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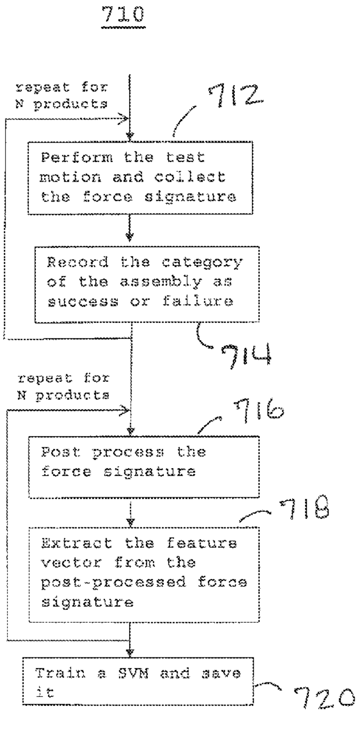
[Continued on next page]

(54) Title: METHOD AND APPARATUS FOR USING POST ASSEMBLY PROCESS INTERACTION SIGNATURES TO DETECT ASSEMBLY FAILURES

Fig. 7a



(57) Abstract: There is described a technique for detecting the success of an automated process that produces an article of manufacture. A statistically significant number of successful and failed articles are produced by the automated process. Each of these articles is interacted with a test platform to measure interaction signatures that indicate successful and failed articles. A correlation of the difference between the interaction signatures is calculated. An interaction signature is then obtained for an article manufactured by the process after the earlier made articles. The new interaction signature is analyzed against the calculated correlation difference to automatically categorize as either a success or a failure the additional article of manufacture. There is also described a technique for optimizing the motion used to test the manufactured articles to improve the correlation of the difference between the interaction signals of successful articles and the interaction signals of failed articles.

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Method and Apparatus for Using Post Assembly Process Interaction Signatures to Detect Assembly Failures

1. Field of the Invention

This invention relates to automated assembly and more particularly to the detection of assembly failures after the assembly is completed.

2. Description of the Prior Art

Automated assembly, such as for example and without limitation robotic assembly, is used in various industries such as automotive, electronics etc. One example of robotic assembly for electronics is described in WO2011153156 published on December 8, 2011.

In-process failure detection methods exist, such as those described in the paper by Rodriguez, et al, entitled *Failure Detection in Assembly: Force Signature Analysis* (from the IEEE CASE conference in 2010). Such methods use data from a sensor that is often corrupted by the dynamics of the assembly process. Post assembly inspection can be performed by automated vision inspection and/or a destructive tension if the concern is the mechanical strength of the assembled parts.

Summary of the Invention

A method for detecting the success of an automated process that produces an article of manufacture includes but is not limited to:

producing a statistically significant number of successful and failed articles of manufacture using the automated process;

interacting each of the successful and failed articles of manufacture with a test platform to measure interaction signatures indicative of the successful articles of manufacture and the failed articles of manufacture;

calculating a correlation of the difference between the interaction signatures of the successful articles of manufacture and interaction signatures of the failed articles of manufacture;

obtaining an interaction signature for an additional article of manufacture produced after the successful articles of manufacture and the failed articles of manufacture are produced; and

analyzing the interaction signature obtained for the additional article of manufacture produced after the successful articles of manufacture and the failed articles of manufacture are produced against the calculated correlation of the successful and the failed articles of manufacture interaction signatures to automatically categorize as either a success or a failure the additional article of manufacture produced after the successful articles of manufacture and the failed articles of manufacture are produced.

A method for detecting the success of an automated process that produces an article of manufacture includes but is not limited to:

calculating a correlation of the difference between interaction signatures of a statistically significant number of successful articles of manufacture and interaction signatures of a statistically significant number of failed articles of manufacture;

obtaining an interaction signature for an article of manufacture produced after the correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated; and

analyzing the interaction signature obtained for the article of manufacture produced after the correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated against the calculated correlation of the successful and the failed articles of manufacture interaction signatures to automatically categorize as either a success or a failure the article of manufacture produced after the correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated.

A method for detecting the success of an automated process that produces an article of manufacture by testing a statistically significant number of successful and failed articles of manufacture produced using the automated process includes but is not limited to:

interacting each of the successful and failed articles of manufacture with a test platform to measure interaction signatures indicative of the successful articles of manufacture and the failed articles of manufacture;

calculating a correlation of the difference between the interaction signatures of the successful articles of manufacture and interaction signatures of the failed articles of manufacture; and

repeating the producing, interaction and calculating steps with changes in the interacting step to minimize the correlation of the difference between the interaction signatures of the successful articles and the interaction signatures of the failed articles by changing the interaction of each the successful and failed articles with the test platform.

Description of the Drawing

Fig. 1 shows a robot holding an assembled product.

Fig. 2 shows the test platform that is used in the post assembly test system in testing the assembled product for assembly failures.

Figs. 3 and 4 show one example of the parts to be assembled into a product that is tested by the post assembly test system.

Figs. 5a to 5c show examples of a faulty assembly for the parts that are that are shown in Figs. 3 and 4 and Fig. 5d shows a correct assembly for those parts.

Figs. 6a and 6b show the motion used by the post assembly test system to detect an assembly failure for the parts shown in Figs. 3 and 4.

Figs. 7a and 7b show flowcharts for two phases in the use of the Support Vector Machine (SVM) for assembly failure detection.

Fig. 8 shows a flowchart for the post processing of the collected force signatures.

Fig. 9 shows the hyperplanes that can be used to classify the collected force signatures.

Figs. 10 and 10b show a flowchart for optimizing the motion used to test the manufactured articles to improve the correlation of the difference between the interaction signals of successful articles and the interaction signals of failed articles.

Detailed Description

Referring now to Figs. 1 and 2, there is shown one embodiment for the post assembly test system. In this embodiment as shown in Fig. 1, an assembled product 16 is held by a gripper 14 mounted on the tip of a robot 10. Robot 10 may, for example, be an articulated 6-axis robot, a Cartesian gantry robot, a robot having less than 6 axes such as a SCARA robot, or a robot having more than 6 axes such as a multi-arm robot. The motion of the robot 10 is controlled by controller 12. As is shown in Fig. 1, test platform 18, which is to contact the assembled product 16, is mounted on a workbench 20.

Test platform 18 can be anything that interacts with the assembled product, that is, article of manufacture, 16. While Fig. 1 shows the test platform 18 mounted on workbench 20 it is well known that the test platform 18 can be held by a robot, not shown in Fig. 1, and robot 10 can bring the assembled product 16 to the robot holding test platform 18 or the robot holding the test platform 18 can bring the test platform 18 into contact with the assembled product 16.

As can be appreciated by one of ordinary skill in this art, the controller 12 of the present invention may include a computer readable medium having computer-readable instructions stored thereon which, when executed by a processor, carry out the operations herein described. The computer-readable medium may be any tangible medium that can contain, store, communicate, propagate, or transport the user-interface program instruction for use by or in connection with the instruction execution system, apparatus, or device and may by way of example but without limitation, be an electronic, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, device, or propagation tangible medium. More specific examples (a non-exhaustive list) of the computer-readable tangible medium include: a portable computer diskette, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read-only memory (EPROM or Flash memory), a portable compact disc read-only memory (CD-ROM), an optical storage device, or a magnetic storage device. Computer program code or instructions for carrying out operations of the present invention may be written in any suitable programming language provided it allows achieving the described technical results. While the controller 12 can perform the operations shown in the flowcharts of Figs. 7, 8 and 10, the embodiment shown in Fig. 1 can also include a separate computation device that communicates with controller 12 to perform those operations.

