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A distributed system for computer vision quality control of clinched boards

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Abstract

Clinching technology allows to join metal sheets by using a cold press. The quality control of joint points, a type of joint buttons, is performed by experts observing the shape of the joint button on the basis of their experience. VISICON IST Research and Development project (partially funded by the European Commission) has realized algorithms and a distributed quality control system for assessing in real time the production of clinched galvanized metal boards. The solution is based on computer vision, software engineering, process modeling, and knowledge representation through object-oriented modeling. The image processing algorithm is based on the *G* Transform. The transform presents interesting properties and is computationally cheap. The VISICON solution has been validated by using a large set of data and statistical analysis for the detection of joint buttons and for their quality assessment. The paper reports a description of the distributed real-time architecture of the VISICON computer based quality control system, the main aspects of the computer vision processing for quality assessment and the results of the validation phase.

1. Introduction

Most factories which are producing *metal boards* for scaffoldings use the weld system to joint different parts of the boards. An alternative system for joining metal sheets by using a cold press joining technique is the so-called *clinching*. In these cases, the joint points are a kind of joint buttons that are grown up by the metal board for pressing it with a punch (see Figs. 1 and 2). Clinching (press joining) is a proven technique for joining metal sheets, tubes and profiles. The permanent joints are created by cold forming alone, without the use of additional parts or welds. The most significant feature of this technique, which is standardized in DIN 8593, is that the joint is formed from the metal parts, which have to be connected.

The clinching press-joining process requires machines, mobile tools or stationary machines that are driven from one side only. The set of tools required to perform a press joint consists of a punch and a die. The die is made of a fixed anvil in the centre and some laterally moving spring plates or sliding pieces. This technique allows a reduction of production and manufacturing costs, the elimination of the rust onset into the junctions and an energy saving of 60% with respect to the welding technique and avoids the use of chemical additives.

The quality of joint button has to be kept under control during the production process. There are several causes of defect that may arise during the board joining and production: defects in the metal sheets in the area of the joint, defects related to the tools for clinching (they have a limited life-time), problems in the production process machine (e.g., pressure), etc. The production process has to be stopped immediately to solve these problems in order to save time and money when recovering such found defects. At present, the typical approach for quality control is based on (i) measuring the join-button size, (ii) evaluating the join-button thickness, (iii) the observation of the joint button from both sides by an expert. Even a single joint over the total of 60 joint buttons on the board can be a reason to reject the board itself, for security reasons in the board use. The inspection has to be carried out within the production time of a board, which is about 20–30 s. Experts can detect such defects by a simple visual

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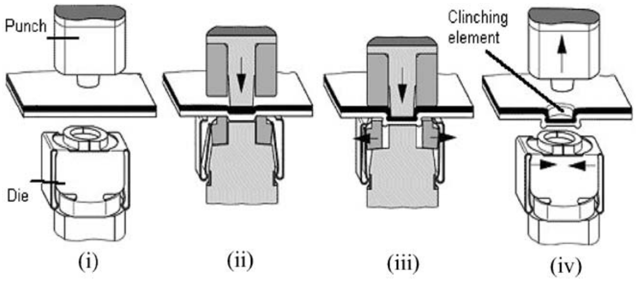


Fig. 1. Phases of joint button production: (i) metal sheets are positioned between the punch and the die; (ii) metal sheets are pressed both by the punch and the die; (iii) the pressure of the punch and an enlargement of the die produces the joint button; (iv) end of pressure and release of metal sheets with the clinching element: joint button.

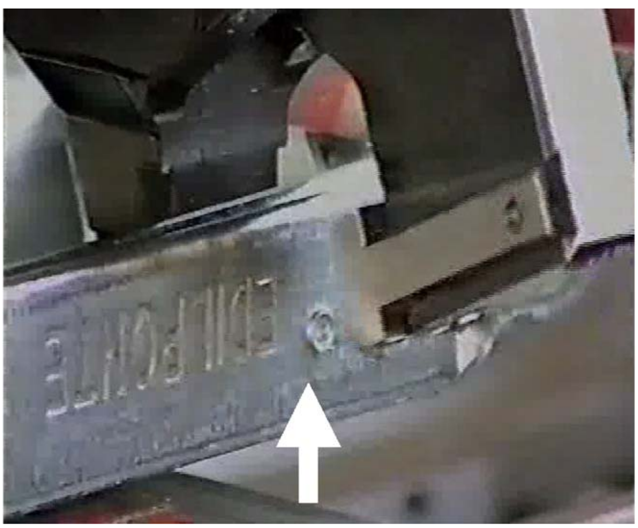


Fig. 2. A particular of the Clinching Process in metal boards production. The image shows a joint button produced by means of a press-joining robot (NUOVACETASS).

inspection on the buttons. This aspect convinced us to start researching a vision-based solution for automating this process.

In this paper, VISICON (VIsion System Inspection for CONtrol of Clinched Boards) FP5 IST Research and Development project, partially funded by the European Commission, is presented. VISICON proposes a solution for realising a distributed quality control system for the controlled production of *clinched galvanized metal boards for civil constructions, scaffolding*. They are used by carpenters to move from one place to another, when building and/or restoring walls, etc. VISICON architecture consists of a set of CCD cameras managed by industrial computers which are controlled by a quality control server for managing the whole process. The image analysis and a priori-knowledge about the joint buttons structure and their position on the board allow deciding whether the joints of metal boards are defective or not. In this manner, the quality of boards and the production efficiency is improved, thus reducing the number of defective boards. The solution integrates aspects of software engineering, process modeling, and knowledge representation and computer vision by using an object-oriented modeling [1,2]. The computer vision algorithms are based on the G Transform that allows the detection and the assessment of circular shapes. The realization of distributed computer vision architectures is becoming very relevant for the realization of real-time processing systems [3–7].

