault diagnosis methodology for compliant sheet metal parts. The proposed methodology enables to detect and isolate simultaneous fixture faults in an *N-2-1* locating scheme. The ability of the methodology to detect fixture faults is studied considering independent fixture faults versus dependent fixture faults and non-nominal fixture elements versus missing fixture elements.

The remainder of this paper is organized as follows. Section 2 discusses the concept of designated components analysis and highlights the main advantages of DCA over traditional PCA and least squares methods. Section 3 presents the proposed diagnosis methodology for multiple fixture fault isolation. Section 4 presents a statistical analysis to determine the significance of each fault. Specific diagnosability conditions are addressed on Sec. 5. To illustrate the proposed method, simulations results for a *4-2-1* locating scheme are presented in Sec. 6. Conclusions are summarized in Sec. 7.

2 Designated Component Analysis

In order to conduct multiple fixture fault detection, Liu and Hu [14] developed a new approach called designated component analysis (DCA). The method first defines a set of mutually orthogonal vectors to represent fault patterns and then measure their statistical significance from measurement data. The fault patterns are defined from product/process knowledge based on part geometries and sensor layout but independent of fixture, tooling layout and measurement data. In other words, the assembly variation is mathematically decomposed in terms of a set of pre-defined orthogonal fault patterns.

The structure for the diagnosis model is given by Eq. (1), where $\mathbf{y}=[y_1 y_2 \ldots y_n]^T$ is an *n x 1* random vector that corresponds to a set of *n* measured points over a part, $\mathbf{D}=[\mathbf{d_1 d_2} \ldots \mathbf{d_q}]$ is an *n x q* constant matrix that represents the designated deformation patterns, $\mathbf{x}=[x_1 x_2 \ldots x_q]$ is a *q x 1* random vector corresponding to the designated components, and $\mathbf{w}$ is an $n\times 1$ random vector with known covariance matrix $\mathbf{\Sigma_w}=\sigma_w \mathbf{I}$ that represents the system noise. $\mathbf{I}$ is the identity matrix. Considering that sufficient amount of data may be obtained from an in-control process, σ_w may be estimated [15]. In this case, σ_w will be the deviations in the measurement data that are only explained by common causes.

$$\mathbf{y}=\mathbf{D}\mathbf{x}+\mathbf{w} \tag{1}$$

The objective of the diagnosis methodology is to estimate the amount of variation in the data $\mathbf{y}$ that can be explained by each fault pattern defined in the matrix $\mathbf{D}$. A fault is defined as a source of variation, instead of a shift in the mean. Therefore, if the variance of a pattern ($\mathbf{x}_i$) is significant, a fault will be identified. Using DCA, the estimated contribution of each pattern may be calculated as,

$$\hat{\mathbf{x}}=\mathbf{D}^{\mathbf{T}}\mathbf{y}$$

On the other hand, least squares estimates the contribution of each pattern as,

$$\hat{\mathbf{x}}=(\mathbf{D}^{\mathbf{T}}\mathbf{D})^{-1}\mathbf{D}^{\mathbf{T}}\mathbf{y}.$$

Comparing DCA with least squares methods. DCA may be considered as a special case of least squares, where the deformation or variation patterns are forced to be orthonormal. Therefore, the estimation of $\hat{\mathbf{x}}$ is simplified by $(\mathbf{D}^{\mathbf{T}}\mathbf{D})^{-1}=\mathbf{I}$. In other words, the measurement data variation is decomposed through projection on a set of known orthogonal patterns. The main advantage on using orthonormal patterns in DCA is that the significance of each pattern may be extracted individually and in any order without changes in the magnitude of the detected fault. In contrast, least square based methodologies must extract the patterns simultaneously. Therefore, ill-conditioned systems may be difficult to diagnose.

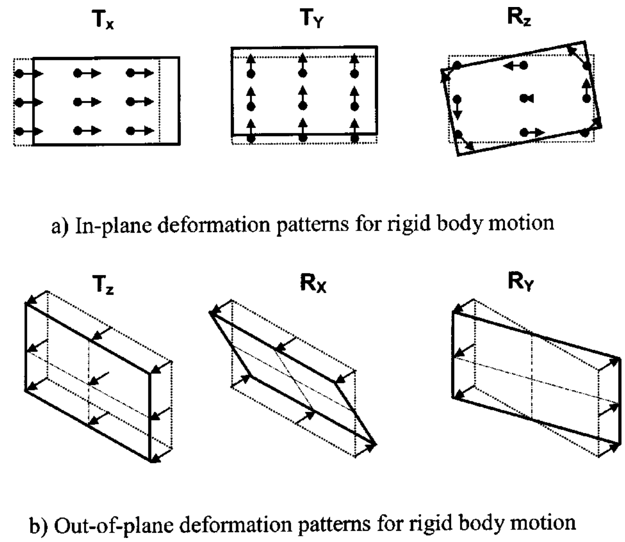

Fig. 1 Variation patterns for rigid body motion [14]

