PROCESS NAVIGATOR FOR AUTOMOTIVE BODY ASSEMBLY PROCESS

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ABSTRACT

In this paper, an integrated process monitoring and diagnostic system - the *process navigator*, is developed for automotive body assembly processes. The objective of the process navigator is to transform in-process 100% measurement data into meaningful, easy-to-understand engineering information by fusing advanced statistical techniques, engineering knowledge, and computer technology into an integrated system. The process navigator includes five modules: on-line monitoring and fault classification, data and alarm bases, variation pattern animation, and knowledge based diagnosis. Both the methodology and implementation are presented in the paper.

1. INTRODUCTION

Quality is one of the most important factors in automobile manufacturing. One aspect of the vehicle quality is the dimensional integrity of the body (body-in-white), which has great effects on the quality and functionality of the vehicle. The current practice of dimensional control in most assembly plants is to manually analyze body-in-white (BIW) data, observe the process, and try to locate the sources of variation. This strategy is complicated because it requires expertise in data analysis, knowledge about the body structure and about the assembly process. It is also a slow and time consuming process when dealing with the huge amount of multivariate data and the many characteristics of an assembly process. As a result, advanced quality control and analysis tools are required for the automobile body assembly process. This necessity can be further elaborated from the following aspects:

(1) In-line Optical Coordinate Measurement Machines (OCMM) are gradually being adopted in many automotive assembly plants. An OCMM can provide 100% sample measurement on as many as 100 process characteristics. Manufacturers are overwhelmed by the large volume of data.
(2) Traditional statistical process control (SPC) techniques are useful in detecting certain process changes. However, they are limited in root causes identification and in handling multivariate information (Faltin and Tucker, 1991).
(3) The body assembly is a long and complex process, involving many subassembly lines and stations. Troubleshooting or diagnosing such a complex process is a challenging task.

The body assembly process is very complex. On average, 50-80 assembly stations, assemble a typical body made of 150 to 250 sheet metal parts. The body assembly process can be divided into subassembly processes and body framing process. The major subassembly processes include underbody assembly and two aperture assemblies (left and right hand). The large number of elements in the assembly process cause difficulties in minimizing the assembly variation, which can be caused by the process major operations such as: part positioning, fixturing and welding.

In this paper, a Process Navigator (PN) is developed as an integrated quality control and assurance system to minimize the dimensional variation. By fusing advanced statistical techniques, engineering knowledge and computer technology into an integrated system, the PN converts the in-process, 100% measurement data into meaningful, easy-to-understand computer animated pictures. Engineering knowledge is represented based on the hierarchical group concept proposed for the auto body representation (Ceglarek et. al., 1994). In this paper, the hierarchical group concept is extended by defining functional modules, which are implemented in an expert system shell.

The PN includes the functions of on-line data collection, on-line monitoring and fault classification, alarm generation and reporting, variation pattern animation, and knowledge based diagnosis (Fig. 1). In this paper, the theoretical development and implementation of the PN are presented in the four sections of the paper. After the introduction, the methodology developed for the on-line monitoring, variation animation, and knowledge based diagnosis techniques are presented in Section 2. In this section, the focus is on the integration of advanced statistics with the engineering knowledge of the BIW assembly. Sections 3 describes the implementation of the process navigator. Finally, conclusions and future work on the subject are summarized.

2. DEVELOPMENT OF THE PROCESS NAVIGATOR

In this section, we describe the theoretical developments for the PN. These include on-line monitoring and fault classification, computer animation of variation patterns using principal component analysis (PCA), and knowledge-based diagnosis.

2.1 On-line monitoring and fault classification

When we are controlling a manufacturing process, it is important to not only detect process changes, but also identify the change patterns. According to Guo and Dooley (1992), "Experience shows that many SPC attempts fail to produce meaningful results because of the lack of diagnostic support for the effort". In an automotive body assembly process, if the change patterns can be identified, root causes of variation can be systematically located because certain change patterns correspond to particular failure modes in the process. Also, by grouping the points with the same process change based on the product and process characteristics, the location of the root cause can be systematically identified. Then corrective action can be made to minimize the production of defective products.

Different change patterns in the process correspond to different root causes. In general, the following three types of process changes are most frequent in an automotive body assembly process:

1. Sustained mean shifts: usually due to tooling failure (e.g., clamp breakage) or material change (e.g., batch to batch).
2. Irregular, sporadic jumps: usually due to interference among parts or interference between tooling and parts.
3. Variance changes: usually due to deteriorating tooling condition (e.g., clamp becoming loose).

A recursive monitoring algorithm is developed to detect and classify these sudden process changes, and group the measurement points with sudden process changes within a few BIWs after changes occur. This algorithm, based on statistical techniques and the knowledge of body structure and body assembly process, can

1. detect which BIW and which measurement point have sudden process changes,
2. classify the process changes as mean shift, sporadic jump, variance change, or any combination of these three, and
3. group the points, classify as having the same process change,

based on the characteristic location for root cause diagnosis.

This algorithm is designed to monitor the OCMM data of each measurement point on bodies. It identifies the dimensional fault using confidence intervals obtained from the sample mean and sample variance of each measurement point before any process change occurs. The sample mean and sample variance could be different from measurement point to measurement point. Therefore, measurement data from the OCMM for the current BIW are normalized before they are sent through this algorithm in order to make this algorithm robust to each measurement point.

The algorithm consists of three parts. The first part uses three different indices simultaneously to check whether process changes have occurred. These indices are: data index, sample mean, and sample variance. These three indices are represented by a vector as (a, b, c). The second part confirms the occurrence of sudden process changes and classifies them using decision making rules. The third part groups the measurement points with the same process change into the direction, opening, and subassembly or part group for root cause diagnosis.

Now we define the three monitoring indices. Each index is determined by comparing the sample statistics with the upper and lower limits of a threshold selected from $100(1 - \alpha)\%$ confidence interval. The principles for the index setting is determined by:

(1) 0 if the data is between the upper and the lower limits,
(2) 1 if the data is larger than the upper limit,
(3) -1 if the data is smaller than the lower limit.