As shown in Fig. 2, the test platform 18 is constructed with at least a lower layer 26 and a top layer 27. The top layer 27 is made of hard materials, while the lower layer 26 is made of compliant materials such as rubber and foam. The purpose of such a design is to provide a compliant and nondestructive contact of the test platform 18 with the assembled product 16. In alternate embodiments, a compliant layer may not be needed due to existence of compliance elsewhere in the system or due to the nature of the assembly operation.

One example of assembled product 16 is shown in Figs. 3 and 4 as the combination of a printed circuit board 24 that has mounted on it various circuit elements, a generally rectangular socket 30 that has therein other circuit elements and a aluminum shield can 36 to cover the generally rectangular socket 30. Socket 30 includes four raised side-walls 32a to 32d that form four corners 34a to 34d.

As can be seen from Fig. 3, the shield can 28 includes a generally rectangular shaped planar face 36.

Side-walls 38a to 38d project upwardly from each edge and form corners 40a to 40d. Shield can 28 is sized to be snap-fit over socket 30. The assembly of the shield can 28 to socket 30 may be performed in a manner well known to those in the robot assembly art by one or more robots (not shown) which are other than robot 10.

Figs. 5a to 5d show the good and the faulty assemblies of the shield can 28 to the socket 30. More particularly, Fig. 5a shows that the shield can 28 is missing, that is, the shield can 28 was not assembled to the socket 30.

When the shield can 28 is assembled to the socket 30, the major fault of that assembly is that one or two of the four corners 40a to 40d of the shield can 28 are not pressed enough into the socket 30. Fig. 5b shows this fault for one corner out of position and Fig. 5c shows this fault for two corners out of position.

Fig. 5d shows a good assembly. As shown in this figure, the shield can 28 covers socket 30 and all four corners 40 to 40d of shield can 28 are in position on the socket 30.

Figs. 6a and 6b show the test motion to detect the assembly failure for the parts illustrated in Figs. 3 and 4 using the setup in Figs. 1 and 2. As shown in Figs. 6a and 6b, the test motion is a rocking motion that presses each of the four corners 40a-40d of the socket 30 against the top layer 27 of the test platform 18. Where the fault is a corner or corners of the shield can 28 when assembled to socket 30 are out of position such as shown in Figs. 5b and 5c, the pressing of each of the four corners 40a to 40d of the socket 30 against layer 27 can result in a fixing of that faulty assembly.

The test motion is executed by the robot 10 and is preprogrammed during the system setup. Due to the high repeatability of the robot 10, this test motion is the same for each assembled product 16. If the gripping of each assembled product 16 is repeatable, then the test condition of the assembly failure has very little variation. As a result, the contact force induced during the rocking and pressing motion is free of other side effects such as the dynamics in the actual assembly process.

The contact force signature obtained from the test motion by use of a force sensor can be processed using many existing algorithms for the failure detection. An exemplar algorithm is the industry-standard statistical classification tool, the Support Vector Machine (SVM). The SVM can classify the contact force signature data into two categories: successful and unsuccessful failures.

As shown in the flowcharts 710 and 722 respectively of Figs. 7a and 7b, there are two phases in using the SVM for assembly failure detection, namely the training phase whose flowchart 710 is shown in Fig. 7a and the testing phase whose flowchart 722 is shown in Fig. 7b. These two phases share common actions, described in more detail below, such as performing the test motion, collecting the force signature, post processing the force signature and extracting the feature vector.

Training of the SVM proceeds with the steps shown in Fig. 7a as follows:

1. Executing at steps 712 and 714 the test motion for each assembled product 16 in a statistically significant number of N assembled products 16 that has roughly half successes and half failures as follows:

a. performing at step 712 the test motion and collecting the force signature information for each of the assembled products 16 in the series; and

b. recording at step 714 the category of each the tested series of assembled products 16 as either a success or a failure.

2. Executing steps 716 and 718 for each assembled product 16 in a series of N assembled products 16.

Post processing at step 716 the force signatures collected at step 712. The flowchart 800 for the post processing is shown in Fig. 8 and has the following steps:

a. resampling at step 802 the recorded force signature if the sampling time is uneven and smoothing to remove the noise (various well known techniques such as for example box car averaging are available to perform this function);

b. aligning at step 804 each collected force signature with a reference signature to remove the offsets caused by different start times; and

c. normalizing at step 806 the force signature data such that the highest value is 1 and the lowest is 0 across all signatures.

Returning now to Fig. 7a, the step 718 is performed after the post processing step 716 is performed. In this step the feature vector of the post processed force signatures is extracted. As is described in L. Smith, “A tutorial on principal components analysis,” Cornell University, USA, 2002 the first few components from Principle Component Analysis (PCA) can be used as the feature vector.

3. After steps 716 and 718 are performed for each of the N assembled products 16, at step 720 the SVM is trained based on the feature vector as is described in C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition", Data Mining and Knowledge Discovery 2, 121-167, 1998 (“Burges”).

The trained SVM can be saved and used in the testing phase for each assembled product. The testing phase uses the same (or similar) system setup that was used during the training phase.

As used herein, a statistically significant number of N assembled products 16 means that enough samples are taken so that force signatures can be categorized with a predetermined level of accuracy. For example, as describe in the reference by C. Burges, an error rate or "actual risk" (p. 156) of a trained SVM can be calculated. If the "actual risk" value of an SVM is too high, based on a predetermined threshold, more samples could be taken, and the SVM retrained until the risk value is acceptable. Alternatively, other SVM attributes could also be used to determine whether or not the number of samples is statistically significant.

The flowchart 722 for the testing phase is shown in Fig. 7b where steps 724, 726 and 728 are identical to steps 716, 718 and 720, respectively of the training phase and therefore do not need to be further described. The contact force signature during the testing phase is recorded and fed into the SVM. After using the same post processing and feature extraction, the feature vector is then input to the SVM which at step 730 runs the trained SVM. The output of the trained SVM predicts whether the assembly of each tested product was either successful or a failure. At step 732 a tested product is discarded when the output of the trained SVM predicts that the tested product was not correctly assembled. In alternate embodiments, different actions could be performed on the product, such as retrying the assembly step or setting the product aside for later manual rework.

Note that for each step, especially post processing and feature extraction, many different algorithms can be used. For example, the resampling of the force signature data can use the simple linear interpolation technique:

$$F'(t) = F(t_a) + \left(F(t_b) - F(t_a)\right)\frac{t - t_a}{t_b - t_a} \qquad (1)$$

where $F'(t)$ is the force data at a new sampling point, and $F(t_a)$and $F(t_b)$ are recorded force data at the original sampling time t_a and t_b.

Examples of the noise removal algorithms include the low pass filter (Eq. 2) and the weighted moving average (Eq. 3). In both equations, $\tilde{F}$ is the force data after the noise is removed.

$$\tilde{F}_k = \alpha F_k + (1-\alpha)\tilde{F}_{k-1}, \qquad 0 < \alpha < 1 \qquad (2)$$

$$\tilde{F}_k = \sum_{i=-m}^{m} \alpha_i F_{k+i}, \qquad \sum_{i=-m}^{m} \alpha_i = 1 \qquad (3)$$

Resampling and noise removal can be dealt with in a single step as shown by step 802 in Fig. 8. The interpolation method mentioned above is a good candidate for this purpose.