The main limitations of PCA for multiple fault isolation are addressed using DCA. First, in PCA, the principal components are orthogonal by definition. However, the fixture faults vectors may not be orthogonal. On the other hand, in DCA, the designated patterns are forced to be orthogonal however the designated components are not constrained to be orthogonal. Second, in PCA, the deformation patterns are data driven, therefore, the eigenvector may lack physical interpretation and can be sensitive to measurement noise. In DCA, the patterns are defined a priori; therefore, they do not change under the presence of multiple failures or measurement noise. Finally, using PCA, multiple individual variation patterns may be compounded in one eigenvector representing the direction of maximum variation, this direction may not have any physical interpretation. In contrast, the designated patterns are product/process based, i.e., there is a direct physical interpretation for each pattern.

The designated patterns in DCA are defined based on a physical interpretation. For example, to completely represent rigid body motion (*3-2-1* locating scheme case), 6 patterns are needed: three translations along the X, Y and Z axes, and three rotations along the X, Y and Z axes. In general for sheet metal parts, rigid body motion can be decomposed into the in-plane and the out-of-plane components. As shown in Fig. 1, in-plane displacements can be represented by two translations (T_X and T_Y) and one rotation (R_Z) and out-of-plane displacements can be represented by one translation (T_Z) and two rotations (R_X and R_Y) (Fig. 1*b*).

For compliant parts, the six patterns defined for rigid body motion are not enough to completely represent the part variation. Therefore, additional patterns must be defined. In theory, there is infinite number of possible deformation modes for compliant parts. However, in real cases a reduced number of patterns should be enough to represent part deformation given fixture failures. Some common deformation patterns for a *5-2-1* locating scheme are defined in Fig. 2. These patterns are defined for the sheet metal parts deformations in the out-of-plane direction. The patterns are simple bending along the X (B_X) and Y (B_Y) axes and twisting (T_W). The number and the type of patterns will depend of the

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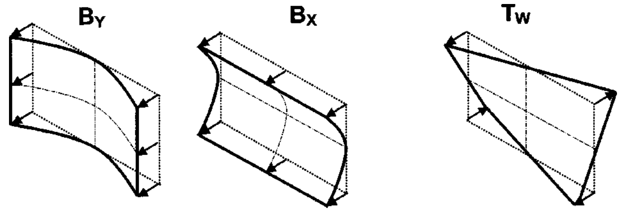

Fig. 2 Additional variation patterns for compliant parts

number of fixture elements. The user must define the patterns accordingly to the expected deformation patterns that are feasible for the located part.

The only requirement for DCA is that the designated patterns must be orthogonal between each other so that the designated components are independent of the calculation sequence. It should be clear that the orthogonality requirement over the set of patterns does not force the designated components to be orthogonal. In fact, designated components will not be uncorrelated since the only vectors that have this property are the principal components. PCA by definition generates independent and orthogonal components.

If the designated patterns do not satisfy the orthogonality condition, the vectors should be orthonormalized. After the vectors are orthonormalized, it must be checked that the physical interpretation of the patterns did not change.

The first step in the DCA methodology is to define the designated patterns. Using the same format as the eigenvectors in PCA, a designated pattern i can be defined as,

$$p_i = \begin{bmatrix} p_{i1} \\ p_{i2} \\ \vdots \\ p_{im} \end{bmatrix}, \quad i = 1, \ldots, q$$

where p_{ij} represent the displacement of the part at the j-th sensor location for the i-th designated pattern, m is the number of sensors, and q is the number of designated patterns. Figure 3 shows an example of a sheet metal part using a *4-2-1* locating scheme with nine $(m=9)$ sensors, M_i. Four clamps, L_1 to L_4, hold the part in the out-of-plane direction.

Combining the variation patterns defined in Figs. 1 and 2, the designated pattern vectors for the out-of-plane displacements can be summarized in Table 1. For simplification only the out-of-plane deformations are considered and it is assumed that the sensors measure part deviation in the z-direction. The designated patterns are defined for the sensor layout shown in Fig. 3.

