Industrial Vision System for Stamped Sheet Metal Inspection

Eusebio de la Fuente†, F.M.Trespaderne†, M.A.González‡, Juan I.Videla‡

†ETS Ingenieros Industriales
Universidad de Valladolid
P°del Cauce s/n 47011 Valladolid
Spain
eusfue@eis.uva.es

‡CARTIF
Parque Tecnológico Boecillo
Parc.205 47151 Valladolid
Spain

Abstract –**An on-line machine vision system for defect detection in large stamped car parts is presented. The acquisition system includes a CCD progressive camera and a diffuse illumination system. Camera and illumination have been mounted on a robot to be moved over the pieces proceeding from a sheet metal forming line. The acquired images are firstly restored using a Markov random field model in order to eliminate the spurious features without modifying the delicate characteristics of the small splits. Defect detection is carried out using an ultra rapid valley detection algorithm. The developed system detect the presence or absence of splits and through cracks greater than 0,2 mm in several designated zones of 10 x 10 cm on the totality of parts produced at a press line. The vision control will determine whether the part will continue in the production flow or be excluded from it.**

I. INTRODUCTION

One of the primary objectives for the highly competitive automotive industry is to cut costs guaranteeing the 100 percent of quality parts. An automatic inspection system that contributes significantly to meeting this goal has been presented.

Today forming processes play a large role in supporting the economies of developed countries. This industry is undergoing several trends. The main trend is toward production cost reduction by using higher production speeds and by reducing human resources.

Despite years of improvements in stamping processes, achieving zero defects in the parts is difficult to accomplish. Significant advances in automated visual inspection systems have been made in recent years. However, human inspectors still dominate the appearance inspection of metallic stamped parts.

A. Metal Forming

Basically, metal forming is a manufacturing process where the sheet metal is bent and stretched using presses and dies. The shape and dimensions of the obtained parts correspond exactly to those of the active elements of the pressing device. Compared to other manufacturing processes (e.g., casting, forging and machining), forming has several technical-economic advantages: presses allow high production rates by fast operation and the use of sequential forming steps, lightweight parts with very complex shapes may be obtained and parts do not require additional mechanical processing.

However in the forming processes the thickness of the stamped part can decrease dramatically from those of the original metal. In car-body manufacturing, where sheet forming involves thin materials, thickness diminution can originate serious problems. In the areas where high demands are placed on (double curvatures, sharp corners, deep recesses...) the metal often splits up under the tensile forces when it is stamped into shape.

Splits often are nearly imperceptible because these defects are only a few tenths of millimeter. However if a batch of these defective parts slips past the normal quality procedures and arrives at the assembling line, the manufacturer will fall into a very costly product return. The detection of the flaw at this point supposes multiply by one hundred the cost of an early detection because additional material, time, energy and labor are wasted.

It is clear that the immediate detection of splits at the output of the stamping line is extremely important. However the on-line inspection is not an easy task due to the subtle characteristics of the defects and the high reflective nature of the metallic surfaces.

Human inspectors have hitherto carried out the inspection in sheet metal forming processes. In the automotive sector, where supplier standards require 100 percent on-line parts inspection and 100 percent quality-parts guarantees, achieving 100% inspection using human inspectors requires high levels of redundancy that increases the cost for inspection.

Apart from the costs involved, other problems such as the fatigue are associated to the performance of visual inspection tasks carried out by human operators. The difficult task of inspecting a great number of parts with complex superficial geometry can not be performed in the best conditions, due to the light reflection of the metallic surfaces. In a framework where the product quality is mainly a competitive value, the inclusion of automatic systems in this type of inspection processes becomes necessary.

B. Metallic Surface Inspection

Recently, image processing technology has enabled to automate many visual inspection tasks in industrial environments and especially in the automotive industry [1]. However, automatic inspection of complex shaped metallic surfaces is extremely difficult. The lighting of highly reflective products is not an easy task. Since products act as mirrors, the camera must not see its own image and moreover the illumination of the product has to be homogeneous in order to characterize defects wherever they are located on the product. Several solutions have been presented for automatically scanning flat reflective surfaces [2] but have not hitherto been applicable to complex shaped surfaces such as sheet metal pieces.

The developed system locates on-line split defects that appear in car-body manufacturing. By detecting defects as soon as they occur, quick action can be taken to remedy the source. Automatic detection avoids furthermore that the manufacturer fall into a very costly product return if defective parts slips past quality procedures and arrives at the assembling line.