Aligning a force signature with a reference signature can be achieved by a cross correlation method:

$$(f * g)_k = \sum_{m=-\infty}^{\infty} f_m g_{k+m} \tag{4}$$

Where f_k is the recorded force signature, and g_k is the reference signature. The argument k at the maximum of the cross correlation function $(f * g)_k$ is the misalignment of the force signature f_k with respect to the reference signature g_k. The aligned force signature is obtained by simply shifting the time index by this misalignment:

$$\widehat{f}_k = f_{k+q} \tag{5}$$

where q is the misalignment.

The normalization of the force signature, step 806, can be done using equation 6:

$$\hat{f}_k = \frac{f_k - \mu}{\sigma} \tag{6}$$

where μ and σ are the mean and standard deviation of force signature f_k.

Note that the post processing of the force signature can have different steps than those shown in Fig. 8, depending on the quality of the recorded force signature.

After the post processing, the force signature will, at step 718, go through the feature extraction. A good candidate algorithm for feature extraction is the Principle Component Analysis (PCA). PCA is a common tool used to reduce the dimension of datasets in learning problems by exploring the dependencies or redundancies among the data. PCA achieves this goal by linear coordinate transformation of the original data. A new basis, called the principal components, is sought to maximize the variance of the data. The first principal component is aligned with the direction of maximum variance in the original dataset, thus containing the most information about the dataset. Each successive principal component is aligned with the direction of maximum remaining variability not captured by previous components. Mathematically, assuming that the dataset contains N measurements, ${}^{i}\mathbf{x}, i = 1 \cdots N$. Each ${}^{i}\mathbf{x}$ is a vector of dimension m such that ${}^{i}\mathbf{x} = [{}^{i}x_1, {}^{i}x_2, \cdots {}^{i}x_m]'$. For force assembly failure detection ${}^{i}\mathbf{x}$ is the post processed force signature. Let **P** be the linear coordinate transformation matrix of dimension m*m, after the transformation the original data ${}^{i}\mathbf{x}$ changes to the new data ${}^{i}\mathbf{y}$:

$$ {}^{i}\mathbf{y} = \mathbf{P}\, {}^{i}\mathbf{x}, \quad i = 1 \cdots N \qquad (7) $$

Writing in a compact form that includes all N measurements, Eq (7) becomes

$$ \mathbf{Y} = \mathbf{P}\mathbf{X} $$

$$ \mathbf{X} = \begin{bmatrix} {}^{1}\mathbf{x} & {}^{2}\mathbf{x} & \cdots & {}^{N-1}\mathbf{x} & {}^{N}\mathbf{x} \end{bmatrix}, \quad \mathbf{Y} = \begin{bmatrix} {}^{1}\mathbf{y} & {}^{2}\mathbf{y} & \cdots & {}^{N-1}\mathbf{y} & {}^{N}\mathbf{y} \end{bmatrix} \qquad (8) $$

The transformation matrix **P** that maximizes the variances is related to the eigenvectors of the following covariance matrix of the original dataset:

$$ \mathbf{C} = \frac{1}{N}\sum_{i=1}^{N} \left({}^{i}\mathbf{x} - \boldsymbol{\mu}\right)^{T} \left({}^{i}\mathbf{x} - \boldsymbol{\mu}\right), \qquad \boldsymbol{\mu} = \frac{1}{N}\sum_{i=1}^{N} {}^{i}\mathbf{x} \qquad (9) $$

Computing the eigenvectors and eigenvalues of the covariance matrix **C** gives

$$ \mathbf{V}^{-1}\mathbf{C}\mathbf{V} = \mathbf{D} \qquad (10) $$

Where **V** is the matrix of eigenvectors, **D** is a diagonal matrix of eigenvalues of **C** arranged in decreasing order. The transformation matrix **P** in Eq (7) then equals matrix **V**. The principal components of a data point ${}^{i}\mathbf{x}$ are given in ${}^{i}\mathbf{y}$.

For assembly failure detection, the first few principal components of a recorded force signature can contain enough information to be selected as the feature vector. For example, a test has shown that the first five (5) principal components are good candidates for the feature vector.

After obtaining the feature vector for each recorded force signature, a classifier is ready to be trained. The training data includes a series of feature vectors and the classes each feature vector belongs to. In the case of the assembly failure detection, the classes are success and failure. A trained classifier can predict which class a new feature vector is in. One good classifier is the linear support vector machine (SVM). Linear SVM tries to divide the feature space by a hyperplane such that the two classes lie on the opposite side of the hyperplane.

As shown in Fig. 9 with a 2D feature space, there are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. This hyperplane, known as the maximum-margin hyperplane, has the optimal stability with respect to the noise. The linear SVM algorithm is to find such a hyperplane in the feature space. Mathematically, assume the training set contains N sets of data:

$$\mathcal{D} = \left\{ \left({}^{i}\mathbf{x}, {}^{i}y \right) \middle| \ {}^{i}\mathbf{x} \in \mathbf{R}^{p},\ \ {}^{i}y \in \{-1, 1\} \right\}_{i=1}^{N} \qquad (11)$$

Where ${}^{i}\mathbf{x}$ is the feature vector of dimension p, the ${}^{i}y$ is either 1 or -1, indicating the class to which the feature vector ${}^{i}\mathbf{x}$ belongs. Any hyperplane in the feature space can be written as the set of points satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0 \qquad (12)$$

where . denotes the dot product and **w** the normal vector to the hyperplane.

The two classes are on the opposite side of the hyperplane, thus the hyperplane satisfies

$$\mathbf{w} \cdot {}^{i}\mathbf{x} - b \geq 1 \text{ for } {}^{i}y = 1$$

$$\mathbf{w} \cdot {}^{i}\mathbf{x} - b \leq -1 \text{ for } {}^{i}y = -1 \qquad (13)$$

or simply ${}^{i}y\left(\mathbf{w}\cdot{}^{i}\mathbf{x}-b\right)\geq 1$, for all ${}^{i}\mathbf{x}$, $i=1\cdots N$.

The margin between the two classes created by this hyperplane is $2/\|\mathbf{w}\|$. So the maximum-margin hyperplane can be found by solving the following optimization problem:

$$\text{Minimize } \|\mathbf{w}\| \text{ Subject to } {}^{i}y\left(\mathbf{w}\cdot{}^{i}\mathbf{x}-b\right)\geq 1,\quad i=1\cdots N \quad (14)$$

Many software programs are available to train the SVM; these are either commerically available or open source.

A trained SVM is parameterized by **w** and b as shown in eq 12. The prediction of SVM during the test phase can use the following decision logic to predict the class to which the new test belongs to:

$$\text{If } \mathbf{w}\cdot{}^{i}\mathbf{x}-b\geq 1 \text{ then } {}^{i}y=1$$

$$\text{If } \mathbf{w}\cdot{}^{i}\mathbf{x}-b\leq -1 \text{ then } {}^{i}y=-1 \quad (15)$$

Otherwise, the SVM cannot predict the output.

It should be appreciated assembled product 16 is only one example of the assembled products that the method and system described herein can be used with to detect assembly failure in the assembled product after the product is assembled. The measure of what is a successful assembly or manufacture or non-successful, assembly or manufacture for those products will depend on the product.

While use of a force sensor is described above to obtain the interaction signature between the assembled product 16 and the top layer 27 of the test platform 18, it should be appreciated that other types of sensors can be used to measure the interaction between the articles and their surroundings. One such sensor is the displacement sensor. In the shield can example described above, the failed assemblies typically have raised corners or edges. When they are pressed against a compliant object, the compliant object will deform more compared to the case of successfully assembled ones. A displacement sensor can therefore be used to obtain the interaction signature between the articles and the compliant object. The procedure and algorithms described above can also be followed to train the SVM and use the SVM to detect the success or failure of the article when the displacement sensor is used. The interaction signature from the displacement sensor can be a measurement along one or more axes position and/or a reorientation around those axes.