The designated patterns shown in Table 1 represent the six modes of positional variation and deformation presented previously. However, they do not satisfy the orthogonality condition

Table 1 Example of designated patterns

Designated Pattern Sensor	p_1 (T_Z)	p_2 (R_X)	p_3 (R_Y)	p_4 (B_X)	p_5 (B_Y)	p_6 (T_W)
1	1	1	1	1	1	−1
2	1	1	0	1	0	0
3	1	1	−1	1	1	1
4	1	0	1	0	1	0
5	1	0	0	0	0	0
6	1	0	−1	0	1	0
7	1	−1	1	1	1	1
8	1	−1	0	1	0	0
9	1	−1	−1	1	1	−1

required for the designated component analysis. For example, $\langle p_1, p_4 \rangle \neq 0$, where $\langle p_1, p_4 \rangle$ is the inner product between vectors p_1 and p_4. Therefore, the vectors should be orthonormalized.

From a defined set of non-orthogonal patterns, it is possible to construct an orthonormal basis using the Gram Schmidt orthonormalization [16]. The Gram Schmidt algorithm makes it possible to find an orthonormal basis for the subspace spanned by the designated patterns (vectors). Figure 4 shows the Gram Schmidt algorithm, where $\|\cdot\|$ represents the Euclidean norm of a vector. By definition vector d_2 will be orthogonal to d_1, therefore, the algorithm subtracts the nonorthogonal components from p_2. This iteration can be repeated for the other vectors in the basis. The result will be an orthonormal basis. This procedure is repeated until the last vector d_N has been defined. It is important to recall that any set of designated patterns represented by the vectors p_i can be transformed in an orthonormal basis. However, they can loose the physical interpretation of the variation patterns. Therefore, the vectors d_i $(i=1,2\ldots,q)$ need to be checked to assure that they keep their physical interpretation. To maintain the physical interpretation the new orthogonal vector should in principle keep its original direction. In other words, it can be translated or scaled but not rotated. The capability to construct the set of orthogonal designated patterns while still maintaining a physical

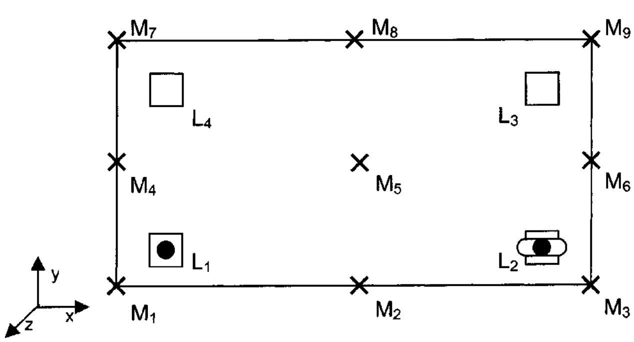

Fig. 3 Sheet metal part with a *4-2-1* locating scheme

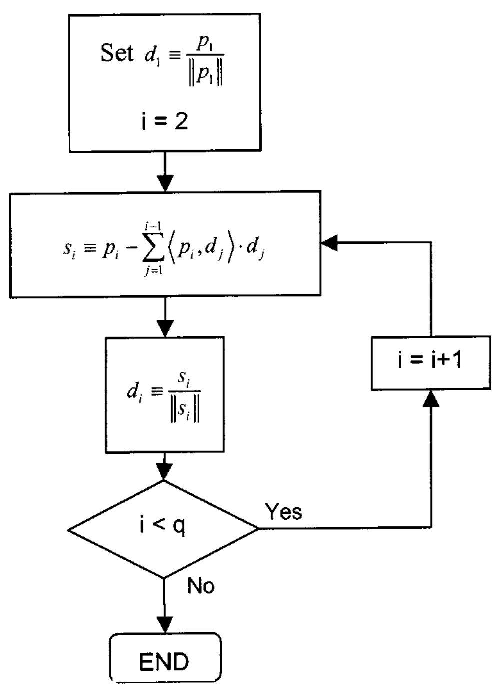

Fig. 4 Gram-Schmidt Algorithm [16]

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interpretation depends of the number of sensors and the sensors layout. Further investigation must be done for optimal sensor placement in order to assure orthogonality.