II. INDUSTRIAL REQUIREMENTS

Our problem is located in a sheet metal forming line where large parts must be inspected such as hoods, trunk lids, door panels... In this case an on-line inspection of the complete surface of every part is not possible. Instead of verifying thoroughly the whole surface of some parts it seems much more reasonable to inspect in every piece only the areas where high demands are placed on the material i.e. the areas where the probability of tearing appearance is high.

In this sense it will be necessary to displace the acquisition system just in front of these conflictive areas. The camera and illumination system have been mounted as a unit on an articulate robot.

The parts are produced in shifts of 8 to 12 hours, at a rate of up to 10 parts per minute. Production change will take between 15 and 30 minutes and thus this will be the available time for the vision system to adapt to the new production reference.

Some parts will be stamped pair-wise, meaning that every 6 seconds two parts may come of the line.

The three 10 x 10 cm zones to be inspected on a part do not change during one production launch, but they are likely to change over time (several months). The system must be flexible enough to allow to easily change the focused zones or offer the choice to pick three out of a larger range at production launch.

The parts are of zinc-coated steel and their maximum dimensions are 3500 mm length, 1500 mm width and a stamping depth of 300 mm.

A final consideration is that the system is to be installed in a press shop, and then the environmental parameters are far from optimum, e.g.:

- Limited available space
- Vibrations (added to the flexibility of the parts)
- Grease
- Variable ambient luminosity
- Temperature changes

III. ILLUMINATION

Illumination is always a crucial aspect regarding image quality and reproducibility of image acquisition conditions but in this case, where highly reflective metals are being inspected, is especially critical.

Several solutions have been presented for automatically scanning flat reflective surfaces typically in an arrangement in which an illumination beam is passed to a flat surface it is simple to predict where the reflected beam will be and to collect the reflected beam suitably. Defects and flaws on the material become obvious by change reflection behaviour.

In the case of a complex shaped object, however, it is extremely difficult or impossible to predict the path of the

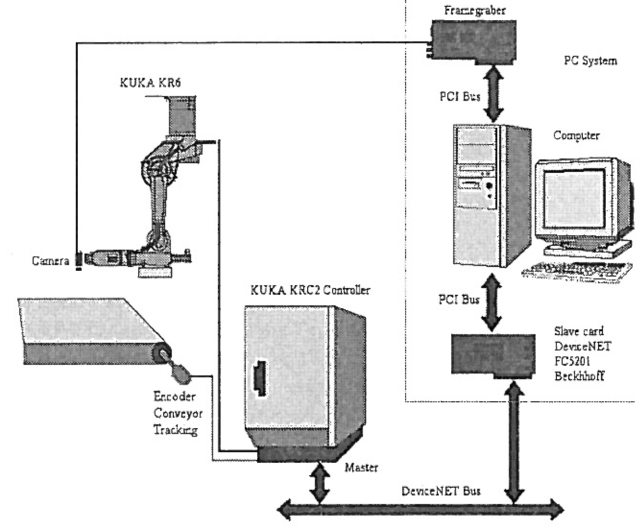

Fig. 1. The developed system includes an articulated robot KUKA KR6/2, a camera SONY XC55N connected to a computer through a Matrox Meteor II Multichannel frame grabber. The computer used is a Pentium IV under Windows 2000. The communication between the robot and the computer is performed through a Beckhhoff FC5201 DeviceNet field bus card.

reflected beam. Another difficulty in dealing with complex shaped objects is that they tend to have complex shaped edges, corners and other features such as mouldings or creases which may produce signals which are similar to that of a defect.

In order to avoid glinting as much as possible, a diffuse ring light has been used. It provides a homogeneous illumination to the metallic parts to be inspected.

IV. IMAGE PROCESSING

In order to detect the subtle flaws, the acquisition system is positioned by the robot only a few centimetres in front of the inspection area. This proximity to the pieces makes that the images contain a great quantity of detail that includes the texture of the metallic surface. If the defect detection algorithm, takes the acquired image as input data, an enormous quantity of hypothetical false defects will be determined. Thus, some filter must be passed before the defect detection stage to eliminate the texture feature. On the other hand, the filter must be extremely careful with other delicate characteristics that point out the existence of a rupture of the material fibres.

Low pass filters have been discarded because, although they would eliminate the texture features of the material, the fine characteristics of a material rupture will not be preserved. Thus a method must be proposed to carry out this task.

A smart solution for this task, that low pass filters can not perform, is to model the image as a Markov random field (MRF). This approach will permit to restore the images optimizing a functional based in local properties.