The determination of the upper and lower limits for each index are different and depends on its distribution. Specifically,

a: "data index" is determined from $x_{\text{upper limit}} = t_{\alpha/2,v}$ and $x_{\text{lower limit}} = t_{1-\alpha/2,v}$ where $t_{\alpha/2,v}$ is the critical value of the t distribution with tailed area $\alpha/2$ and degree of freedom v.

b: "sample mean index" is determined from

$$\mu_{\text{upper limit}} = \bar{x} + t_{\alpha/2,n-1}\left(\frac{s}{\sqrt{n}}\right), \text{ and}$$

$$\mu_{\text{lower limit}} = \bar{x} - t_{\alpha/2,n-1}\left(\frac{s}{\sqrt{n}}\right),$$

where $\bar{x}$ is the mean value using the sample size of n, $t_{\alpha/2,n-1}$ is the critical value of the t distribution with tailed area $\alpha/2$ and n-1 degrees of freedom, and s is the sample standard deviation.

c: "sample variance index" is determined from

$$\sigma^2_{\text{upper limit}} = \frac{(n-1)s^2}{\chi^2_{1-\alpha/2,n-1}} \quad \text{and} \quad \sigma^2_{\text{lower limit}} = \frac{(n-1)s^2}{\chi^2_{\alpha/2,n-1}},$$

where n is the sample size for calculating the sample variance, s^2 is the sample variance, and χ^2 is the critical value of the χ^2 distribution.

To detect any sudden process change quickly, a moving window is used to calculate the sample mean and sample variance. For example, the sample mean at car number 20 for a specific measurement point is the average value of the measurements from car number 1 to 20, the sample mean of car number 21 is the average value from car number 2 to 21. etc.

Table 1 summarizes the upper and lower limits for the data range, mean, and variance. A 95% confidence interval and a sample size of 20 for calculating the sample mean and variance are used when a set of normalized data with mean 0 and variance 1 is considered. The sample size, which is used to calculate the sample mean and variance, will influence the sensitivity and the detection speed of this algorithm, which was addressed in [Roan, 1993].

TABLE 1. SUMMARY OF LOWER AND UPPER LIMIT OF DATA, SAMPLE MEAN, AND SAMPLE VARIANCE WITH A 95% CONFIDENCE INTERVAL AND A SAMPLE SIZE OF 20 FOR THE MOVING WINDOW.

	Data Index	Sample Mean	Sample Variance
Lower Limit	-2.09	-0.47	0.58
Upper Limit	2.09	0.47	2.13

The second part of the monitoring algorithm is to identify the types of changes once any part of the 3-digit index is out of the predetermined range. If the 3-digit index is (0 0 0), which indicates no change in the process, then the second part of the monitoring method will not be triggered. On the other hand, if the 3-digit index is (1 0 0) for some specific measurement point for the current assembled car, it means that this raw data is outside the control limits, but the sample mean and sample variance are still within range. At this moment, instead of concluding that this measurement point has a sporadic jump, the second part of the monitoring will filter ambiguous information from the first part of monitoring. In fact, if the raw data is identified as out of range by the first part of monitoring (3-digit index), it could be the beginning of a mean shift, a sporadic jump, a variance change, or any combination of these. Therefore, the second part of the monitoring, which uses some decision making rules and more sample statistics, is necessary to determine what type of dimensional fault has occurred. Similarly, if the sample mean or sample variance is out of range, more statistics need to be checked before any conclusions can be drawn.

Figure 2 is the flow chart for the first and second part of the monitoring, which detects and classifies process changes. Note that a sample size of 20 is utilized to estimate the sample mean and variance. For each BIW, the grouping stage (the third part of monitoring) will not be triggered until all measurement points go through the first and second parts of monitoring. The procedures to detect and classify process changes are listed as follows:

1. Calculate the sample mean and sample variance once data are available for the current BIW using a sample size of 20.
2. Form the 3-digit index by comparing raw data, sample mean, and sample variance with the upper and lower limits of their corresponding 95% confidence interval. These upper and lower limits are determined based on the mean and variance of each measurement when no process change has occurred.
3. If the 3-digit index is:
   a. (0 0 0), the process is in control.
   b. (0 1 1) or (0 -1 1), then find sample mean and sample variance for the last 20 data, excluding sporadic jump data. A mean shift and/or variance change is identified if the sample mean and/or sample variance are/is outside the limits.
   c. (0 0 1), then find sample variance for the last 20 data excluding sporadic jump data. A variance change is detected if sample variance is outside the limits.
   d. (0 1 0) or (0 -1 0), then find sample mean for the last 20 data excluding sporadic jump data. A mean shift is identified if the sample mean is outside the limits.
   e. (1 i j) or (-1 i j), where i is -1, 0, or 1 and j is 0 or 1, then
      (1) find sample mean and sample variance for the next 5 measurements. A mean shift and/or variance change are/is detected if the sample mean and/or sample variance are/is out of range.
      (2) a sporadic jump is detected if the two 3-digit indices before and after are all (0 x y), where x and y are -1, 0, or 1.

The third part of the monitoring algorithm groups the process faults according to the characteristic locations of the measurement points if multiple points experience the same process change for the current BIW. Figure 3 is the flow chart for the grouping stage.

1. After each measurement point is investigated by the first and second part of monitoring, group the points with process changes into mean shift, sporadic jump, and variance change groups.
2. Group the points with the same process change into the direction, opening, and subassembly or part groups according to their characteristic locations.

After the points are effectively grouped using the above strategy, the variation pattern of each group is further analyzed using the Principle Component Analysis (PCA), and displayed using computer animation techniques.

2.2 Computer animation of variation patterns

After grouping the identified measurement points $\{x_1, x_2, ..., x_n\}$

into a variation problem as discussed in the last section, a Principal Component Analysis (PCA) is conducted by solving:

$$[\mathbf{Q} - \lambda_i \mathbf{I}]\,\mathbf{X}_i = \mathbf{0} \qquad (1)$$

where $\mathbf{Q}$ is the covariance matrix obtained from the variables, $\mathbf{I}$ is an identity matrix, λ_i and $\mathbf{X}_i$ are an eigenvalue and its corresponding eigenvector.