The paper is organized as follows. In Section 2, the VISICON architecture is reported by describing both hardware and software aspects. Section 3 describes the Object-Oriented data model used for modeling software on quality control supervisor and on local image inspectors. Furthermore, the synchronization process and model for the estimation of the overall quality are reported. In Section 4, details regarding the computer vision algorithms and process are reported. Section 5 presents the experimental results with their corresponding statistical analysis and configuration details. Conclusions are drawn in Section 6.

2. The VISICON system architecture

VISICON is a distributed image acquisition and processing system where a number of industrial computers (called Local Inspectors) simultaneously process images of different parts of a clinched board in order to evaluate the quality of the individual joints and out of such datum inferring the general quality of the board. VISICON allows a continuous on-line quality control (rather than the use of sampling or off-line techniques). Continuous automatic control improves overall quality and reduces variations in the final product caused by the subjective judgements made by human operators who may change along the process. The consequent reduction in the number of rejected boards results in substantial savings.

In this section, the hardware and software architecture of VISICON solution are presented. This part introduces a set of terms and components used throughout the paper. The main idea is focussed on building a quality control area placed at the end of the production machine for clinched boards, in order to process in real time all the produced boards with throughput which can keep up with the clinching machine.

The distributed system for quality control developed for VISICON is general enough to be applied in different contexts. The number of used Local Inspectors may vary according to the board type and the speed of the production line. This enables the system to be scaled

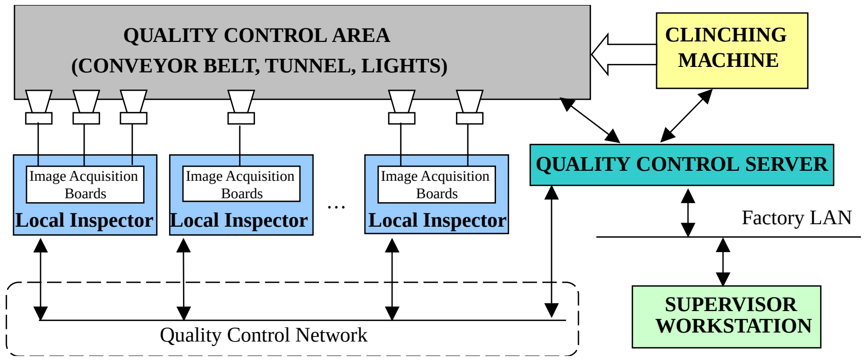


Fig. 3. VISICON hardware architecture.

according to the requirements of that particular application.

The hardware architecture is depicted in Fig. 3. The main components are as follows:

Quality control area: The quality control area consists of: a tunnel containing a set of CCD cameras, an illumination system, a conveyor belt, an optical placement sensors, etc. It is the area where the clinched boards are assessed. The positioning of each board is performed by means of a conveyor belt, so as to allow the assessment by acquiring their image with the CCD cameras. The grabbing and board positioning is managed by the Quality Control Server who asks Local Inspectors for image processing tasks. The number of CCD cameras is enough to get all board joints, but not all at the same time. The conveyor belt is used to move boards in front of cameras. Each CCD camera has a medium resolution black and white CCD and an 16 mm optics. The illumination system provides uniform lighting in order to minimize the reflections on the board metal. Lights are also controlled by independent signals. The tunnel surrounding the conveyor belt has a dark inner surface to avoid reflections and thus reducing the influence of external lights.

Quality control server (QCS): QCS is a computer system performing multiple activities. It executes the software for the general management of the VISICON quality control area and therefore it provides the user interface of the whole VISICON system. It is the decision-making centre for the activity of quality control and the production process. The decisions are taken according to the set up information and the results of the quality control process carried out by the Local Inspectors. The QCS sends/receives messages (alarm, synchronization messages, images) to/from the Local Inspectors and controls the position of the boards, the lights and the synchronizations with the Clinching Machine. The QCS also produces WWW pages with a set of control and statistical parameters for monitoring the whole activity by means of any computer connected to the Factory LAN, such as the Supervisor Workstation. Additional details about the QCS are reported in Section 3.

Local inspector (LI): Each LI consists of an Industrial Computer equipped with one or more Image Acquisition Boards for frame grabbing by means of one or more CCD cameras. The Local Inspectors are endowed with a user interface only during the development, whereas during the operative quality control in the industrial environment their user interface is removed. Each Local Inspector reads the synchronization and communication commands coming from the QCS. The Local Inspector grabs the image(s), executes the image analysis for quality control, communicates results to the QCS and, when requested, sends the current images to the QCS. Typically, this occurs when some defective buttons are detected. This is done to trace the history of the defects and of the decisions taken. Details about the image processing algorithms used in the Local Inspectors and the results obtained are reported in Section 4.

Quality control network: It is a TCP/IP based local area network based on Ethernet 100 Mbps. It provides the support for the communication between the units of the VISICON architecture. The communication is mainly managed by the QCS. This network is kept apart from the Factory Network to avoid excessive workload that could be generated by the Factory Network in the Quality Control Network and vice versa. In fact, if there are several quality control areas and all of them share the same network, the exploitation of the network to send images to the corresponding QCS could be high in the same specific cases.

Supervisor workstation: It is a personal computer, which allows the monitoring activity of the production; it can ask for WWW pages to the Quality Control Server of each production line. This permits to check multiple production lines from a single computer having VISICON quality control.