After defining the designated patterns, d_i's, the corresponding designated components can be calculated with the measurement data using the following equation:

$$[x_{i1}\ \ x_{i2}\ \ \ldots x_{in}]=[d_{i1}\ \ d_{i2}\ \ \ldots\ \ d_{im}]\cdot\underbrace{\begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ & & \cdots & \\ y_{m1} & y_{m2} & \cdots & y_{mn}\end{bmatrix}}_{Y_{(mxn)}} \quad (2)$$

where $i=1,2,\ldots,q$; q is the number of variation patterns; m is the number of sensors, x_i's are the designated components; and y_{ij} is the j-th observation of the measurement data for the i-th sensor. The measurement data matrix, **Y**, can approximately be written as a sum of rank 1 matrices [14] corresponding to the designated components.

$$\mathbf{Y}\approx\mathbf{P_1}+\mathbf{P_2}+\mathbf{P_3}+\ \ldots\ +\mathbf{P_q} \quad (3)$$

$$P_{i(mxn)}=\begin{bmatrix} d_{i1} \\ d_{i2} \\ \vdots \\ d_{im}\end{bmatrix}\cdot[x_{i1}\ \ x_{i2}\ \ \ldots\ \ x_{in}] \quad i=1,\ldots,q$$

$$\mathbf{Y}\approx\mathbf{d_1x_1^T}+\mathbf{d_2x_2^T}+\ \ldots\ +\mathbf{d_qx_q^T}$$

The variation of each designated component can be calculated individually. If the variation patterns are defined as unit vectors, it can be proven that for rigid body motions the sum of the component variance is equal to the sum of the variances of the raw data. However, for compliant parts, the designated patterns may not necessary explain all the variation from the measurement data. It is necessary the exact deformation modes to completely represent compliant part deformations.

Then,

$$\sum_{i=1}^{q}\sigma_{x_i}^2\leq\sum_{i=1}^{n}\sigma_{Yi}^2=trace(\Sigma_Y) \quad (4)$$

The contribution of each designated component (C_i) can be calculated individually as the proportion of the measurement data variation explained by each designated component (Eq. (5)). In other words, C_i is the significance level of each variation pattern and depends of how much of the production data variation can be explained by the deformation mode i.

$$C_i=\frac{\sigma_{x_i}^2}{\mathrm{trace}(\Sigma_Y)}\times100\% \quad (5)$$

By definition designated components are not necessarily independent. Therefore, the correlation among the designated components can be calculated using Eq. (6).

$$\eta_{ij}=\frac{\sum_{k=1}^{n}x_{ik}\cdot x_{jk}}{\sqrt{\sum_{k=1}^{n}x_{ik}^2\cdot\sum_{k=1}^{n}x_{jk}^2}} \quad i,j=1,2,\ldots,q \quad (6)$$

3 Multiple Fixture Fault Diagnosis

The presence of one or multiple faults in the assembly system is reflected in the measurement data obtained on-line. The objective of any diagnosis methodology is to be able to identify the fault or faults root causes from the available data. As presented in the previous section, using DCA, it is possible to extract the contribution of each designated pattern to the total variation of the measurement data.

The designated patterns are defined off-line using the CAD data for part geometry and sensor layout. Orthogonality must be checked, if the set of patterns are not orthogonal, the Gram-Schmidt algorithm may be used. It must be noted that the definition of the designated patterns does not depend on the number of fixtures or fixture layout. After identifying the variation patterns, the relation between these designated patterns (for example: T_Z, R_X, R_Y, B_X, B_Y, T_W) and the fixture failures must be obtained. There are two ways to establish these relationships. First, a kinematic analysis can be done. The expected result of one fixture faults is analyzed and explained in terms of the known designated patterns. For example, if fixture elements L_1, L_2, L_3 and L_4 fail simultaneously and dependently (Fig. 3), it is expected that the part is moving in the z-direction. From DCA, almost a 100 percent of the data variation will be explained by the translation pattern, T_Z. Therefore, the following logic relation can be constructed,

$$T_Z\Rightarrow L_1\wedge L_2\wedge L_3\wedge L_4$$

where, the symbol "$\wedge$" represents the logic AND (the faults occur simultaneously). The same analysis can be used to obtain other relations between fixture faults and variation patterns and their correlations. However, for compliant part analysis and multiple fixtures, these logic relations may be difficult to obtain. Therefore, the second method proposed is to generate the relationships using computer simulation. For each fault, simulated data may be generated, and using DCA, the significant variation patterns may be obtained. In addition, the correlation among the designated components may be obtained. Next section includes an example where the entire logic table is constructed for a 4-2-1 locating scheme. The logic table is generated using finite element methods. For each fixture element failure a random displacement with distribution N(0,1) is applied on the corresponding fixture. Measurement data is recorded for each sensor in the FEM model. Applying DCA the contribution and correlation of each pattern is obtained for each simulated fault.