In statistics, it has been shown that the PCA allows to estimate the patterns of the data and interpret their importance based on the variance criterion (Jolliffe, 1986). In addition, it has been proven that the magnitude and direction of eigenvectors can represent the variation pattern if there is only one single root cause (Ceglarek and Shi, 1994). In the PN, the eigenvalue-eigenvector pairs (λ_i - $\mathbf{X}_i$, i=1, 2, ...n), obtained based on the PCA, are interpreted as the variation pattern in the following way (Hu and Wu, 1992):

(1) For each eigenvector, the relative magnitudes and directions of its elements are equivalent to the body movement represented by position and directions of the measurement points;
(2) The number of the eigenvalue - eigenvector pairs represents the number of patterns involved in the variation problem;
(3) The importance of each pattern is defined by the eigenvalues related to each eigenvector. In most cases, the first and second eigenvector represent more than 90% of the total variation.

In the animation algorithms, the procedures can be summarized as follows. First, measurement points are grouped according to the rules presented in last section. Then, the covariance matrix of the data from the measurement points is calculated. Next, eigenvectors and eigenvalues are estimated based on the covariance matrix. Finally, the elements of the eigenvectors corresponding to the measurement points are displayed graphically on the screen. The magnitude and direction of eigenvectors represent the variation pattern, and are simultaneously animated graphically on computer. Thus, users can see the variation pattern of the analyzed problem.

The variation pattern animation provides a graphical interpretation of the complex variation problems. More importantly, there are no requirements for users to master advanced statistics to understand the analyzed results. The user may identify the root causes of variation by looking into the relative magnitude and directions of the animated variation patterns. An example of the animated variation pattern is given in section 2.3.4.

2.3 Variation root cause diagnosis

The variation animation developed in the last section provides an intuitive tool for graphical interpretation of the variation problems. This section develops a systematic knowledge based diagnostic technique for root cause identification. The presented approach enables quick localization of the assembly process fault based on dimensional measurement. It consists of three parts: body assembly knowledge representation, case identification, and diagnosis reasoning.

2.3.1 Body-in-white (BIW) assembly and its knowledge representation.

In the development of the PN, a body structure is represented by using extended version of hierarchical groups (Ceglarek et. al., 1994), where each group is defined as a functional module.

Figure 4 shows a body-in-white assembly process emphasizing the left hand aperture. The symbols S_1, ..., S_5 in the figure represent geometrical assembly stations, where parts are positioned and welded. Stamped parts, called components, are represented as $C_{i,j}$. A functional module is defined as MOD_{ij} = { C_{ij}, P_{ij}, S_i , MLP_{ij}}, here C, P, S and MLP represent the components (parts), principle locating points, geometric assembly station, and measurement locating points respectively. The subscript "i" defines the layer number in the representation, and the subscript "j" represents the number of consecutive components in that layer, which will be discussed later. Figure 5 shows an example of body assembly representation using the aforementioned modules for a side aperture subassembly.

In general, a module can be understood as a minimal set of elements necessary to describe an assembly operation. The number of modules is equal to the number of components (parts or subassemblies) in the whole assembly process. Compared with the hierarchical grouping representation technique (Ceglarek, et al., 1993), the representation approach in this paper presents knowledge of the body structure, assembly sequence, assembly tooling and measurement in an "integrated" format. Thus, the relationships between key features of the assembly process are represented. Before further analysis, some useful terms are defined with the help of the graph theory (Bondy and Murty, 1976):

Definition 1: A bipartite graph is an undirected graph G(V_1, V_2, E), where V_1 and V_2 are sets of vertices and E is a set of edges, in which no two vertices in the same set are linked by an edge.

Definition 2: An n-partite graph is an undirected graph G(V_1, V_2,..., V_n, E_1, E_2,..., E_{n-1}), where each V_i, $1 \le i \le n$, is a set of vertices, and each E_j, $1 \le j \le (n-1)$, is a set of edges, in which the edges in E_j link vertices in V_j to those in V_{j+1}, and no two vertices in the same set are linked by an edge.

The bipartite and n-partite graphs are used to define body assembly representation in the following way:

Definition 3: A body assembly representation, BA, is an l -partite undirected graph

$$BA(MOD_1, MOD_2, \ldots, MOD_l, E_1, E_2, \ldots, E_{l-1}), \qquad (2)$$

where $MOD_1, MOD_2, \ldots, MOD_l$ are sets of vertices, and $E_1, E_2, \ldots, E_{l-1}$ are sets of edges, with l equals to the number of assembly layers.

The vertices MOD_i is a set of all modules in the i-th layer:

$$MOD_i = \bigcup_{j=1,n_i} MOD_{i,j}, \qquad (3)$$

where n_i is the number of modules in the i-th layer. The Edge E_i is the set of all links between components in layers: i and (i+1), shown in Fig. 5:

$$E_i = \bigcup_{\substack{j=1,n_i \\ k=1,n_{(i+1)}}} E^{(i)}_{j,k}, \qquad (4)$$

where $E^{(i)}_{j,k}$={0,1} represents link between components $C_{i,j}$ and $C_{i,k}$. If components $C_{i,j}$ and $C_{i,k}$ are linked in the body structure then $E^{(i)}_{j,k}$ is equal to 1, otherwise $E^{(i)}_{j,k}$ is equal to 0.

The body assembly is represented as parent-siblings links which define the assembly operations conducted in one station. Parent-siblings link can be described by an input-output relation, with inputs being components entering station S_i (siblings) and output being the component leaving station S_i (parent) (Fig. 6). It can be defined as:

Definition 4: A parent-siblings link (PS) of the component $C_{i,j} \equiv Parent_{i,j}$, is defined as an undirected bipartite graph $PS(MOD_{i,j}, Siblings_{i,j}, E^{(i)}_{j,k})$ with one vertex representing component $C_{i,j}$, and the other ones defined as $Siblings_{i,j} \subset MOD_{(i+1)}$, such that the edges satisfy $\forall_k\, E^{(i)}_{j,k} = 1$.