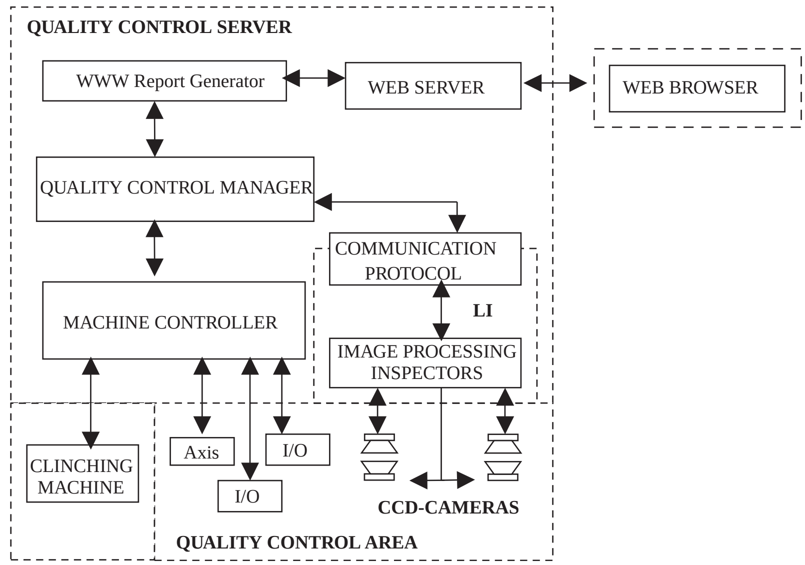


Fig. 4. VISICON software architecture.

2.1. Software architecture

The software architecture of VISICON is reported in Fig. 4. The structure of the software architecture can be regarded as made of five modules:

- The Quality Control Manager.
- The Machine Controller.
- The Image Processing Inspector in the Local Inspectors.
- The communication protocol, and
- The WWW Report Generator.

In Fig. 4, these software components are mapped on the main hardware components of the hardware architecture reported in Fig. 3. Please note that both hardware and software architectures of VISICON could be used for building other quality control systems based on Computer vision for differently manufactured objects. What follows is the description of the components, with a particular attention focussed on the data structure and on the communication and real-time aspects, which are the most interesting features making VISICON a flexible and efficient solution for distributed vision based quality control.

The *Quality Control Manager* (QCM) estimates the whole production quality and considers the quality of each single board by assessing the quality of each single joint button via the Local Inspectors. Its main task is managing the components involved during the quality inspection and synchronising the activities controlled via the Machine Controller. The QCM manages the whole decision-making process of the quality control, it produces actions and it analyses the results provided by the Local Inspectors. For this reason, the decision-making algorithm has been implemented paying attention to detect the right condition for declaring as good/bad the examined joint buttons. In this sense, values of the threshold/configuration for the acceptance have been identified and fixed in order to define the right decisional criteria and the optimal values of sensibility and specificity. Their value is content dependent, meaning that different positions of the joints have to be considered in different manner (they could be less relevant for the total quality and/or they may need different parameters for their assessment). In the case of one or more defective joint buttons, alarms have to be produced to request a human intervention for the correction of the occurred problem. One of most important task of QCM is the management of the synchronization between the QCS and the Image Processing Inspectors and the QCS and the Machine Controller.

The *Machine Controller* controls the synchronization between Clinching Machine and the Quality Control Area. It manages the positioning of the boards under the CCD cameras by controlling the conveyor belt of the Quality Control Area. It also controls the conditions of positioning and produces the synchronization signals and commands to the I/O units and axis of the motor to position the joint on the board under the CCD cameras.

The *Image Processing Inspector* is the software component performing the image acquisition and analysis on the Local Inspector. This process runs on the Local Inspector and is reached by the QCM by means of a Socket based communication. Its aim is the frame capture of the joint button images according to the configuration taken. The acquired images have to be analysed in order to detect the position of one or more joint buttons in the same image, and for each of them to assess their quality. The results of each phase are communicated to the QCM. This module provides the following functionalities: (i) image acquisition, (ii) image processing for joint button detection and position verification, (iii) measurement of joint buttons features, and (iv) assessment of joint button defects.

The *Communication Protocol* is based on TCP/IP sockets and it is used to deliver messages, signals, alarms, and images, thus for the communication between the QCM and the Image Processing Inspectors.

The *WWW Report Generator* acquires information about the control process from the QCM so as to publish a report in HTML about the status of the whole process. This report contains statistical and quality aspects, and information about the productive flow trend, etc. A WEB server is available on the Quality Control Server making the produced WWW pages public. The produced Web page can be read from any computer connected to the Factory Network.

3. Object-oriented modeling and quality control process

The software architecture has been designed according to the object-oriented paradigm by making a Problem Domain Analysis [1–3,8]. The Object Model Identified included all the elements of the VISICON architecture and in order to implement a general framework which can be used for building other quality control systems for industrial machines. The analysis highlighted the needs of classes reported in Fig. 5. Object-oriented relationships of specialization, aggregation and association are reported. The organization has been chosen by modeling the aspects of the real world and by avoiding the definition of lists where the search can be expensive in favour of direct references.

Class *QCManager* controls the whole quality control process implementing a large part of the activities of the QCM. This class is the core class of the QCS and manages the most important data structures. The QCS presents several other classes for implementing the user interface. The *QCManager* includes an array of detectable *Items* (instances of the class *Item*), an array of all possible *Views* (instances of the Class *View*), an array of

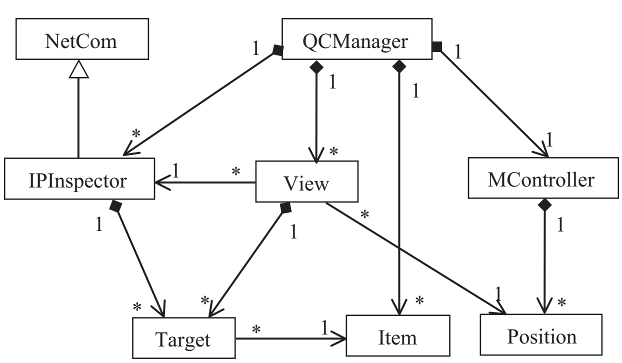


Fig. 5. Object-oriented UML model.