Comparing the components contribution and correlation obtained on-line from the measurement data and the logic table generated by simulation, the faults can be isolated. Figure 5 shows a flow chart for the proposed methodology. The significance of each fault is obtained by statistical testing.

4 Statistical Analysis

Using DCA, the contribution of each pattern to the total variation of the systems can be determined. However, it is necessary to find the statistical significance of each fault. For example, even for

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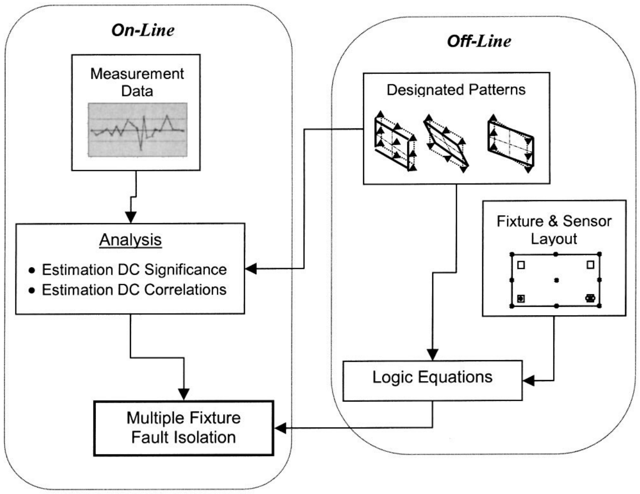

Fig. 5 Multiple fixture fault diagnosis methodology using DCA

in-control situations (no fault), the noise in the data may generate large values for each Ci. Therefore, a large Ci value does not imply that pattern *i* is significant. Using statistical hypothesis testing, the statistical significance of each fault may be determined. The proposed approach assumes that the covariance matrix of **w** (Eq. 1) is known and $\mathbf{x}_i$ (designated components) has a normal distribution. Based on these assumptions, the variance of each fault ($\sigma_{x_i}^2$) for in-control conditions ($\mathbf{y}=\mathbf{w}$) can be calculated as:

$$\boldsymbol{\Sigma}_{\mathbf{x}}^{(w)}=\sigma_w^2\mathbf{I}$$

$$\{\sigma_{x_i}^2\}_w=\sigma_w^2$$

Therefore, using hypothesis testing for the variance of a normal population, the test in Eq. (7) may be conducted to identify if the contribution of a designated pattern is significant. The interpretation of the test is that for each designated component i, the variance of the pattern must be statistically greater that the variance of the noise **w** to diagnose a pattern.

$$H_0:\sigma_{x_i}^2=\sigma_w^2$$
$$H_1:\sigma_{x_i}^2>\sigma_w^2 \quad i=1,\ldots,q \tag{7}$$

To evaluate the hypothesis, we will use the test statistic:

$$\chi_0^2=\frac{(m-1)S_{x_i}^2}{\sigma_w^2}$$

where, $S_{x_i}^2$ is the estimate of the variance of the designated component i, and m is the number of observations in the data **y**. The null hypothesis H_0 will be rejected if

$$\chi_0^2>\chi_{\alpha,m-1}^2$$

If the null hypothesis is rejected for a specific deformation pattern j, then, the pattern is a significant contributor of the system variation.

5 Discussion on Diagnosability

Once the methodology has been developed, some diagnosability issues must be analyzed. Diagnosability is defined as the ability of a diagnostic procedure to detect and isolate a specific fixture element failure or a set of fixture elements failure. The diagnosability analysis is divided in two cases: 1) the case where a single fixture element fails in the system; and 2) more than one fault occur simultaneously. The type of failure will also impact the fixture diagnosability. Three types of fixture faults are identified: the fixture element is loose or not present, fixture elements offset are independent, and fixture elements offset are dependent.

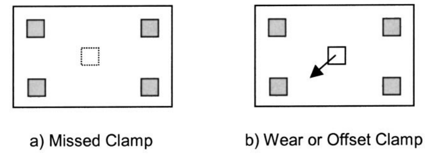

Fig. 6 Different fault types for clamps

(1) Single Fixture Element Failure. When one and only one fixture element fails in a *3-2-1* locating system, the proposed methodology can successfully detect and isolate a fixture fault, as many of the previous proposed methodologies (PCA, least square approach). However, for an *N-2-1* ($N>3$) locating scheme, if one of the clamps or holding elements is not present, the system will not be able to detect this fault. A missing clamp will not affect the part location and therefore will not affect the measurement data. Figure 6(a) shows an example of a missing clamp, the part is successfully located and held, and there is no sign of a fixture fault in the data. This is characteristic of an over constrained locating system. However, if the loose element is a locator, the part will move freely in one direction and the fault will be detected and identified. These situation will be valid if do not consider the effect of the gravity force is not considered. If the gravity force actuates in the direction constrained by the missing clamp, it will always possible to diagnose a missing clamp.