The body assembly representation also enables us to describe two levels of assembly sequences. The first level shows the sequence of stations used in the assembly process, i.e., for example S_6 -> S_5 -> S_4 (Fig. 5). And the second level shows the sequence of components entering a single station. These two levels are represented by vertical and horizontal links among the modules. The vertical connections among the modules represent the sequence of stations in the assembly process. The horizontal links of the sibling-modules, for given parent-module, describe the sequence of the component entering a single assembly station.

2.3.2 Case identification of sustained dimensional variation.

The procedure of case identification for sustained dimensional variation selects and classifies the information pertaining to measurements captured during a given period of time. If measurement data include variation caused by PLP failure, the pattern described by the data will follow the pre-determined pattern of the faulted PLP (Ceglarek and Shi, 1994). Therefore, based on the characteristics of body structure and tooling locators, some points will "move" together during the assembly process. In a statistical sense, "moving" together can be interpreted by correlation between the measurement points. These correlated points can then be grouped into a variation problem, or case study. The purpose of grouping them into a case, is to localize and isolate root cause of the problem. This procedure is based on the assumption that there is a limited number of root causes which usually occur in one of the geometrical stations. Clustering methods and correlation analysis (Kaufman and Rousseeuw, 1990) are used to find variation problems shown by measurement data.

Initially, a case is pre-defined based on two user selected thresholds: variation (T_v) and correlation (T_c). The variation threshold defines the magnitude of a problem, and the correlation threshold defines the scope of the problem by showing measurements with variation caused by one root cause. The procedure of case identification by clustering sensor information is summarized as follows (Fig. 7):

(1) Calculate 6-sigma variation σ_{MLP} for all MLP points using a selected sample size:

$$\sigma_{MLP} = \frac{\sqrt{\sum_{i=1}^{N}(\chi_i - \bar{\chi})^2}}{N-1} \tag{5}$$

where χ_i is an i-th measurement of MLP, $\bar{\chi}$ is a mean of the i-th measurement, and N is the sample size.

(2) Group all MLP points according to their variation levels and a variation threshold (T_v). In general, T_v is determined so that 70% of the inspected points fall below that level.

(3) Calculate correlation for all MLPs in the group obtained in step (2).

$$\mathrm{Corr}_{\chi,\zeta} = \frac{\sum_{i=1}^{N}(\chi_i - \bar{\chi})(\zeta_i - \bar{\zeta})}{\sqrt{\sum_{i=1}^{N}(\chi_i - \bar{\chi})^2 \sum_{i=1}^{N}(\zeta_i - \bar{\zeta})^2}} \tag{6}$$

where χ and ζ are two MLPs.

(4) Decompose the group obtained in step (2) into subgroups according to their levels of correlation. Highly correlated measurements will be grouped into one sub-group. Thus, a correlation threshold (T_C) is proposed for the decomposition. The correlation threshold is a second constraint in grouping measurements according to a single fault symptom, which is based on the assumption that the measurements with large variation are strongly correlated if and only if their variations are caused by the same root cause.

(5) For each selected sub-group, calculate the correlation between measurements (MLPs) from that sub-group and other measurements that were rejected earlier for having variation below variation threshold T_V but manifesting one root cause.

The selected MLPs, which are a group of measurement points with large variation and strong correlation, are called Candidate MLPs (CMLPs).

2.3.3 Variation root cause diagnosis reasoning.

The root cause diagnosis conducts three tasks (Fig. 8): identification of the candidate component (fault component), localization of the candidate station (fault station), and isolation of a root cause.

Determination of the Candidate Component. The Candidate Component $C^c_{i,j}$ is a component in the body structure which manifests the symptom of the variation problem. The Candidate Component is determined based on the number of MLPs and CMLPs located on each component. The information about the number of MLPs in each component is defined in the body assembly representation (Section 2.3.1). The number of CMLPs is obtained by the case identification procedure presented in Section 2.3.2. In order to explain the procedure of determining Candidate Component, the following definitions are presented:

Definition 5: An assembly path is an undirected n-partite graph

$$\mathrm{AP}(\mathrm{MOD}_{1,j_1}, \mathrm{MOD}_{2,j_2}, \ldots, \mathrm{MOD}_{l,j_l}, E^{(1)}_{j_1,j_2}, E^{(2)}_{j_2,j_3}, \ldots, E^{(l-1)}_{j_{(l-1)},j_l}) \tag{7}$$

where the vertices of the graph are the modules $\mathrm{MOD}_{1,j_1}, \mathrm{MOD}_{2,j_2}, \ldots, \mathrm{MOD}_{l,j_l}$, and $E^{(1)}_{j_1,j_2}, E^{(2)}_{j_2,j_3}, \ldots, E^{(l-1)}_{j_{(l-1)},j_l}$ are the edges, defined by body assembly representation, such that $E^{(1)}_{j_1,j_2} = E^{(2)}_{j_2,j_3} = \ldots = E^{(l-1)}_{j_{(l-1)},j_l} = 1$. The $E^{(i)}_{j,k}$ is defined in Eq. (4).

Figure 6 shows examples of the assembly paths in the body structure, for instance, path C_{35} - C_{41} - C_{52} - C_{61}.

Definition 6: A membership $\eta_{i,j}$ of the component $C_{i,j}$ in a module is the ratio of the number of CMLPs $n^{*}_{i,j}$ for identified case, to the number of the MLPs $n_{i,j}$ in that module:

$$\eta_{i,j} = \frac{n^{*}_{i,j}}{n_{i,j}}, \tag{8}$$

The procedures of determining Candidate Component (Fig. 8) are:

(1) Calculate the membership $\eta_{i,j}$ (Eq. 8) for each component;

(2) Select the component with maximum membership for each assembly path AP

$$\forall_{AP}\, C^c_{i,j} = \{C_{i,j} : \eta_{i,j} = \max_{(k,l)\in AP}(\eta_{k,l})\}, \tag{9}$$

(3) Check the membership for each parent-sibling link

$$(\exists_{\mathrm{Siblings}_{i,j} \equiv C^c}\ \forall_{C \in \mathrm{Siblings}_{i,j}}\ \eta(C) \neq 0) \Rightarrow (\mathrm{Parent}_{i,j} \equiv C^c \ \&\ \mathrm{Siblings}_{i,j} \neq C^c), \tag{10}$$

This step allows us to determine the candidate component in the situation where one sibling from siblings related to the $S_{i,j}$ is selected as a C^c in step (2), but all other siblings from the same parent are also affected by the variation case. In this situation, the candidate component is not the siblings, but their parent.