It should also be appreciated that the interaction signature can be a combination of the interaction signatures from a force sensor and a displacement sensor.

Referring now to Figs. 10a and 10b, there is shown a flowchart 1000 for optimizing the motion used to test the manufactured articles to improve the correlation of the difference between the interaction signals of successful articles and the interaction signals of failed articles.

Blocks 1002 and 1004 shown in Fig. 10a, are two operations that are repeated for each of N products. At block 1002, the test motion is performed for each of the N products and the force signature resulting from performing that motion is collected. At block 1004, the success or failure category of the assembly for each of the N products is record.

When all of the operations in blocks 1002 and 1004 are completed for the N products, the flow proceeds to a second group of two operations that are performed for each of the N products. At block 1006, the force signature for each of the N products is post processed. At block 1008, the feature vector is extracted for each of the N products from the post process force signature for each of the N products.

When all of the operations in blocks 1006 and 1008 are completed for each of the N products, the flow proceeds to block 1010 where a SVM is trained for the N products.

After the SVM is trained at block 1010, the flow proceeds to block 1012 shown in Fig. 10b where the test motion is changed for the N products. The change of the test motion can for example and without limitation be with regard to the test motions shown in Figs. 6a and 6b that a different location of the socket 30 is pressed against the test platform top layer 27 by the rocking motion. Alternatively, the test motion parameters such as for speed, angle etc. are changed or are read from different force sensors that are in place in different positions and orientations of the test platform 18.

The flow then proceeds to blocks 1014 and 1016 that are two operations that are repeated for each of N products. The operations performed at blocks 1014 and 1016 are identical to the operations performed at blocks 1002 and 1004, respectively, except that they are for the changed test motion for each of the N products.

When all of the operations in blocks 1002 and 1004 are completed for the N products, the flow proceeds to a second group of two operations at blocks 1018 and 1020 that are performed for each of the N products. The operations performed at blocks 1018 and 1020 are identical to the operations performed at blocks 1006 and 1008, respectively, except they are for the feature vector extracted for the changed test motion for each of the N products.

Upon completion of operation 1020 for the N products the flow proceeds to block 1022 where a SVM is trained. As can be appreciated, this trained SVM is for the N products that have had the changed test motion at block 1012.

The flow then proceeds to block 1024 where it is determined if the test motion has to be optimized to improve the correlation. The goal of flow 1000 is to minimize the correlation of the difference between the interaction signals of successful articles and the interaction signatures of failed articles. If the correlation has to be improved, then the test motion has to be optimized and the flow returns to block 1012 where the test motion is again changed. If the correlation difference does not have to be improved, then the flow proceeds to block 1026 and the training of the SVM is completed. The minimization of the correlation difference is ended when the difference meets a predetermined criteria for that difference.

The predetermined criteria can for example and without limitation be, the value of the improved correlation is lower than a preset threshold (which means the optimized test motion can generate a clear difference on the force sensor signature between a successful and failed assembly); or after all the different test motions are preformed no decrease on the value of the correlation (which means the optimized test motion is best among all the test motions to generate the difference on force sensor signature between a successful and a failed assembly); or the overall test number of products is over a preset number; or the overall time to produce the N products for optimization is over a preset time.

It is to be understood that the above description of the exemplary embodiment(s) is (are) intended to be only illustrative, rather than exhaustive, of the present invention. Those of ordinary skill will be able to make certain additions, deletions, and/or modifications to the embodiment(s) of the disclosed subject matter without departing from the spirit of the invention or its scope, as defined by the appended claims.

What is claimed is:

1. A method for detecting the success of an automated process that produces an article of manufacture comprising:

producing a statistically significant number of successful and failed articles of manufacture using said automated process;

interacting each of said successful and failed articles of manufacture with a test platform to measure interaction signatures indicative of said successful articles of manufacture and said failed articles of manufacture;

calculating a correlation of the difference between said interaction signatures of said successful articles of manufacture and interaction signatures of said failed articles of manufacture;

obtaining an interaction signature for an additional article of manufacture produced after said successful articles of manufacture and said failed articles of manufacture are produced; and

analyzing said interaction signature obtained for said additional article of manufacture produced after said successful articles of manufacture and said failed articles of manufacture are produced against said calculated correlation of said successful and said failed articles of manufacture interaction signatures to automatically categorize as either a success or a failure said additional article of manufacture produced after said successful articles of manufacture and said failed articles of manufacture are produced.

2. The method of claim 1 wherein said interaction is to have the article come in contact with a force sensor mounted on said test platform to obtain a force signature.

3. The method of claim 1 wherein said interaction signature is obtained by measuring the displacement of said article of manufacture using a displacement sensor.

4. The method of claim 1 wherein said correlation calculation uses a Support Vector Machine (SVM).

5. The method of claim 1 wherein said interaction signatures of successful and failed articles of manufacture is normalized prior to calculating said correlation of said difference between said interaction signatures of said successful articles of manufacture and interaction signatures of said failed articles of manufacture.

6. The method of claim 1 wherein Principle Component Analysis (PCA) is used prior to calculating said correlation of said difference between said interaction signatures of said successful articles of manufacture and interaction signatures of said failed articles of manufacture.

7. A method for detecting the success of an automated process that produces an article of manufacture comprising:

calculating a correlation of the difference between interaction signatures of a statistically significant number of successful articles of manufacture and interaction signatures of a statistically significant number of failed articles of manufacture;

obtaining an interaction signature for an article of manufacture produced after said correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated; and

analyzing said interaction signature obtained for said article of manufacture produced after said correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated against said calculated correlation of said successful and said failed articles of manufacture interaction signatures to automatically categorize as either a success or a failure said article of manufacture produced after said correlation of the difference between interaction signatures of successful articles of manufacture and interaction signatures of failed articles of manufacture are calculated.

8. A method for detecting the success of an automated process that produces an article of manufacture by testing a statistically significant number of successful and failed articles of manufacture produced using said automated process, said method comprising:

interacting each of said successful and failed articles of manufacture with a test platform to measure interaction signatures indicative of said successful articles of manufacture and said failed articles of manufacture;

calculating a correlation of the difference between said interaction signatures of said successful articles of manufacture and interaction signatures of said failed articles of manufacture; and

repeating said producing, interaction and calculating steps with changes in said interacting step to minimize said correlation of the difference between said interaction signatures of said successful articles and said interaction signatures of said failed articles by changing said interaction of each said successful and failed articles with said test platform.

9. The method of claim 8 wherein said repeating of said producing, interaction and calculating steps with changes in said interacting step to minimize said correlation difference is ended when said minimization meets a predetermined criteria for said correlation difference.