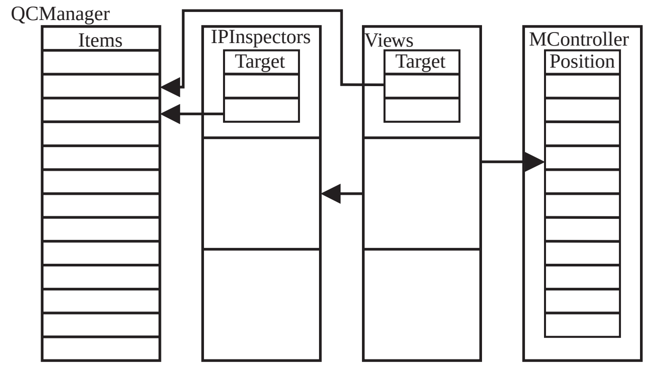


Fig. 6. Structure of the Class QCManager.

all available *IPInspectors* (instances of the class *IPInspector*) and an instance of the class *MController*.

Each instance of the class *Item* (see Fig. 6) represents a visual entity, which has to be detected and assessed in the image. It is modeled by a set of attributes (some of them are used in the detection process, others in the recognition process) and it contributes to the general quality of the system under observation with its score. In VISICON, both good and defective joint buttons are Items, where different defects of joint buttons are modeled with different Items. They represent the basic knowledge used during the recognition and quality assessment process.

The *View* class models the image view that can be acquired by a CCD camera when the board (object under inspection) is placed in some valid position inside the Quality Control Area. A value of relevance is also associated with the View and influences the estimation of the general quality. For example, in a board there are about 64 joint buttons and among them 12 are strongly relevant for security reasons (those joining the frontal parts of the board), 16 are quite relevant, while the remaining are marginally relevant for the security of the people who will be walking on the board. The View class contains also an array of *Targets* which are uploaded into the related Inspector when the board moves into the related Position.

A *Target* represents a feature to be searched in the acquired image and contains both its presumed position/size and an array of symbolic references to Items corresponding to all possible search results for that button. This array allows feature classification only on the basis of the Items which are actually expected to be located in some particular position of some particular *View*, and not according to all detectable *Items*.

Class *IPInspector* represents both the logic reference to a physical Local Inspector from the side of the QCS and the real process in the Image Processing Inspector (see Fig. 5) when the class is used to implement the software for the Local Inspector. The Class *IPInspector* represents the software model of Image Processing Inspector at logical level.

The QCM commands the image acquisition and image processing to the instances of the class *IPInspector* on the QCS. The QCS communicates with the corresponding *IPInspector* instances which are physically located on the Local Inspectors and it is the Local Inspector which eventually executes the command. The *IPInspector* contains an array of *Targets* which are expected to be found in the obtained image when the board is placed in the position specified by the *View*. In each *View* several joint buttons to be assessed may be expected. For each instance of the *IPInspector* running on a remote Local Inspector there is a corresponding instance of the same class in the QCS.

The *MController* class implements the software entity responsible to manage board positioning along the conveyor belt, lights and clinching machine interface, the responsibilities of the Machine Controller module. It hides all the CANbus management details to the *QCManager* and contains a vector of all possible *Positions*.

Class *Position* represents a board position along the conveyor belt and contains the control parameters required to drive the board until the Position is reached. When the position is reached a stop signal is sent to the Machine Controller. Instances of *Position* also contain parameters needed to set up proper lighting conditions for image acquisition.

3.1. Quality control process

The process used to assess the general quality of a board is driven by the knowledge associated with the structure of the board, the position of the joint buttons, their relevance, their shape and features, acceptance level, etc. This information is organized as described in the previous section in order to be quickly used during the quality assessment and fault detection. The Overall Quality, OQ, of a board has a range from 0 to 1 and it is estimated by using a weighted sum according to

$$OQ = \frac{\sum_P^P \sum_v^{V_P} W_{pv} \sum_t^{T_{pv}} S_t}{\sum_P^P \sum_v^{V_P} W_{pv} |T_{pv}|},$$

where P is the set of Positions p of the board for getting all the images corresponding to the joint buttons; V_p is the set of Views of board Position p; W_{pv} is the weight of View v of Position p; T_{pv} is the set of Targets of View v of Position p; S_t is the score assigned to the Target t from the quality assessment process that has identified the most likely Item for the Target, t; and $|T_{pv}|$ is the number of Targets in the View v of Position p.

The OQ assumes the value of 1 when all Joint Buttons (Targets) are recognized as GOOD buttons (maximum Score equal to 1), see the description of the Items reported in the following.

The weight associated with each View and Position represents the relevance of the Joint Buttons, which are reported in the View for global reliability/quality of the board itself. Their values have been obtained by collecting specific questionnaires filled by experts of clinching machines and production process. As to the considered boards, three different types of Views have been identified with different relevance for the reliability/quality of the board. The frontal and lateral Views host buttons that are strongly relevant and influence the quality of the board for the 10% and 85%, respectively. The remaining buttons/views are along the planar face of the board for the 5%. These values have been estimated as the median values of relevance weights given by the interviewed experts. These values depend on the dimensions and on the design of the board. They may differ for the number of buttons in the views, for the thickness of the metal, for the number of buttons along the plane, for the number of transversal reinforcements, etc. In order to estimate the weights, the normalized relevance percentage of each type of View has to be divided by the number of buttons in the same View. This brings the denominator to be equal to 1 and allows simplifying the formula of OQ to

$$OQ = \sum_P^P \sum_v^{V_P} W_{pv} \sum_t^{T_{pv}} S_t.$$

The OQ is compared to the defined thresholds in order to determine the category of acceptance of the board or its possible rejection leading to stop the production. The OQ is not the only parameter used to interrupt the production, also the number of insufficient scores (when the score S_t is lower than a certain threshold) is a very important parameter. These additional criteria prevent from accepting as good boards which compensate the presence of few not good enough buttons with a lot of good ones. Another criterion to identify bad boards is the estimation of the ratio among buttons presenting higher and lower score with respect to the threshold. This can be provided with a range quality measure of the buttons being on the board. The evolution of these criteria along the production gives the global trend of the quality and allows predicting possible critical conditions.