(4) Candidate Components are components selected in steps (2) and (3).

Localization of Candidate Station. An assembly station where a fault has occurred is called a Candidate Station, denoted by S^c_i. The approach to determine a S^c is based on the information about the candidate components and the body assembly representation, which is summarized as:

(1) For one candidate component $C^c_{i,j}$, the candidate station S^c is determined as:

$$S^c = \{S_k : S_k \in \mathrm{MOD}_{i,j}\}, \tag{11}$$

(2) For two candidate components $C^c_{i,j}$ and $C^c_{k,m}$, a candidate station is determined as:

$$\exists_{AP_1} \exists_{AP_2} (C^c_{i,j} \in AP_1 \text{ and } C^c_{i,j} \in AP_1) \Rightarrow$$

$$S^c = \{S : \exists_{\max(p)} \mathrm{MOD}_{p,r} \in (AP_1 \text{ and } AP_2) \text{ and } S \in \mathrm{MOD}_{p,r}\}, \tag{12}$$

(3) For more than two candidate components, each pair of the components is treated separately in the way described in items (1) or (2).

The candidate station determination procedure described above selects the assembly station as the nearest station between candidate component(s) in the body structure (Fig. 5).

Identification of the Root Causes. After successfully determining the candidate components and stations, the root cause identification is conducted by focusing on the tooling systems and its fault symptoms. Principles for the root cause identification can be summarized as: (1) Root cause is a locating pin problem if all measurement points on the candidate component are CMLPs; (2) Root cause is a clamp or welding spot related problem if some measurement points on the candidate component are CMLPs; (3) Root cause is an interference problem if CMLPs involve three axes. A detailed study of root cause identification is presented by Ceglarek and Shi (1994).

2.3.4 Example of a case study: B-Pillar variation in the Y direction.

The presented case study illustrates the procedures of determining: CMLPs, Candidate Component, Candidate Station and root cause of variation.

(1) Selection of CMLPs: The variation and correlation thresholds were set as T_v=2.0 mm (6-sigma) and T_c=0.7 respectively. The following MLPs were identified as CMLPs { $M_{\bullet,21}$, $M_{\bullet,22}$, $M_{\bullet,23}$}. All CMLPs have measurement axes in Y direction. Fig. 9 shows all the MLPs and CMLPs on a side aperture.

(2) Selection of Candidate Component: Fig.10 shows membership values for all components of the body structure. Following Eq. (9), the maximum membership for path l= {$C_{5,1}$-$C_{4,1}$-$C_{3,5}$} is equal to $\eta_{5,1}$=1.0, suggesting that $C^c_{5,1}$ is a Candidate Component. Checking the membership for each parent-siblings link (Eq. (9)) does not suggest any other Candidate Components.

(3) Location of Candidate Station: Following Eq. (11), the Candidate Station is defined by module $MOD_{5,1}$ describing the Candidate Component $C^c_{5,1}$ (Fig.5). From Fig. 5 and following the procedures in the last section, the Candidate Station is located as station S_5.

(4) Root cause identification: From the aforementioned analysis, it is known that: (1) all selected CMLPs measure component in the Y axis, (2) $C^c_{5,1}$ is the Candidate Component, and (3) S_5 is the Candidate Station. Therefore, it is suggested that the fault is caused by tooling in Station S_5 controlling component $C^c_{5,1}$ in the Y axis.

The variation animation also helps in the root causes determination. By applying the PCA to the CMLPs ($M_{\bullet,21}$, $M_{\bullet,22}$, $M_{\bullet,23}$), the first and second eigenvalue - eigenvector pairs are obtained as shown in Table 2.

TABLE 2. AN EXAMPLE OF THE PCA RESULTS

Eigenvalues	Eigenvectors
λ_1=4.20	$\mathbf{a}_1$=[0.44, 0.53, 0.73]
λ_2=1.03	$\mathbf{a}_2$=[0.62, 0.65, 0.45]

Fig. 11 shows the variation pattern corresponding to the dominant eigenvector. The eigenvalues define the importance of the variation pattern described by the eigenvector. According to the level of the first eigenvalue, the first pattern (dominant eigenvector) contributes around 76% of the total variation in the analyzed problem. Therefore, elimination of the variation described by the dominant eigenvector significantly reduces the process variation .

Detailed investigation of the assembly station S_5 discovered that a clamp controlling B-pillar inner was not functioning. After the clamp was repaired, the variation was significantly reduced (see Table 3).

TABLE 3 CASE EXAMPLE - EVALUATION OF CORRECTIVE ACTION

MLPs	BEFORE (6-sigma, Sample of 100)	AFTER (6-sigma, Sample of 100)
21 (Y)	2.40	1.44
22 (Y)	2.83	1.46
20 (Y)	3.85	1.47

3. PROCESS NAVIGATOR - IMPLEMENTATIONS

The PN is implemented in PC based Novell's local area network (LAN) linked with measurement station (OCMM). Four major modules, on-line monitoring and fault classification, data and alarm bases, variation pattern animation, and knowledge based diagnosis are implemented. A brief description for each module is summarized as follows:

(1) On-line monitoring and fault classification: An interface between the OCMM and the PN has been developed using C++ language. By using the interface, the dimensional measurement data can be automatically transferred from the OCMM to the PN data base in real time. The on-line monitoring and fault classification algorithm has been programmed and linked with the data collection software. Therefore, alarms about the occurrence of sporadic jumps, mean shifts, or variation changes, will be detected and classified in real time. A CUBIX board, which is installed in the file server, is used to run the module to acquire and monitor the in-line OCMM data. Each CUBIX board can collect the data from two OCMM stations. Serial ports are used for communication between the OCMM and the CUBIX board.