A. Image Restoration: MRF

Markov Random Fields possess several characteristics that make them useful in image restoration. Properties such as smoothness and continuity of regions over an entire image can be enforced using only dependencies among local neighbours. Discontinuities, which separate homogeneous regions, may be computed, and then smooth regions can be found.

The essence of the MRF model is that the probability distribution of the configuration of the fields, given a set of data, is a Gibbs distribution. The model is specified by an energy function that can be modelled to embody a priori information about the system. The basic idea of MRF is that each pixel must have some relations with its neighbouring pixels. Details of MRF theory can be found in references [5] and [6].

From a Bayesian point of view, it is possible to know the *a posteriori* model of the image following the Bayes rule:

$$p(u/d) = p(u,d)/p(d) = \frac{p(d/u)\cdot p(u)}{p(d)} \qquad (1)$$

where u is the restored image and d is the noisy observed image. Using a maximization criterion for $p(u/d)$ the idea is to find the u that maximizes the equation (1). To accomplish this task is necessary to know the joint distribution, which is not available. However this difficulty is alleviated considering the *Hammersley-Clifford* theorem: X is a Markov random field with respect to Γ if and only if X is a Gibbs field respect to Γ.

A random field X is a Gibbs random field with respect to a neighborhood system Γ if and only if its joint distribution is a Gibbs distribution (GD) of the form:

$$p(X) = Z^{-1}\cdot e^{-\frac{1}{T}U(X)}$$

where Z is a normalizing constant called *partition function*, T is a constant and $U(X)$ is the *energy function*:

$$U(X) = \sum_{c\in C} V_c(X)$$

i.e. $U(X)$ is the sum of the *energy* of every clique c of the set of cliques (C). A *clique* is the set of sites that are neighbors.

The Hammersley-Clifford theorem provides the means to calculate the a posteriori probability. It establishes the equivalence between the conditional probabilities of the local characteristics in the MRF and local energy potentials in a GD:

$$p(u/d) = Z^{-1}\cdot e^{-U(u/d)} \quad (2)$$

This equation is maximized looking for $u^* = \arg\min_u(U(u/d))$ that can be decomposed in a sum of some local energy terms. Designing an energy functional U that penalizes non-desired configuration of pixels, the restored image u can be obtained.

In our model two coupled MRF are considered: one MRF on the image pixels and the other on the contours that can appear between every two pixels. These two MRF are not independent and they interact: contours are formed and simultaneously the interior regions are smoothed. The functional includes several terms that consider different effects [7]: $U = U_d + U_i + U_l$ where:

- U_d involves the difference between the actual observed data and the current MRF state (or predicted image).
- A smooth constrain is incorporated in terms of the gradient, U_i, that origins the anisotropic diffusion of the regions
- And finally, the cost of adding a new discontinuity in the restored image U_l, i.e, the cost of separating two pixels in order to assign them to different regions.

These three energy terms are weighted in the functional by three constants (α, λ and β). Since the direct minimization of the energy functional is prohibitively expensive, an efficient method which leads to convincing results is used. The energy minimization is carried out using a Hopfield network [8]. The system iterates following the equations of the network dynamics until there is no change in the image. However, it can be seen experimentally that the major changes are produced in the first iterations and after them the restoring process slow down dramatically. Furthermore, the idea is not to obtain the segmented image but only to smooth the regions preserving the contours. Therefore, the process, which could precise several thousands of iterations to converge to the final restored image, has been limited to one hundred iterations to establish a trade off between the quality of the final result and the computation time. The time for one hundred iterations is under one second for a 640x480 image in a Pentium 2.6GHz.

B. Valley Detection in the Grey Level Profile

When dealing with shaped objects the major difficulty is that they tend to have complex shaped edges, corners and other features such as moldings or creases which may produce contours which are similar to that of a defect. It is essential to carefully characterize splits in order to distinguish between real defects and features of the surfaces such as moldings, creases, edges, corners, holes... which are intended to be present in the surface.

Split defects are characterized by the existence of parallel contours faced by the opposite direction of their gradient vectors. Given a contour the flaw detection could be performed by searching the opposite contour until a predefined distance [9].

However the split characteristics can be extracted from the intensity image more rapidly looking for valleys in vertical profiles of the image. Valley detection provides a robust method to eliminate the remaining spurious features in an ultra fast manner.

In figure 2 a profile example is shown. Maximums and minimums on the left and on the right of the valleys are marked.