The above criteria can be used by the production responsible to predispose the actions of intervention. They can be a simple alarm when quality is lower than planned or the automatic stop of the production when quality is unacceptable and/or some real problem is detected, such as the breaking of the clinching tool.

In order to understand the operational relationships among classes, the typical operations performed by

VISICON during the quality control process are detailed as follows.

The general algorithm for quality assessment is:

(1) Initialize the board position from the initial reference position
(2) For each Position:
  (2.1) Impose the Position of the board via the Control Manager according to the list of positions.
  (2.2) Identify the set of Views related to the reached position.
  (2.3) For each View:
  - Activate the views.
    - upload the View parameters and detectable Item Attributes on the remote Inspector;
    - upload the Targets of the View on the remote Inspector.
  - Acquire the image from the CCD camera and activate the image processing.
    - image acquisition;
    - compute the image gradient;
    - start the search for a Target by using the position, size, etc.;
    - for each confirmed Target:
      - estimate the corresponding set of metrics which allows Target classification in terms of Items;
      - compute the assigned model by giving a score for each possible Item, expressing the confidence to which a given target is recognized as a possible Item;
      - assign the quality value to the Target;
  - Sum the quality value to that of all the other Targets of the same View.
  - Multiply the quality value estimated for the Targets of the view for the View weight to compute its quality score.

  (2.4) Sum the quality score of the View with those of the other Views in the same Position to estimate the quality score of the Position;
(3) Sum the Position quality score with those of the other Positions in order to estimate the general quality score of the board.
(4) When the last Position has been reached, the Manager:
  (4.1) compares the board quality score with the threshold and determines the status of fault or not;
  (4.2) in the case of acceptable quality, the control of another board can begin.

The Quality Control Server manages the synchronization process between Local Inspectors and Machine Controller. The main steps of this process are reported hereafter:

(1) The QCManager tests any board presence at the beginning of the Quality Control Area.
(2) When a new board is ready for the quality control process the QCManager sends command to the Machine Controller in order to move the board forward.
(3) When the board reaches the zero sensor the Machine Controller stops the board and sets of the origin of the reference system.
(4) The Manager sends command to the Machine Controller in order to move the board to the first position:
  (4.1) For each position:
  - it waits for board placement;
  - it identifies the set of Views related to the reached position;
  - it sends command to Local Inspectors in order to activate the CCD cameras on the right view;
  - it sends command to involved Local Inspectors to acquire and process images;
  - it waits for image acquisition signal from involved Local Inspectors;
  - it sends command to the Machine Controller in order to move the board to the next position;
  - it waits for results from involved Local Inspectors;
  - it evaluates the partial quality score.

  (4.2) When the last position has been reached:
  - it evaluates the whole quality score of the board;
  - it compares the board quality score with the threshold and determines the status of fault or not;
  - it updates the HTML pages with the last results.

(5) If quality is acceptable, it starts the control of another board, otherwise it stops the process and sets the appropriate output signals (alarm, process status, etc.).
(6) During the whole phases of the process, the input signals (emergency, stop request, failure, etc.) are tested inside a timer cycle in order to stop the quality control process.

The set up of the system, and thus the configuration parameters of each item are produced during an installation phase. This phase is supported by a guided process to set up all positions through a learning phase based on examples. During that process, the operator moves the board under the Quality Control Area and verifies each position in real time via the CCD Cameras. For each position, parameters are set. According to the dimension and the geometry of the boards, specific configuration sets can be loaded. Furthermore, the configuration includes also the recognition and threshold parameters. These are estimated during a learning phase according to the acceptance criteria defined by the company (see Section 5). The software tools support also such phases in a semiautomatic manner. This allows the use of the tools by untrained people.

4. Computer vision overview

The process for the image acquisition and analysis is located on the Local Inspector and is controlled by the QCM. Its aim is the frame capture of the joint button images and its processing for the quality assessment of the included joint buttons. The acquired images have to be analysed in order to detect the position of one or more joint buttons in the same image and then to assess their quality. The results are communicated to the QCM. This problem is re-conduced to the problems of circle detection and assessment.

Computer vision based approaches for circle detection have been proposed many times in literature, most of them are based on Hough transform or its derivations [9–12]. The Hough transform based methods are typically implemented by having each single point of the image voting for each possible solution which represents a circle passing through each selected point. This requires image preprocessing in order both to transform the grey-scaled images in binary ones and to highlight the points which are potentially located on the circles by using edge detection and thinning operators. Voting solutions often presents problems of resolution since the results depend on the structure used to collect votes, meaning, usually, a tridimensional array. A considerable amount of work has been spent to improve the performance of such methods, through specific structures to implement parallel and multi-resolution strategies [13,14]. On the other hand, the adoption of a Hough transform based method implies a heavy preprocessing phase during which local operators are used. Most of them present a computational complexity which is linear when compared to the image surface and quadratic with respect to the operator size. The overall complexity of these methods typically depends on the amount of candidate points extracted from the preprocessing phase and on the size of the structure which has been adopted to collect votes.

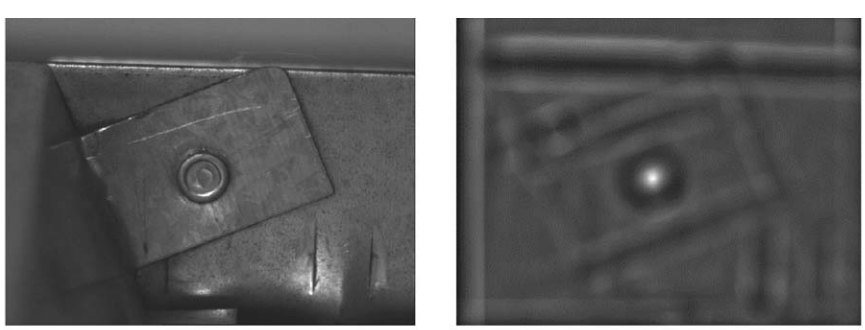
In this paper a completely different approach for circle detection is proposed. It deals with the particular gradient evolution determined by the presence of an annular shape by directly working on real world images without any preprocessing phase. An early attempt at carefully scrutiny of the intensity profiles of circular features has been given by Davies [15].