On the other hand, if the locating elements become worn or are displaced from their original nominal position, but still present, the part will be forced to a non nominal position and the methodology will be able to successfully detect and identify the fault (Fig. 6(b)). In this case, the methodology is valid for in-plane and out-of-plane failures caused by locating or clamping elements.

(2) Two or More Fixture Failure Simultaneously. In the presence of two or more fixture faults simultaneously, the proposed methodology will be able to detect and isolate the faults depending of the relation among the faults. Simultaneous faults are grouped in three cases abovementioned, fixture elements are loose or not present, independent fixture elements offset, and dependent fixture elements offset.

a) Missing Fixture Elements: Diagnosability for multiple fixture elements depends on whether the missing fixtures are locators or clamps. For a missing locator, it is always possible to identify the fault, if the sensor layout is able to produce an orthogonal set of designated patterns. However, if the missing fixtures are clamps, the system will not be always diagnosable. The diagnosability condition can be written as,

$$N-n_c<3 \tag{8}$$

where N is the total number of clamps in the *N-2-1* locating scheme and n_c is the number of simultaneous faults. Eq. (8) represents the over constrained scenario described in the single failure section. If the part is over constrained, it will not be possible to diagnose a missing clamp until several elements fail simultaneously and the part become under constrained.

b) Independent Fixture Element Offset: Assuming that the fixture element failures are independent, then the variance of the fixtures will be different and the fixture deviations are not significantly correlated.

$$corr(X_{L_i},X_{L_j})\approx 0 \quad i,j=1,\ldots,n_c$$

X_{L_i} is the fixture deviation for fixture element i; and n_c is the number of simultaneous faults. In this situation, diagnosability cannot be assured.

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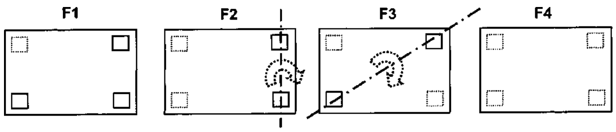

Fig. 7 Missing fixture elements failures

c) Dependent Fixture Element Offset: The basic assumption is that the fixture failures are related with each other, therefore they move in the same direction.

$$\sigma_{L_i} \approx \sigma_{L_j} \qquad corr(X_{L_i}, X_{L_j}) \approx 1 \qquad i,j = 1, \ldots, n_c$$

σ_{L_i} is the standard deviation for fixture element i. The proposed methodology is able to detect and isolate any fault for dependent fixture element offset, independently of the number of fixture failures and the fixture element, clamp or locators.

6 Simulation Results

In this section, the proposed diagnosis methodology is applied for a simulated case. Multiple fixture diagnosis is applied for a *4-2-1* locating scheme. Four clamps are used to hold the part in the out-of-plane direction, and a 4-way pin-hole locator and a 2-way pin-slot locator are used to locate the part in the in-plane direction. Specifically, this simulation applied DCA to diagnose failure in the out-of-plane direction. In general, the same procedure can be applied for the in-plane (rigid body) fault diagnosis. A nine sensor layout is used to measure out-of-plane deviations (Fig. 3). The designated patterns used for DCA are the same defined previously in Table 1, after been orthonormalized using the Gram-Schmidt algorithm.

Kinematics analysis and logic table approach will be used to show the reach of the algorithm. First, kinematic analysis is applied to study some possible faults for single and multiple missing clamps. Figure 7 shows faults F_1, F_2, F_3 and F_4. In fault F_1, clamp L_4 is missing, this fault is not possible to be detected in a *4-2-1* locating scheme, under the assumption of no gravity. Under the gravity force action, the analysis for any missing fixture will change. In fault F_2, the clamps L_1 and L_4 are missing. In this case the part can freely rotate along an axis through L_2 and L_3. Using DCA the analysis gives that the rotation along the y-axis and the translation along the z-axis (out-of-plane) are significant. The rotation and translations patterns occur simultaneously because the part is not rotating along the rotation axes defined for R_Y. In addition, both patterns are positive correlated. Therefore, fault F_2 can be diagnosed if:

$$T_Z \wedge R_Y \wedge \mathrm{Corr}(T_Z, R_Y)$$

The same analysis can be followed for fault F_4, where all the clamps are missing. In this case if we have measurement data that shows that the part is moving in the z-direction, the only possible fault is F_4. The significant designated pattern is T_Z.