A pixel of the column profile i with gray level $I(i)$ is a maximum on the right M_R if $I(i-1) < I(i) \geq I(i+1)$

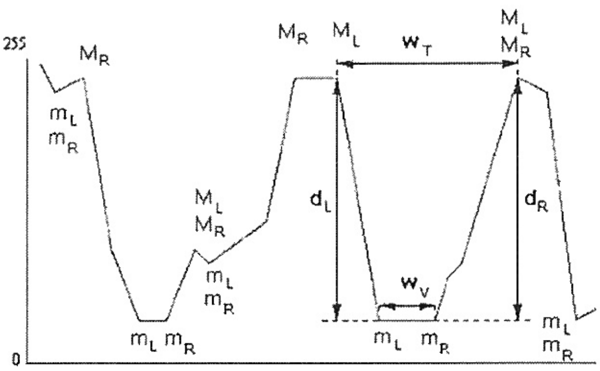

Fig. 2. Maximums and minimums in the gray level profile

Analogously, we define:

Maximum on the left M_L if $I(i-1) \leq I(i) > I(i+1)$

Minimum on the right m_R if $I(i-1) \geq I(i) < I(i+1)$

Minimum on the left m_L if $I(i-1) > I(i) \leq I(i+1)$

The algorithm looks for valleys in the gray level profile looking for the sequence M_L - m_L - m_R - M_R

The maximum and minimum detection algorithm has been modelled as a finite state machine with five different states. The transition function that maps current states to a next state is based on Dif, the difference between the gray level of the current pixel I(i) and next pixel I(i+1). Computation begins in the start state with every column of the image. It changes to new states depending on the gray level profile. Five possible states have been established in the algorithm (fig.5):

Once the maximums and minimums are established, all the sequences M_L - m_L - m_R - M_R appearing in the profile can be determined. Then some constraints are posed to these sequences in order to detect the sharp valleys corresponding to splits:

1. The depth of the valley must go beyond a pre-established threshold T_1

$$d_L = I(M_L) - I(m_L) > T_1$$
$$d_R = I(M_R) - I(m_R) > T_1$$

2. *The width on the top of the valley w_T must be under a threshold T_2 and the width down the valley w_v must be below T_3.*

$$w_T = M_R - M_L < T_2$$
$$w_v = m_R - m_L < T_3$$

3. The maximum slope in both sides of the valley must surpass the threshold T_4.

Only if a valley in the profile satisfies these three constraints it is considered as a split. The exact value of the thresholds T_i are not critical in the detection of split valleys due to the particular shape these valleys.

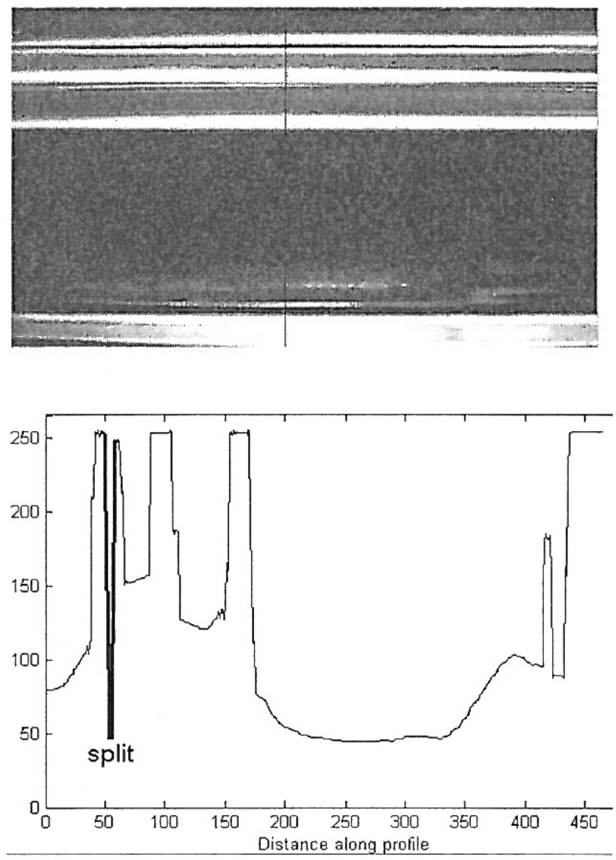

Fig. 3. a) Acquired image of an open rupture on a stamped part b)Vertical gray level profile along the marked line in the MRF restored image (100 iterations). The metal texture has been smoothed but other visual features such as the deep valley corresponding to the split have been preserved. The sudden fall and rise in the gray level profile correspond to the split in the image.