(2) Data base and alarm base module: Both the data base and alarm base were developed using Novell Betrieve Software. (a) The design of the data base can store 150,000 data records, which is estimated to save six months of production data with a production rate of 1000 units per day. A management menu system for the data base has been implemented. The management of the data base includes search files, list files, show raw data files, and delete files (with passwords). (b) The alarm base is designed to manage the alarm messages generated by the on-line monitoring program. The alarm message includes the type of an alarm (SJ, MS, VC), magnitude of the alarm, alarm occurred Job Sequence Number (JSN), date, time, and MLPs. Alarm reports have been developed to help the user utilize the alarm message efficiently. The alarm reports includes summary reports, detail reports and alarm frequency reports (Fig. 12). Other features, such as alarm search by JSN, date and time, recent samples, and report generation based on the combination of different types of alarms, are also included in the software.

(3) Variation pattern animation module: Variation pattern animation reports have been developed to show the variation pattern for a given body opening or a given panel. The animation of variation patterns was realized by using the principle component analysis and prepared computer graphic packages written in C++. By using the animation, the variation pattern can be visually inspected and analyzed. Currently, the animation is developed for each body opening (doors, hood, deck lid, etc.). An example of the animation results using production data is shown in Fig. 13.

(4) Knowledge-based diagnosis module: An expert system development shell, Nexpert Object^{TM} produced by Neuron Data Inc, was used for implementation. The diagnosis approach, presented in section 2.3, was realized using hybrid knowledge representation: production system (rules) and frames (classes-objects-slots). The frames are used to represent the body structure in the form of classes and objects (functional modules) with necessary description presented as slots (C_{ij}, P_{ij}, S_i , MLP_{ij}). The Nexpert Object^{TM} describes the static relation between failure and body structure as a set of IF - THEN - ELSE rules. The dynamic relations are described as reasoning, and stored in the Nexpert as agenda and inheritance. The reasoning part of the shell uses forward and backward propagation to identify candidate component and candidate station. The rules, describing procedure of candidate component and candidate station determination, are linked in the Nexpert through context link option. The outline of the implementation is shown in Fig. 14. A brief summary of the implementation is shown in Table 4.

TABLE 4 THE SUMMARY OF THE IMPLEMENTED KNOWLEDGE-BASED DIAGNOSIS

Name	Rules	Objects	Classes	Properties	Slots
Number	102	73	10	79	113

e developed diagnosis approach has been evaluated using case studies solved in a domestic automobile assembly plant. The conducted evaluation indicates that implemented diagnostic approach can solve 83.3% of cases.

4. CONCLUSIONS

This paper develops a process navigator (PN), a dimensional quality control and assurance system for automobile body assembly. The proposed system includes real-time dimensional data collection, on-line monitoring and fault classification, dimensional data base, alarm message base with reports, variation pattern animation, and knowledge-based diagnosis.

The major contribution of the developed PN is integration of advanced statistics with knowledge about the body assembly during process monitoring and problem solving, and presentation of results as a pictorial, user-friendly computer reports. The integration of statistics with body assembly knowledge required developing and implementing the following issues:

(1) On-line monitoring and fault classification algorithm. Three-digit index is applied to monitor and classify in real time the three most common variation patterns caused by tooling faults in the assembly process.

(2) Variation pattern animation: The PCA is integrated with body structure and knowledge about assembly process. The eigenvalue-eigenvector pairs are used to interpret variation problems in the following way: the magnitude and direction of the eigenvector represents relative movement between the measurement points, and the eigenvalue represents the importance of the variation pattern corresponding to the eigenvector.

(3) Variation root cause diagnosis: Knowledge about the body assembly is described by developed functional modules, which integrates knowledge about the assembly process and body structure in the knowledge-based computer shell. A step-by-step diagnostic reasoning strategy is developed based on the proposed knowledge representation, which determines the root cause of variation. The presented diagnosis identifies correctly 83.3% of the tested cases.

4) Process navigator implementation: The implementation of the aforementioned technologies and algorithms allows development of integrated quality control and assurance systems for the auto body assembly manufacturing. In addition to the development and implementation of the proposed methodology, great efforts were undertaken to design pictorial user friendly reporting system. Therefore, the PN provides an effective tool allowing the plant staff benefit from the results of advanced statistics without requiring expertise in advanced statistics.

ACKNOWLEDGMENT

The project is funded by the National Institute of Standard and Technology, Advanced Technology Program(ATP), and Classic Design Inc. The authors would like to thank Mr. J. Steimel, Dr. J. Roan, Mr. S. Wang, Dr. L. Jin, and Mr. H. Tang for their contributions to the development of the process navigator.

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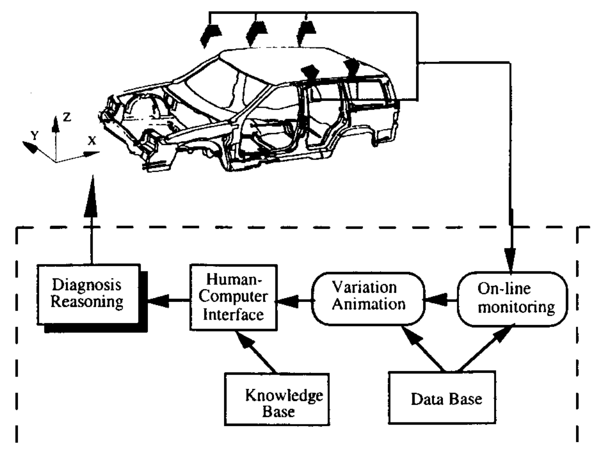