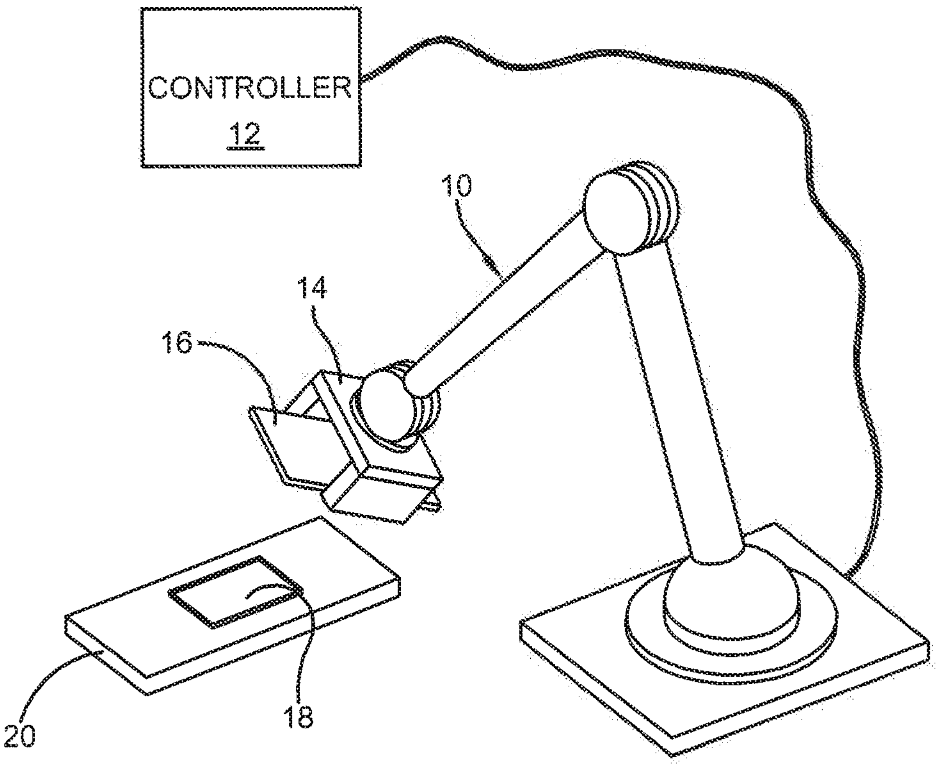


FIG.-1

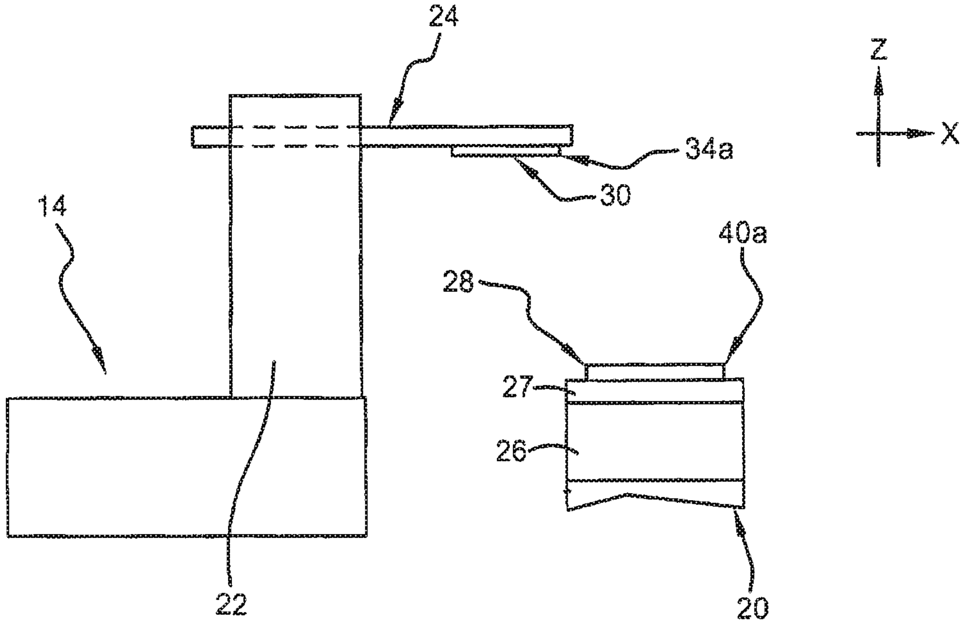


FIG. 2

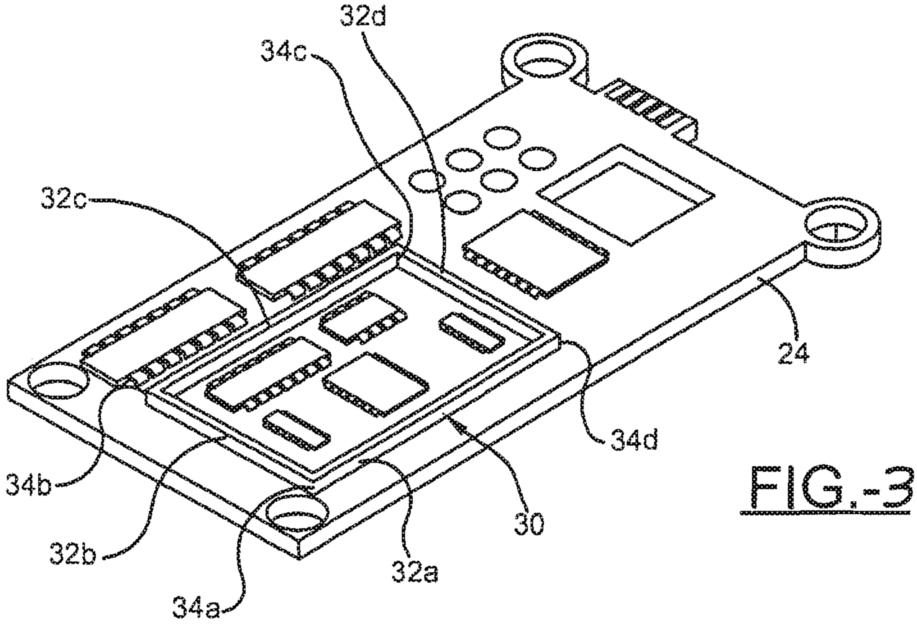

32d
34c
32c
24
34d
34b
30
32b
32a
34a

FIG.-3

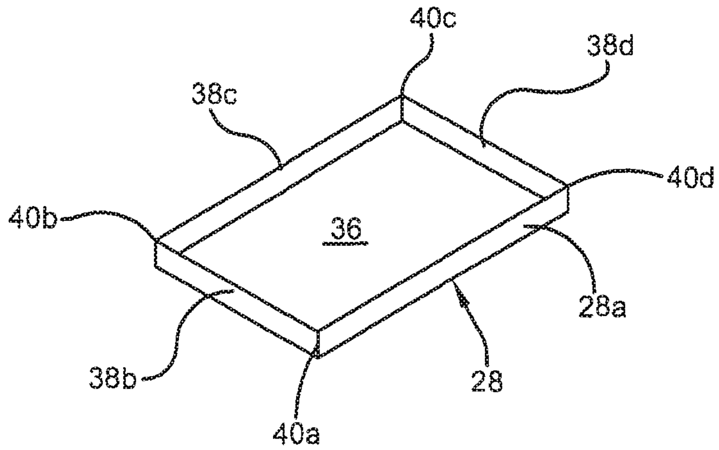

40c
38d
38c
40d
40b
36
28a
38b
28
40a

FIG.-4

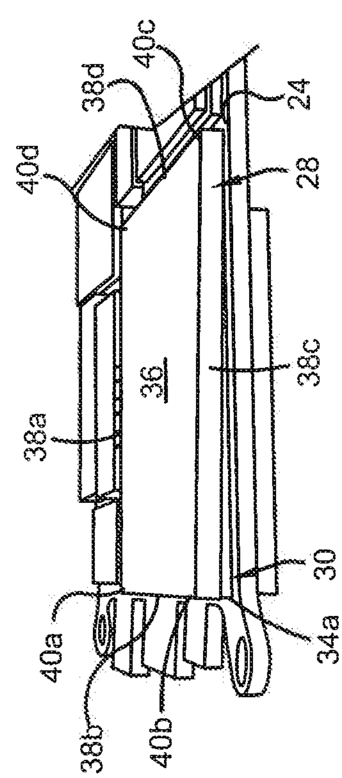


FIG. 5B