V. RESULTS

The experiments have been carried out checking the results on a set of 150 parts corresponding to different references and defects. One hundred of these 150 parts were defective and fifty do not present any kind of defect. The reliability of the detection for different types of defects is presented in table1.

TABLE 1. PERCENTAGE OF CORRECT CLASSIFICATION: SPLITS, NECKING AND FALSE POSITIVES

TYPE OF DEFECT	NUMBER OF SAMPLES INSPECTED	NUMBER OF DEFECTS DETECTED	RELIABILITIY %
Splits(gap>0.5mm.)	52	52	100
Splits(gap<0.5mm.)	35	33	94,28
Necking *	13	7	53,85
Without defect (false positives)	50	1	98

**Necking: rupture of the material fibres without an open split*

The splits with a maximum aperture greater than 0,5 millimetres are detected with reliability. In this case the defect is detected without any difficulty because of the presence of wide and deep valleys in the image profiles. When the split is very large the detection is carried out only in the extremes of the split, where the aperture is not excessive. In the other zones with a large gap the program do not detect the valley because its width surpass the maximum valley threshold. This threshold could be increased but due to that the detection is reliable in the extremes it has not been modified. Furthermore, if this threshold is increased, the possibility of mark a part without any defect as defective (false positive) increases also.

In the experiment, carried out on 50 acceptable parts, the system has marked one of these good parts as defective. Then, it does not seem very convenient to increase notably this threshold.

TABLE 2. THRESHOLDS OF THE VALLEY DETECTION PROCESS

THRESHOLD	VALUE
T1: Minimum fall on the left/right $d_L = d_R$	128 grey levels
T2: Maximum width in the top of the valley w_T	30 grey levels
T3: Maximum width of the valley bed w_v	15 grey levels
T4: Minimum slope falling/rising	20 grey levels/pix

In the splits with a minor aperture, the reliability does not reach the 100% as in the previous case but it is near the 95%. Taking into account that we are talking about the detection of defects under half a millimetre on large metallic parts, this reliability is very acceptable.

The detection of the necking, characterised by a rupture of the material that do not present an open gap, is not good. In this case, due to the extreme weakness of the visual characteristics the detection is very poor. This is a line for future work.

VI. CONCLUSIONS

Automatic inspection of complex shaped surfaces of stamped sheet metal is extremely difficult due to the subtle characteristics of the defects and the high reflective nature of the metallic surfaces.

A fast and accurate image technique has been developed in order to inspect on-line large car-body panels. The combination of the MRF model and the valley detection algorithm has proved to be robust and fast in the split detection on the images.

Unlike other inspection methods, this system has been especially designed for use on the factory floor. The developed algorithm is fast enough to inspect every manufactured part as they are being made on a production line. Furthermore, the image processing algorithm is very flexible because it does not require any reference image of the inspected zone. The system is easy to reprogram for the inspection of different parts and zones. It is insensitive to vibration and does not require controlled illumination conditions in the press shop.

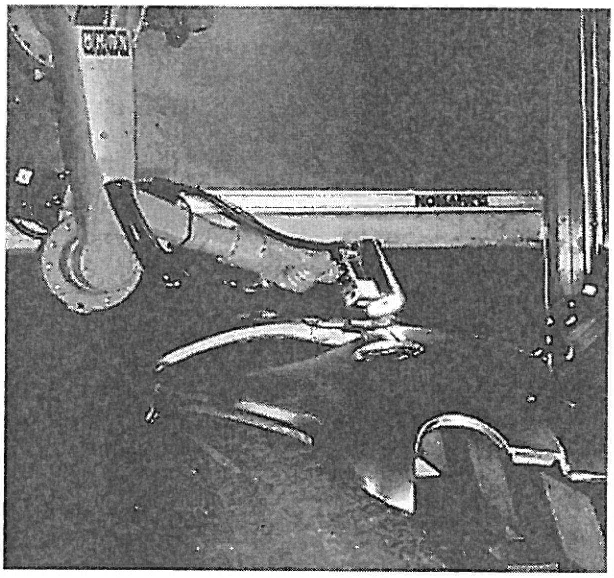

Fig. 4. The complete automatic inspection system for flaw detection on car-body parts.

The developed system provides additional tools to visualize and classify the defects that have appeared in the manufacturing process. This capability allows process engineers to see the classified defects that were previously impossible to locate. Expert analysis of the defect images often point to specific process problems that can be corrected, thereby improving the process and reducing the overall frequency of defects.

VII. ACKNOWLEDGMENT

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