Each CCD camera is connected to a frame grabber, which acquires images (384×288 with 8 bit per pixel) of the button(s) under the control of a Local Inspector task on an industrial computer. The image resolution has been defined as a compromise value between processing time and analysis precision.

4.1. Image processing algorithms

When requested, the Local Inspector performs the button detection process starting from the presumed positions which have been previously uploaded on the Local Inspector by the QCS according to the configuration (board geometry). Joint Button detection is accomplished by maximizing a specifically designed transform and operators, the so-called mathematical operator G transform [16]. The solution taken for image processing has been compared with other techniques in [17]. This operator transforms the image so that each peak of the transform corresponds to the centre of a circular region on the original image. These circular regions to be highlighted by the G Transform have to present a radial symmetry and a radial gradient, such as the annular shape of a joint button (see Figs. 7a and b).

In this section, the G transform is presented. It is able to highlight shape with annular structure. Annular shape is highlighted in such a way that it is easy to both locate its centre on the transformed image and associate a value, which can make the classification easier. The transform is not based on any circle extraction through an explicit parameterization; nevertheless, it may occasionally highlight them as particular



(a) (b)

Fig. 7. (a) A joint button in its context. (b) The G transform of the image, lighter values are higher.

cases of rings. It turns out to be able to deal with complex images having rings, which may be visually very different from one another. This method can be applied to a large number of circle detection and classification.

G transform has been defined as the ratio between two surface integrals, according to:

$$\gamma(\xi,\eta)=\frac{\int\int_{C_R}|\nabla_{x,y}[f(\xi+x(S),\eta+y(S))]\cdot \underline{i}_r(\theta(S))|\,\mathrm{d}S}{\int\int_{C_R}|\nabla_{x,y}[f(\xi+x(S),\eta+y(S))]\cdot \underline{i}_\theta(\theta(S))|\,\mathrm{d}S},$$

where C_R is the circle with radius R centred in the origin and scanned by the surface unit dS, i_r and i_θ are, respectively, the radial and tangent unitary vectors and θ is the angle comprised between the radial unitary vector and the positive semi-axis of abscissas.

The G transform produces higher values if the Integral area is closer to the button dimension [16]. This means that in each analysed image segment (see Fig. 7a) a maximum of the G transform is obtained. If the value of the maximum is above an assigned threshold (e.g., 2.0), a button or any other circular shape (e.g., a hole), has been detected and its position is that of the maximum with an error lower that 2 pixels. This avoids discharging a great part of the false negatives, whereas most false positives, like holes, are discarded by fixing an upper bound to 4.0 on the allowed value of found maxima. In fact, the 98% of joint button centres analysed during statistical analysis of the initial test cases for validation presented maxima values between 2.0 and 4.0 whereas holes, reflexes and other common false positives usually generate much higher values.

The G transform is invariant with respect to the luminance and contrast changes and commutative with respect to reflections, translations and rotations [16]. On the contrary, classical Hough transform based methods imply a heavy pre-processing phase [17].

The G transform can be used to find out the centres of radially symmetric shape, by both locating the relative maxima of $\gamma(\xi,\eta)$ and extracting a subset of them on the account of their positions and value. For instance, it is possible to select a number amongst the highest maxima or all maxima being over a given threshold, provided that the shape to be searched is unknown; otherwise maxima can be selected amongst those fulfilling further geometric constraints based on their presumed location.

It may occur that what is visually perceived as annular shape has a centre which does not meet this criterion. On the other hand, some points conforming to the former are not centres of any recognizable rings.

4.2. Detection process

The estimation of the above mentioned transform is performed only in the image segments where the Targets are supposed to be (see Fig. 8a). To limit the processing time, Greedy searches are started from a grid of points in the supposed area. This constraint allows considering as good buttons only those which are correctly positioned and reduces the computation complexity of the whole process. An alternative detection method has been implemented if the presumed buttons' positions are not known with adequate accuracy, as in the case of a faulty clinching machine. This method performs a scan of the whole image by applying the same detection algorithm after having initialized it with a fixed grid of points. The alternative method is more robust but slower than the standard one and can be used if enough industrial PCs are available with respect to the production line speed.

In Figs. 8a and b, the target position and the results of the G Transform are reported for three buttons.

4.3. Calculation

The use of polar coordinates makes easier to understand $\gamma(\xi,\eta)$ behaviour, but in order to confront its calculation it is better to rewrite the right hand side of the above definition of $\gamma(\xi,\eta)$ in Cartesian coordinates:

$$\gamma(\xi,\eta)=\frac{\beta(\xi,\eta)}{\alpha(\xi,\eta)}=\frac{\int_{-R}^{R}\int_{-\sqrt{R^2-y^2}}^{\sqrt{R^2-y^2}}\left|\frac{\partial f(\xi+x,\eta+y)}{\partial x}\cos\tan^{-1}\frac{y}{x}+\frac{\partial f(\xi+x,\eta+y)}{\partial y}\sin\tan^{-1}\frac{y}{x}\right|\mathrm{d}x\,\mathrm{d}y}{\int_{-R}^{R}\int_{-\sqrt{R^2-y^2}}^{\sqrt{R^2-y^2}}\left|\frac{\partial f(\xi+x,\eta+y)}{\partial y}\cos\tan^{-1}\frac{y}{x}-\frac{\partial f(\xi+x,\eta+y)}{\partial x}\sin\tan^{-1}\frac{y}{x}\right|\mathrm{d}x\,\mathrm{d}y}.$$

consider only the case where $\alpha(\xi,\eta)\neq 0$. The purpose of this section is to define a discrete version of the above equation, to be computationally light and able to estimate the values sampled on a square grid with step equal to the pixel size $\varepsilon>0$. After having assigned R, the integration domain boundaries through the vector $B_i=\sqrt{(R/\varepsilon)^2-i^2}$ is estimated.