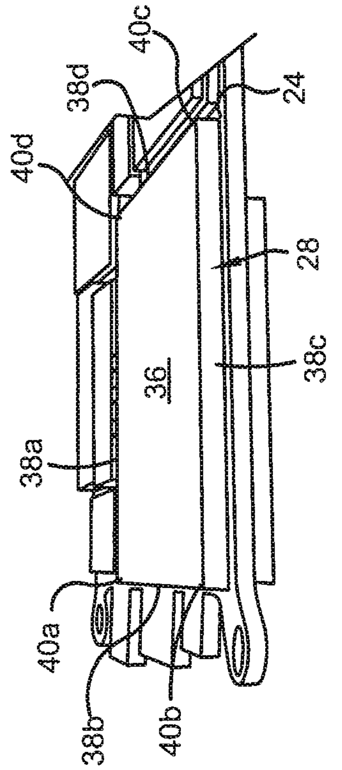


FIG. 5D

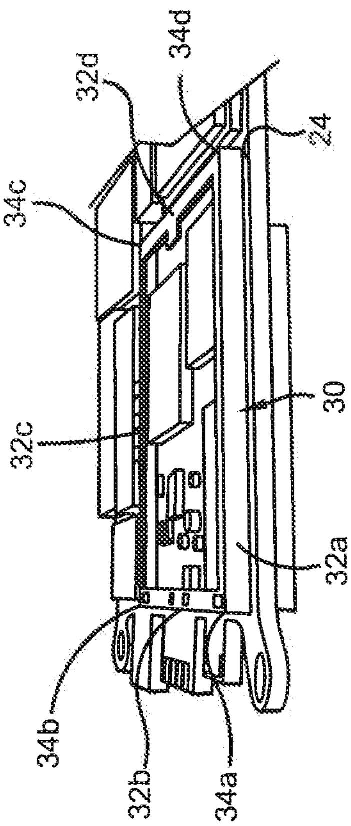


FIG. 5A

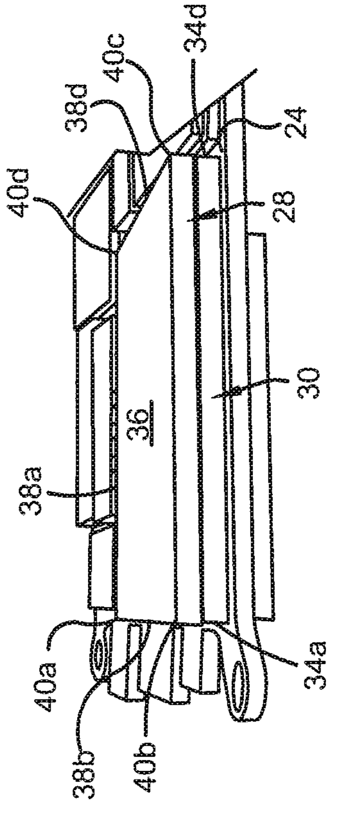


FIG. 5C

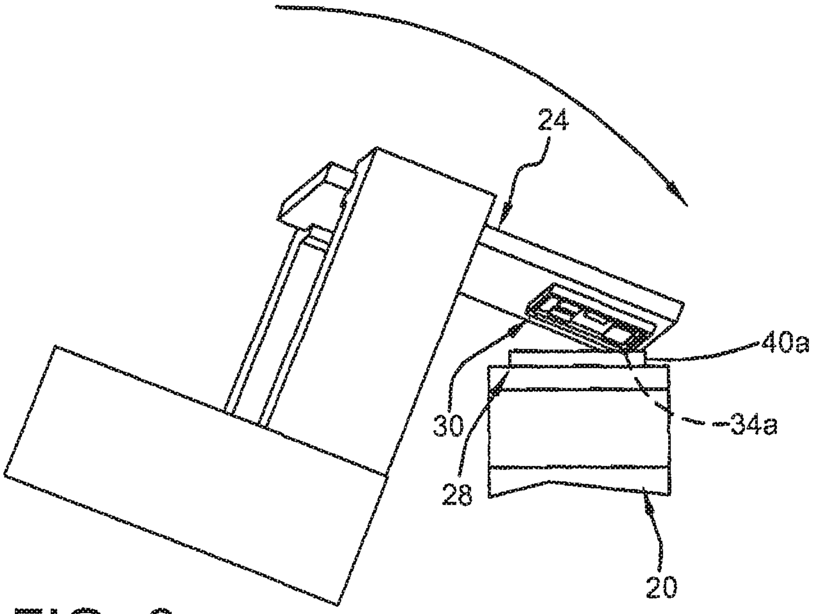


FIG.-6a

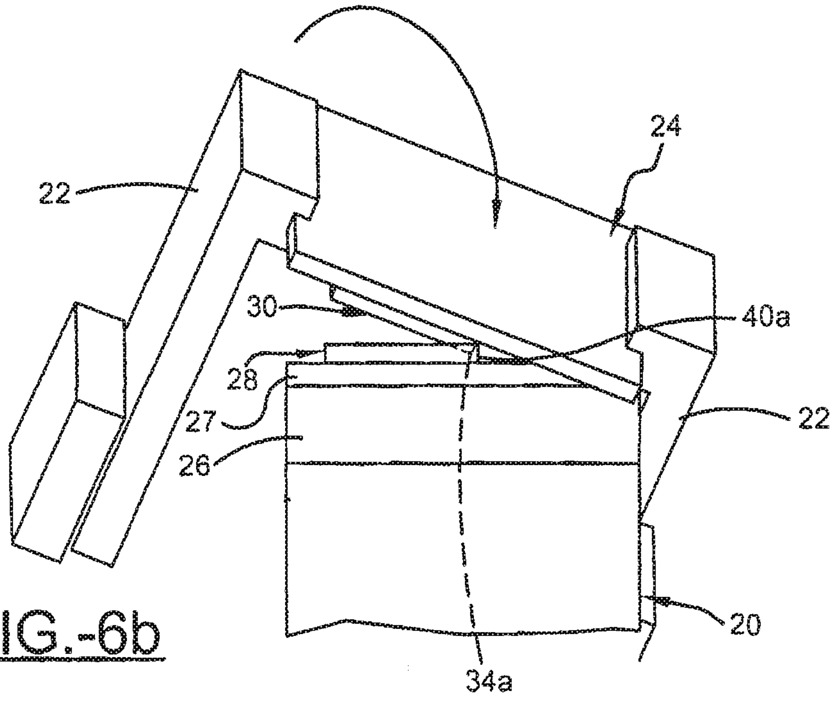


FIG.-6b

Fig. 7a

710

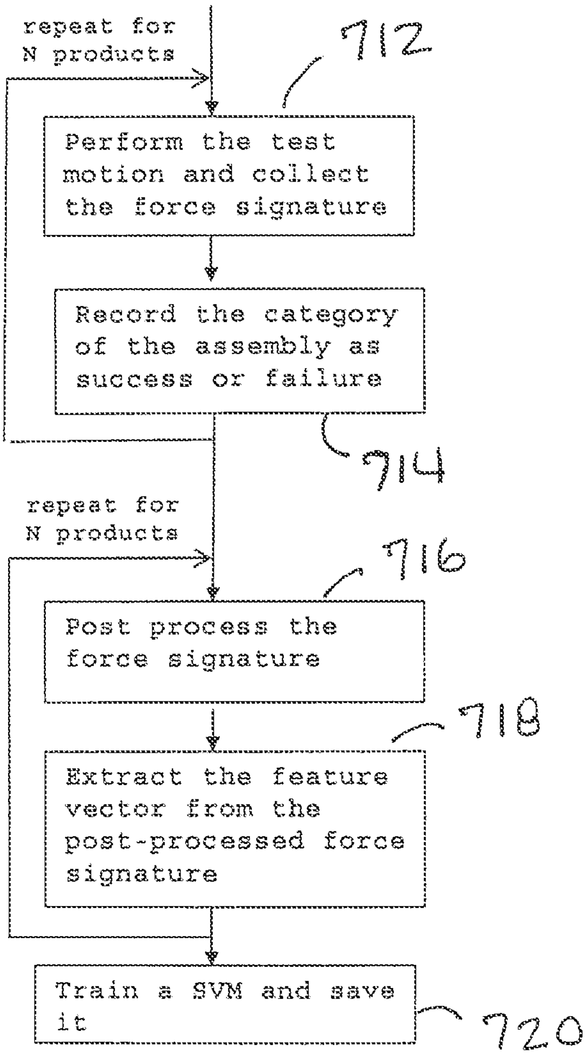