For more complex fault patterns, it may be difficult to map the significant designated patterns with the failure fixtures, then a logic table can be used. The logic table may be constructed for all the potential different combinations of faults using the simulation method. Each potential fault is simulated and the DCA results saved in the table. In this case a logic table was obtained for the 4-2-1 locating scheme assuming that: only the holding fixture elements can fail; and the fixture fault offset are dependent. Table 2 shows the relationship between different faults and the designated patterns. For example, if after extracting the designated patterns from the measurement data, we have that: the significant patterns are T_Z, R_X, R_Y, T_W and from the correlation analysis, that $\mathrm{Corr}(T_Z, -R_X)$, $\mathrm{Corr}(T_Z, -R_Y)$, $\mathrm{Corr}(T_Z, T_W)$ are significant; then we can conclude that clamps L_1, L_2 and L_3 are failing (Case 11, Table 2). The negative sign in the correlation coefficients denote a negative correlation. From Table 2, it may also be noticed that the patterns B_X and B_Y do not represent any of the fixture faults. For the 4-2-1 locating layout used in this case only four designated patterns may be sufficient to diagnose the described faults.

Table 2 Logic relations for fixture fault diagnosis (4-2-1 fixture layout) considering dependent fixture faults

Case	Designated Patterns	Fixture Fault
1	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, -R_X) \wedge \mathrm{Corr}(T_Z, R_Y) \wedge \mathrm{Corr}(T_Z, T_W)$	L_1
2	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, -R_X) \wedge \mathrm{Corr}(T_Z, -R_Y) \wedge \mathrm{Corr}(T_Z, -T_W)$	L_2
3	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, R_X) \wedge \mathrm{Corr}(T_Z, -R_Y) \wedge \mathrm{Corr}(T_Z, T_W)$	L_3
4	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, R_X) \wedge \mathrm{Corr}(T_Z, R_Y) \wedge \mathrm{Corr}(T_Z, -T_W)$	L_4
5	$T_Z \wedge R_X \wedge \mathrm{Corr}(T_Z, -R_X)$	$L_1 \wedge L_2$
6	$T_Z \wedge T_W \wedge \mathrm{Corr}(T_Z, T_W)$	$L_1 \wedge L_3$
7	$T_Z \wedge R_Y \wedge \mathrm{Corr}(T_Z, R_Y)$	$L_1 \wedge L_4$
8	$T_Z \wedge R_Y \wedge \mathrm{Corr}(T_Z, -R_Y)$	$L_2 \wedge L_3$
9	$T_Z \wedge T_W \wedge \mathrm{Corr}(T_Z, -T_W)$	$L_2 \wedge L_4$
10	$T_Z \wedge R_X \wedge \mathrm{Corr}(T_Z, R_X)$	$L_3 \wedge L_4$
11	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, -R_X) \wedge \mathrm{Corr}(T_Z, -R_Y) \wedge \mathrm{Corr}(T_Z, T_W)$	$L_1 \wedge L_2 \wedge L_3$
12	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, -R_X) \wedge \mathrm{Corr}(T_Z, R_Y) \wedge \mathrm{Corr}(T_Z, -T_W)$	$L_1 \wedge L_2 \wedge L_4$
13	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, R_X) \wedge \mathrm{Corr}(T_Z, R_Y) \wedge \mathrm{Corr}(T_Z, T_W)$	$L_1 \wedge L_3 \wedge L_4$
14	$T_Z \wedge R_X \wedge R_Y \wedge T_W$ $\mathrm{Corr}(T_Z, R_X) \wedge \mathrm{Corr}(T_Z, -R_Y) \wedge \mathrm{Corr}(T_Z, -T_W)$	$L_2 \wedge L_3 \wedge L_4$
15	T_Z	$L_1 \wedge L_2 \wedge L_3 \wedge L_4$

7 Conclusions

PCA presents several limitations for multiple faults detection: principal components are orthogonal (independent) by definition, however, the fixture faults vectors may not be orthogonal; PCA are data driven, therefore, the eigenvector direction may be sensitive to measurement noise; using PCA, multiple individual variation patterns are compounded in one eigenvector representing the direction of maximum variation, this direction may not have any physical interpretation. Designated component analysis addresses these limitations: the designated components do not need to be orthogonal, DCA is process driven, and it is capable to isolate multiple fixture failures.