If $i\in[-R/\varepsilon,R/\varepsilon]\cap Z$ and $j\in[-B_i,B_i]\cap Z$ where $(\varepsilon i,\varepsilon j)\in C_R$ and Z is the set of integer numbers; the trigonometric functions can be computed in advance by estimating the arrays:

$$c_{i,j}=\cos\tan^{-1}\frac{j}{i};\quad s_{i,j}=\sin\tan^{-1}\frac{j}{i}.$$

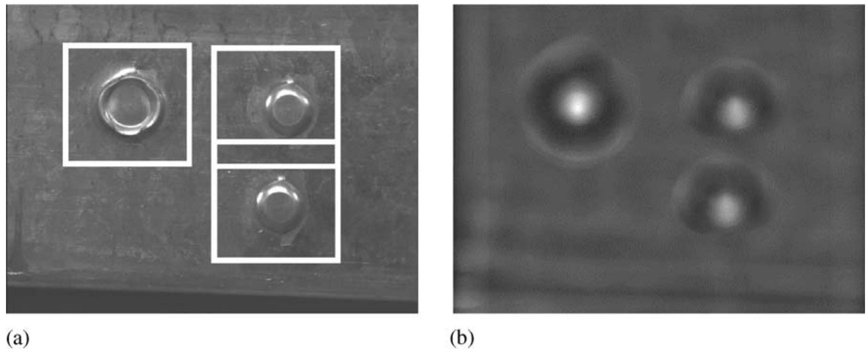


Fig. 8. (a) A good and two defective buttons (on the right) with Target image segments. (b) The G transform on the whole image.

Furthermore, on the basis of the image, the partial derivatives can be estimated:

$$u_{p,q} = \frac{\partial f(x,y)}{\partial x}(\varepsilon p, \varepsilon q); \quad v_{p,q} = \frac{\partial f(x,y)}{\partial y}(\varepsilon p, \varepsilon q),$$

where $p, q \in \mathrm{Z}$ are suitable values to scan the image. Since the gradient of the translation of a function is the same as the translation of the gradient of the same function, the formula can be finally written down and it is actually used for the transformation:

$$\gamma(\varepsilon p, \varepsilon q) \cong g(p,q) = \frac{\sum_{i=-R/\varepsilon}^{R/\varepsilon} \sum_{j=-B_i}^{B_i} |u_{p+i,q+j} c_{i,j} + v_{p+i,q+j} s_{i,j}|}{\sum_{i=-R/\varepsilon}^{R/\varepsilon} \sum_{j=-B_i}^{B_i} |v_{p+i,q+j} c_{i,j} - u_{p+i,q+j} s_{i,j}|}.$$

Therefore, the asymptotic computational complexity of $g(p, q)$ is linear towards the image surface and quadratic towards the radius R determining the integration domain extent.

4.4. Single button assessment

Once the detection phase has been completed, the quality evaluation of each button is performed by interpreting G transforms maxima values as a quality index of the corresponding buttons. In fact, most high-quality buttons present maxima values over 3.0 and by assuming this number as a quality threshold for button classification, it is possible to distinguish between defective buttons and good ones. The method performance has been improved by also using other metrics based on the G Transform estimated with different concentric annuluses, so as to get a vector of values describing the radial distribution of circular features. In this case, the overall quality of the button is computed as a weighted sum of the indexes produced by the selected metrics.

The adopted model has been based on logistic regression. The quality of single joint buttons is represented by a dichotomist variable, the value of which is the nearest integer to a real quality index between 0 and 1, which is computed according to

$$Q = \frac{1}{1 + \mathrm{e}^{-P}},$$

where

$$P = \beta_1 M_1 + \beta_2 M_2 + \cdots + \beta_m M_m,$$

where β_i are the weights to be estimated and M_i are the values of G transform for different value of radius R, m has been set to 6. A different set for Radius and corresponding weights can be used for using different models in different Views when the observed buttons are visually different, for example when they are observed with a given angle. The weights can be estimated by using selected learning cases where the quality value is expressed by some experts assigning a value of quality for each button in the from 0 to 1. Weights have been estimated by a blockwise method so as to minimize the prediction error with respect to a known set of quality assessments, or tuples containing both the metrics evaluated for a set of joint button images and the reference quality assessments of the corresponding joint buttons.

5. Experimental results

The validation of VISICON solution has been performed at Ediltavole, an Italian SME which produces clinched boards for the building trade. Ediltavole operators submitted to quality control the defective boards they collected by monitoring one of their three production lines for one week, while attempting to achieve a wide enough set of defect types and positions.

Ediltavole operators provided a quality assessment which could be used as reference, since they carried out their task as usually, by a visual evaluation of the shape of the joints. Moreover, since buttons belonging to the same region are produced by the same tool and most defects are due to tool breakdown, reference quality assessment provided by Ediltavole was region-based and this introduced errors in the evaluation of the region which is being clinched when the tool breaks.

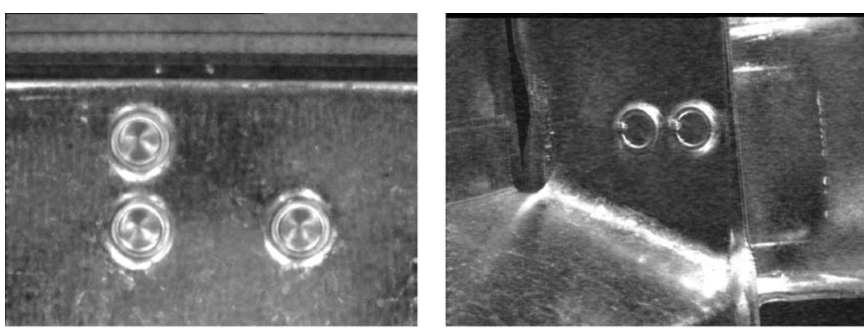
During the validation performed at Ediltavole their present production was assessed. For each defective board, 76 different images have been acquired. Captured images belong to one of the following views, which are classified as views of type A–C. The views of type A are 4 images of views captured by two different CCD cameras, containing three buttons each and representing the front and back side corners (see Fig. 9a). The relevance of these buttons is very important to the safety of the metal board. The views of type B are taken from 8 CCD cameras having a non-perpendicular position with respect to the plan containing the buttons (see Fig. 9b). Each view contains two buttons representing the front and back heads of the metal board. The views of type C are frontal and present a single button. In each board there are 64 views of type C.