Process Navigator

FIG. 1 THE ARCHITECTURE OF THE PROCESS NAVIGATOR

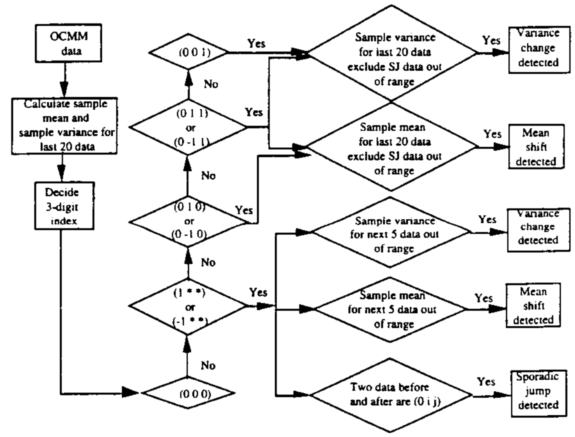
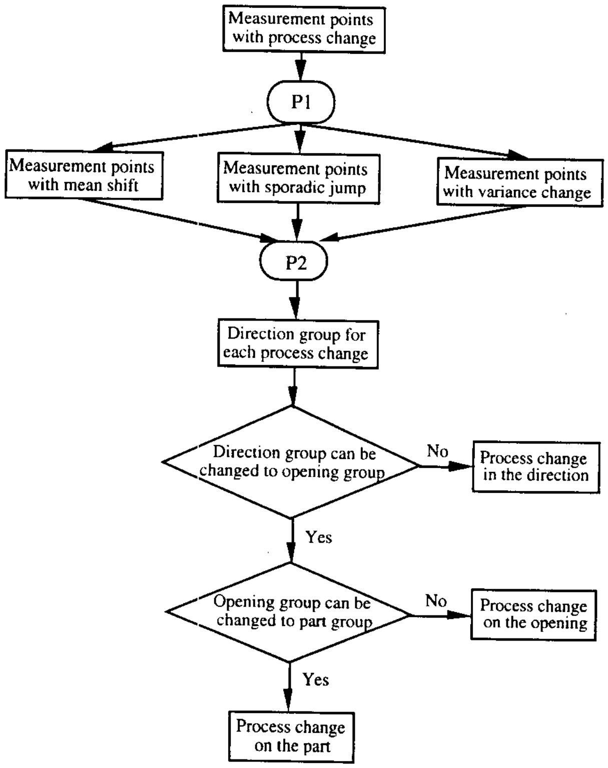


FIG. 2 FLOW CHART FOR DETECTING AND CLASSIFYING SUDDEN PROCESS CHANGES



P1: Grouping according to the type of process changes.
P2: Grouping according to the F/A, I/O, and U/D direction.

FIG 3. FLOW CHART FOR GROUPING THE POINTS WITH PROCESS CHANGES.