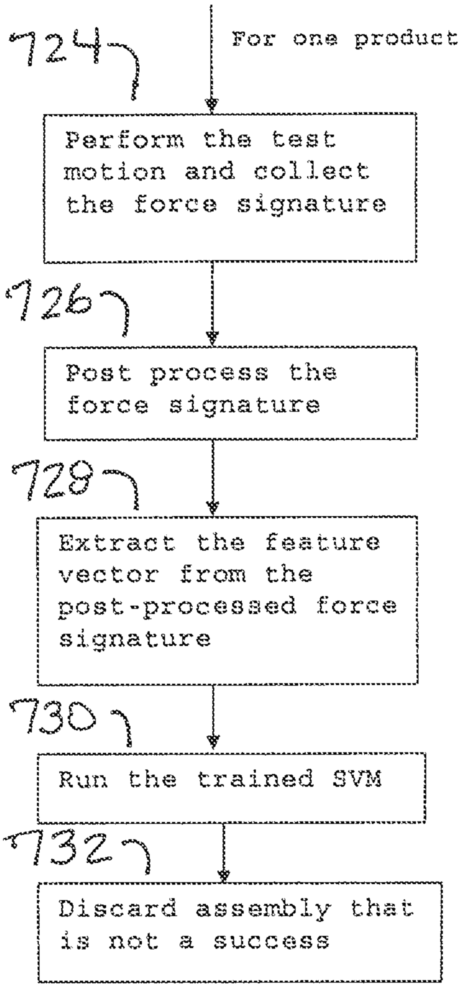


Fig. 7b

722



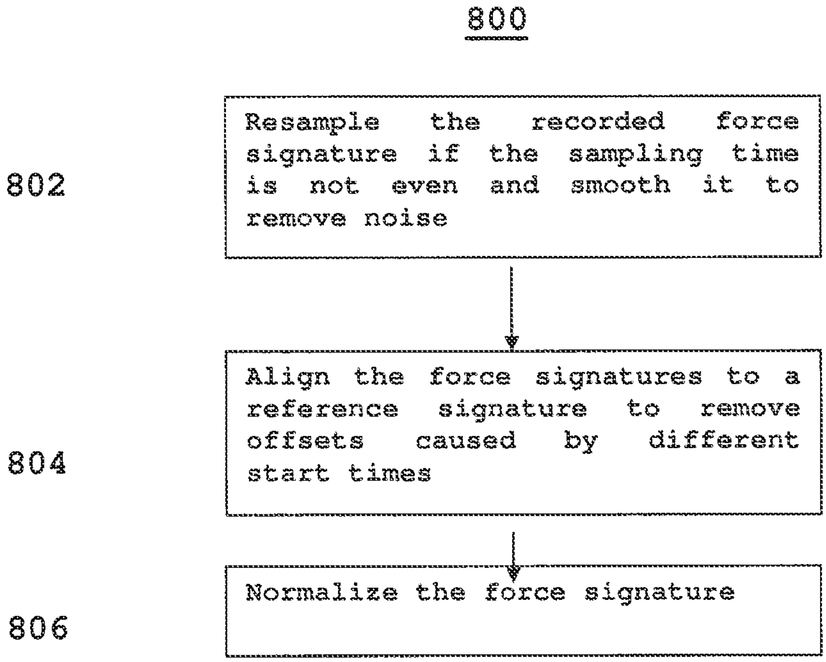

800
802
Resample the recorded force signature if the sampling time is not even and smooth it to remove noise
804
Align the force signatures to a reference signature to remove offsets caused by different start times
806
Normalize the force signature