DCA is used to identify multiple fixture faults in compliant sheet metal assembly systems. An *N-2-1* locating scheme is considered. Extracting the significance contribution of each designated pattern to the total variation of the measurement data and the correlation among them is possible to detect different fixture faults. The designated components are defined off-line using the CAD data for part geometry and sensors layout, and are independent of the fixtures layout.

The ability of the proposed procedure to detect and isolate a specific fixture or a set of fixture failure is studied. Multiple fixture diagnosability depends of the number of fixture faults that occurs simultaneously; the type of fixture elements, clamps or locators and the correlation among the faults. In general, it can be concluded that locator faults are always diagnosable. On the other hand, clamps are not always diagnosable. In addition, dependent faults are more diagnosable than independent type of faults.

A simulation study is presented for multiple fixture diagnosis in a *4-2-1* locating scheme. The methodology shows a good potential for on-line multiple fixture diagnosis.

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Acknowledgment

The work presented in this paper was sponsored by the General Motors Collaborative Research Laboratory at the University of Michigan.

References

[1] Cai, W., Hu, S. J., and Yuan, J. X., 1996, "Deformable Sheet Metal Fixturing: Principles, Algorithms, and Simulations," ASME J. Manuf. Sci. Eng., **118**, pp. 318–324.

[2] Ceglarek, D., and Shi, J., 1995, "Dimensional Variation Reduction for Automotive Body Assembly," Manufacturing Review, **8**(2), pp. 139–154.

[3] Hu, S. J., and Wu, S. M., 1992, "Identifying Sources of Variation in Automobile Body Assembly Using Principal Component Analysis," Transactions of NAMRI/SME, **XX**, pp. 311–316.

[4] Ceglarek, D., and Shi, J., 1996, "Fixture Failure Diagnosis for Autobody Assembly Using Pattern Recognition," ASME J. Eng. Ind., **118**, pp. 55–66.

[5] Ding, Y., Ceglarek, D., and Shi, J., 2000, "Modeling and Diagnosis of Multi-Stage Manufacturing Process: Part II—Fault Diagnostics," *Japan-USA Symposium of Flexible Automation*, Ann Arbor, MI.

[6] Ceglarek, D., and Shi, J., 1999, "Fixture Failure Diagnosis for Sheet Metal Assembly with Consideration of Measurement Noise," ASME J. Manuf. Sci. Eng., **121**, pp. 771–777.

[7] Shiu, B. W., Ceglarek, D., and Shi, J., 1996, "Multi-stations Sheet Metal Assembly Modeling and Diagnostics," Transactions of NAMRI, **XXIV**, pp. 199–204.

[8] Barton, R., and Gonzalez-Barreto, D., 1996, "Process-Oriented Basis Representations for Multivariate Process Diagnosis," Quality Engineering, **9**, pp. 107–118.

[9] Apley, D., and Shi, J., 1998, "Diagnosis of Multiple Fixture Faults in Panel Assembly," ASME J. Manuf. Sci. Eng., **120**, pp. 793–801.

[10] Rong, Q., Shi, J., and Ceglarek, D., 2001, "Adjusted Least Square Approach for Diagnosis of Ill-Conditioned Compliant Assemblies," ASME J. Manuf. Sci. Eng., **123**, pp. 453–461.

[11] Chang, M., and Gossard, D., 1998, "Computational Method for Diagnosis of Variation-related Assembly Problems," Int. J. Prod. Res., **36**, pp. 2985–2995.

[12] Colon, H. Espada, and Gonzalez-Barreto, D., 1997, "Component Registration Diagnosis for Printed Circuit Boards using Process-Oriented Basis Elements," Computers and Industrial Engineering, **33**, pp. 389–392.

[13] Carlson, J., Lindvist, L., and Soderberg, R., 2000, "Multi-Fixture Assembly System Diagnosis Based on Part and Subassembly Measurement Data," *Proceedings of 2000 ASME Design Engineering Technical Conference*, Baltimore, MD.

[14] Liu, Y. G., and Hu, S. J., 2003, "Assembly Fixture Fault Diagnosis Using Designated Component Analysis," Submitted to ASME J. Manuf. Sci. Eng.

[15] Apley, D., and Shi, J., 2001, "A Factor Analysis Method for Diagnosing Variability in Multivariate Manufacturing Processes," Technometrics, **43**, pp. 84–95.

[16] Strang, G., 1988, *Linear Algebra and its Applications*, Harcourt College Publishers, 3rd Edition.

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