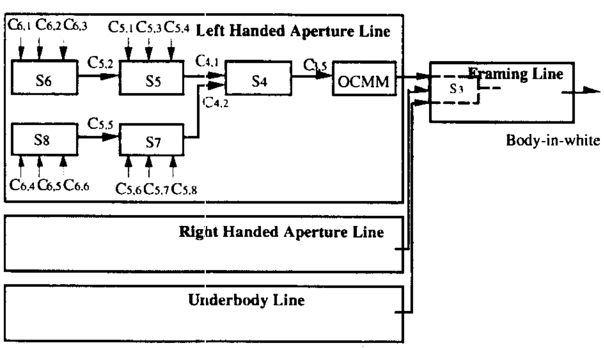


FIG. 4 BLOCK DIAGRAM OF A BODY ASSEMBLY PROCESS

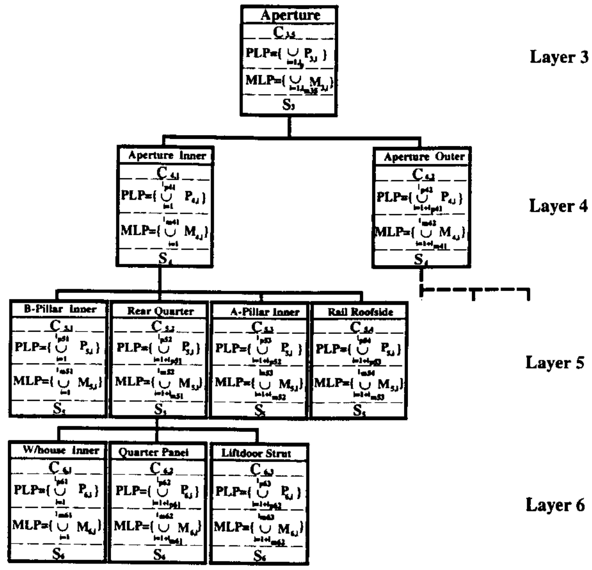


FIG. 5 BODY ASSEMBLY REPRESENTATION WITH DEFINED FUNCTIONAL MODULES

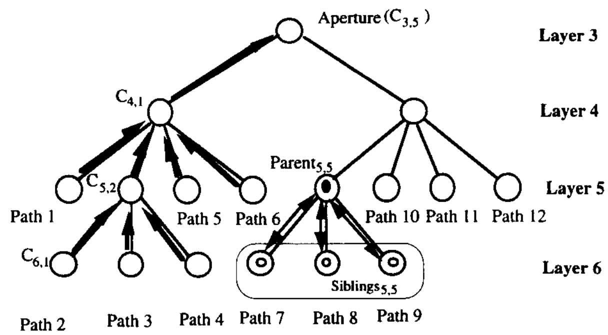


FIG. 6 EXAMPLES OF ASSEMBLY PATHS AND PARENT-SIBLINGS LINK IN THE BODY ASSEMBLY REPRESENTATION

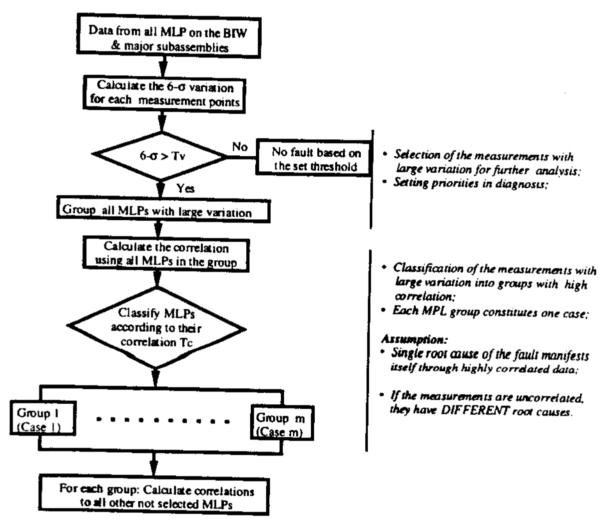


FIG. 7 THE PROCEDURE OF CASE IDENTIFICATION AND CLUSTERING OF SUSTAINED DIMENSIONAL VARIATION

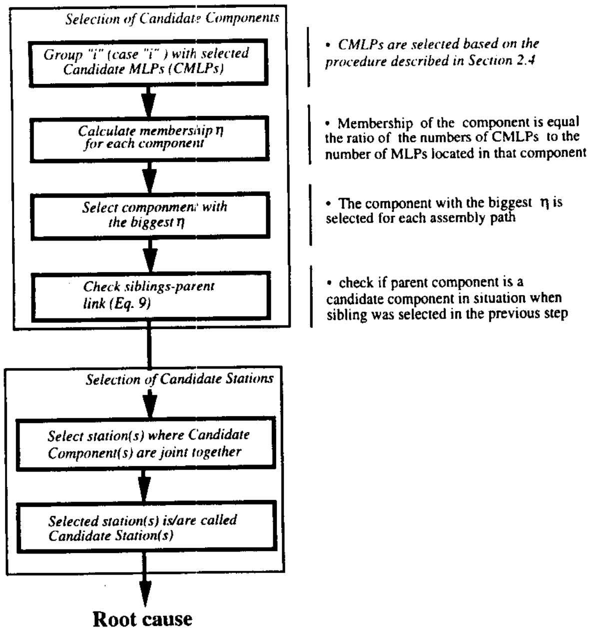


FIG. 8 THE FLOW CHART OF THE DIAGNOSTIC REASONING

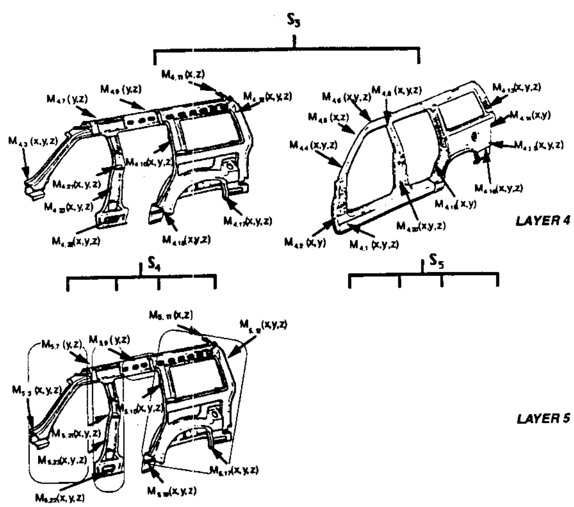


FIG. 9 AN EXAMPLE OF MEASUREMENT LOCATING POINTS (MLPS)

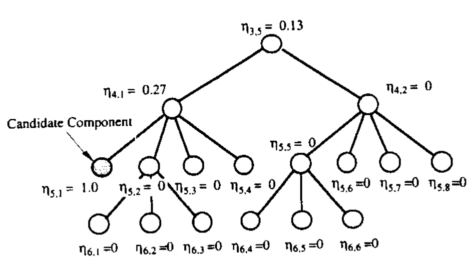


FIG. 10 CASE EXAMPLE - MEMBERSHIP OF THE ALL COMPONENTS

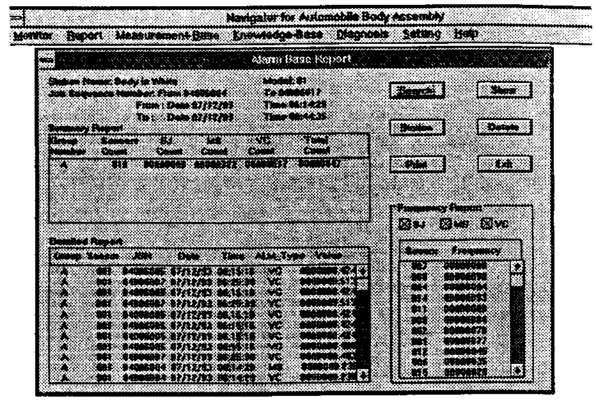


FIG. 12 THE ALARM REPORT IN THE PN

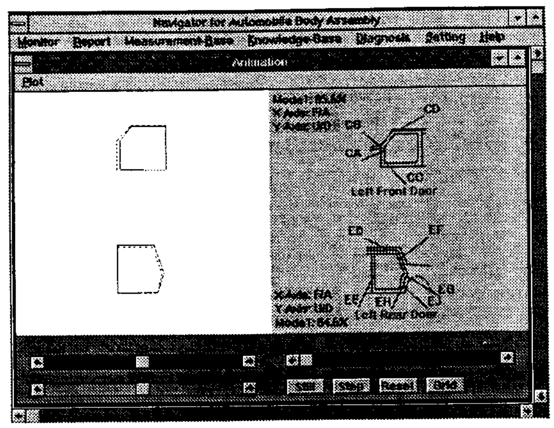


FIG. 13 AN EXAMPLE OF THE VARIATION PATTERN ANIMATION

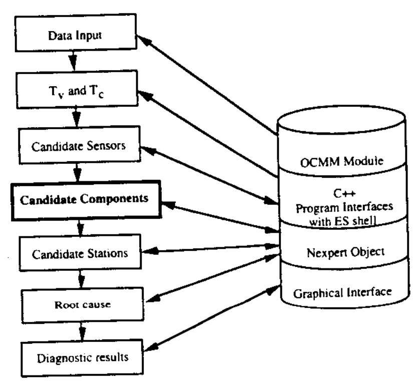


FIG. 14 THE IMPLEMENTATION OUTLINE OF THE KNOWLEDGE BASE DIAGNOSIS

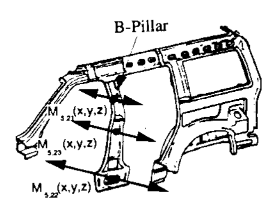


FIG.11 VARIATION ANIMATION FOR B-PILLAR VARIATION