Fig. 8

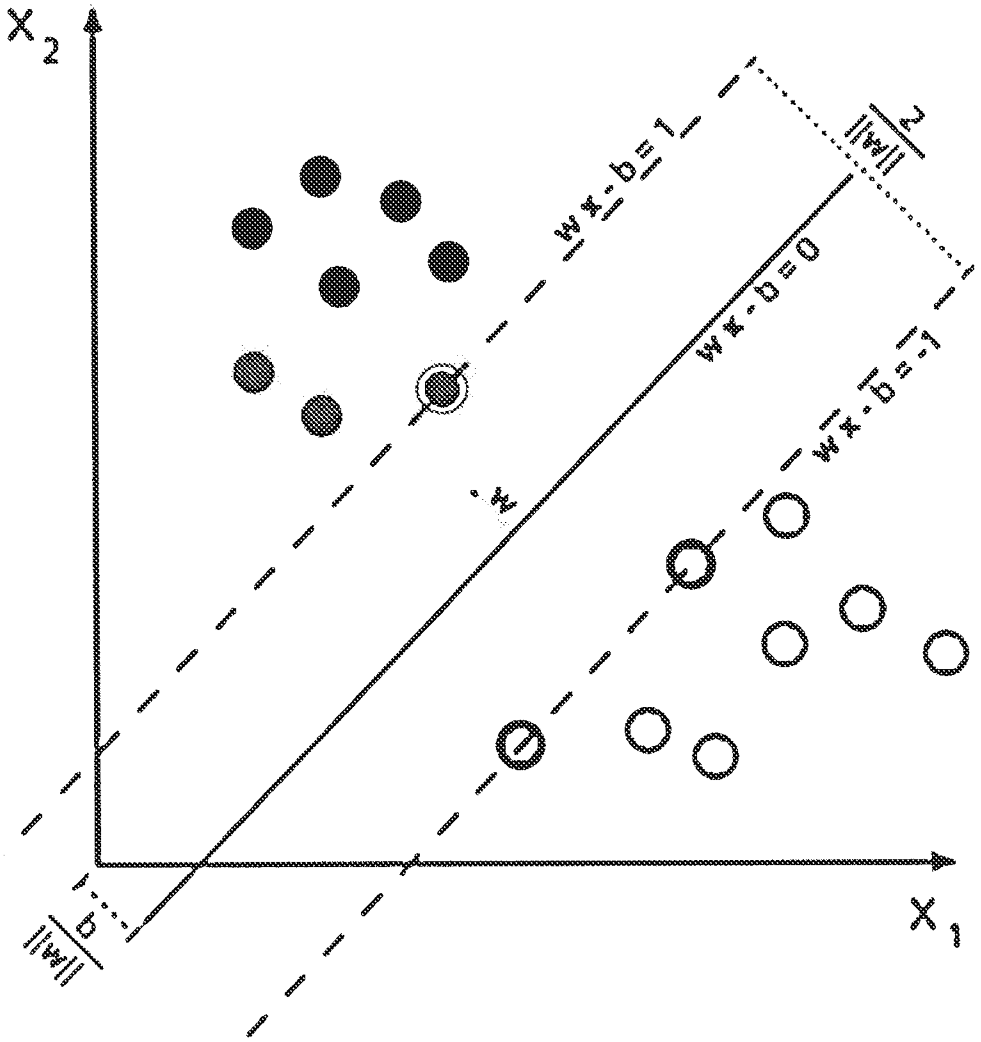


Fig. 9

Fig. 10a

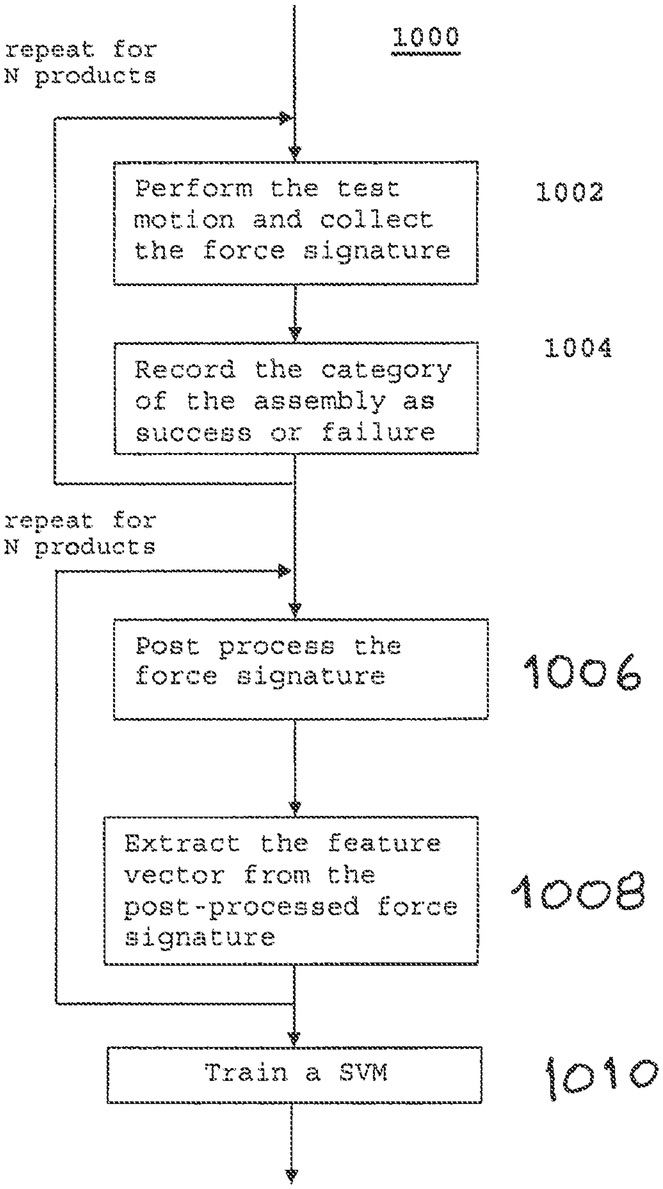
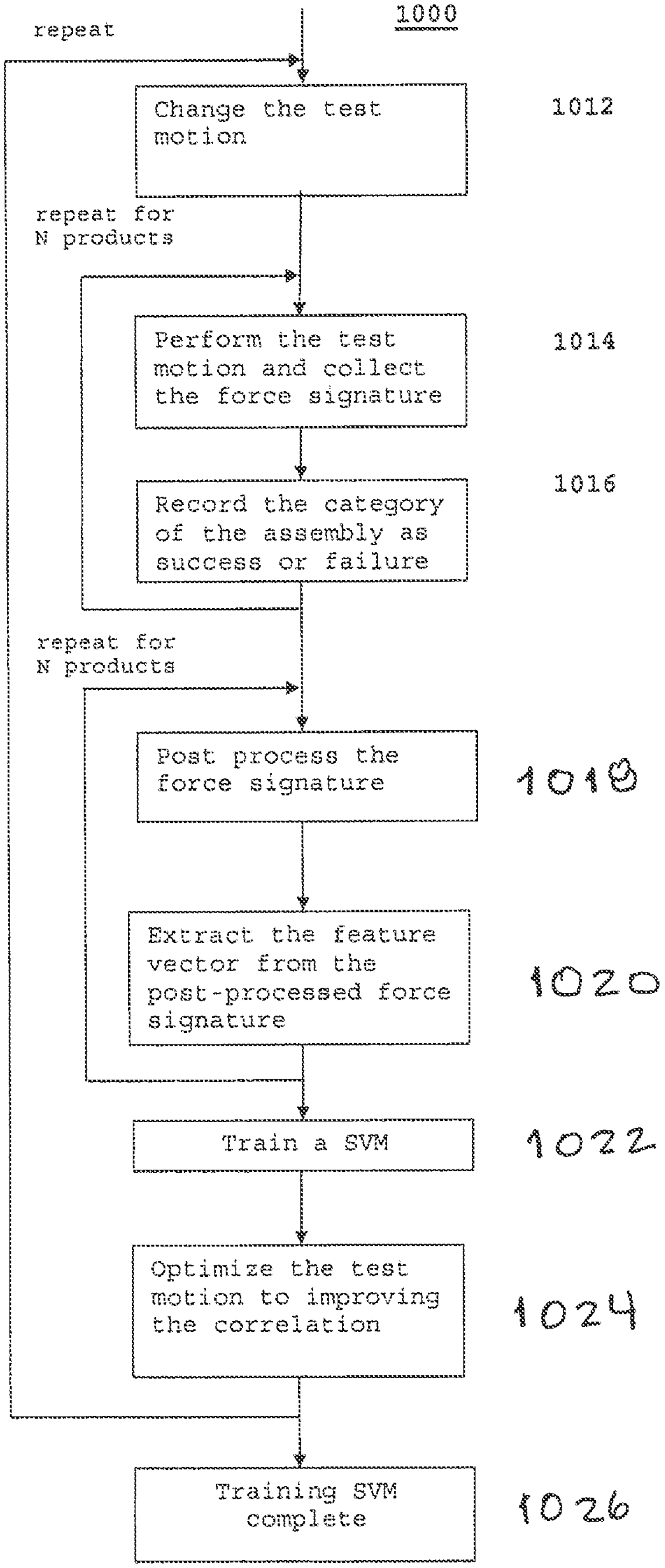

1000
repeat for
N products
Perform the test motion and collect the force signature
1002
Record the category of the assembly as success or failure
1004
repeat for
N products
Post process the force signature
1006
Extract the feature vector from the post-processed force signature
1008
Train a SVM
1010

Fig. 10b


1000
repeat
Change the test motion
1012
repeat for N products
Perform the test motion and collect the force signature
1014
Record the category of the assembly as success or failure
1016
repeat for N products
Post process the force signature
1018
Extract the feature vector from the post-processed force signature
1020
Train a SVM
1022
Optimize the test motion to improving the correlation
1024
Training SVM complete
1026