According to the user requirements and specification, the priority attention has been given on views of type A, for their relevance on the robustness of the board. Type B views are worth to be considered both for their slantness and the high number of different CCD cameras used, which have consequences on the eccentricity of the button shape and on the variability of reflexes. It should be noted that in the case of type B buttons, their shape is not circular but elliptical. The eccentricity of the elliptical shape has to be limited to limit the negative influence on the estimation of the transform. In that case, the detection threshold is different from the threshold defined for type A views. If the orientation of the plane is known and is very relevant, different solutions could be (i) to integrate $g(p,q)$ on a non-circular shape, (ii) to de-rotate the image so as to have it on a perpendicular view.

In the following Table 1, the most relevant properties of each view are summarized, together with the acquisition conditions of the corresponding images. Figures are different between detection and classification phases because only a subset of processed views had a reference quality assessment, which could be used to evaluate classification performance.

In Fig. 10a a schematic top view of the tunnel is reported with the location of the 14 CCD cameras. It shows also the connection of CCD cameras to the four Local Inspectors. Fig. 10b depicts the top view of a board, where joint buttons are highlighted and the alignment positions of the board in the tunnel are reported.

Table 2 reports for each alignment position which CCD cameras (grouped by Local Inspector) are active and how many buttons there are in the captured image. From Table 2 what can be deduced is the following: for each position each Local Inspector has to process at most one image; moreover for each position the image complexity (number of buttons to be assessed) is the same for all the active inspectors. Due to the parallel execution of the assessment in each inspector the time needed to asses a position is related to the number of buttons in one image (3, 2 or 1) and not to the total number of buttons captured (see Fig. 10).



(a) (b)

Fig. 9. (a) An image taken from a view of type A. (b) An image taken from a view of type B.

Table 1
Characteristics of the views

View type	View characteristics		Acquisition conditions				
	Target orientation	Target relevance	# Images per board	# Cameras per board	# Buttons per image	# Buttons per board	# Positions
A	Normal	High	4	2	3	12	2
B	Oblique	Medium-high	8	8	2	16	2
C	Normal	Low	64	4	1	64	16
		Total	76	14	No sense	92	20

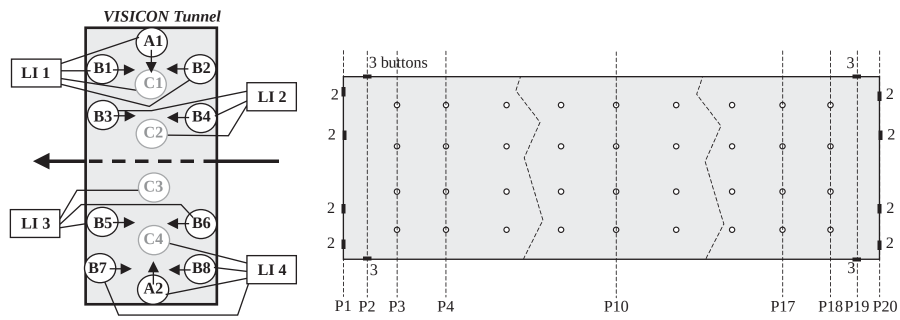


Fig. 10. (a) The schematic top view of the tunnel. (b) The top view of a board with positions.

Table 2
It reports for each position the active CCD cameras and the number of captured buttons

Position	Local inspector 1				Local inspector 2			Local inspector 3			Local inspector 4			
	A1	C1	B1	B2	B3	B4	C2	B5	B6	C3	B7	B8	A2	C4
$P1$			2		2			2			2			
$P2$	3												3	
$P3-P18$		1					1			1				1
$P19$	3												3	
$P20$				2		2			2			2		

The evaluation process was totally supervised by the Ediltavole personnel in order to identify all the defective buttons and thus the amount of defective boards in the weekly production. As a result several images of defective buttons have been taken. The collection resulted in 31 defective boards containing at least one defect, over a production of about 5000 boards. The boards where the defective buttons were detected contained a significant number of good buttons as discussed hereafter. The process validation for detecting good and bad buttons was based on the buttons contained in such boards. For this reason, the general validation could be based on 2356 images distributed as reported in Table 1 and Fig. 10a.

The validation process has been based on a lower number of images and buttons since processing all images in real time would take too much time. For this reason, some compromises have been necessary in order to guarantee the full control of the production in real time, as reported in Section 5.1.

The whole process of assessment is divided into two phases: the detection and the quality assessment, reported in Sections 5.2 and 5.3, respectively. The detection has to verify the presence of the button and its precise position in order to align the estimation of G operator for the successive assessment.

5.1. Real-time processing

The production process builds a new table every 30–35 s according to the length of the board. The board can be for example of 1.8 m, or 2.0 m. The considered boards are of 1.8 m and are produced every 30 s. This means that the quality control has to assess each board in the same time duration. This will allow the same production rate to be kept, by introducing an initial delay equal to the production process rate itself.

The processing time to perform the quality control depends on the number of buttons to be detected and assessed per each position and on the whole board. The typical time to detect a button is of 0.25 s while the assessment is of 2.2 s (this distinction will be better explained later on). These values have been estimated with the Local Inspector implemented by using a Pentium 3 at 600 MHz. Better performances can be obtained with more powerful CPU. On the other hand, the low profile industrial computers which were used are very reliable and low cost. They were selected to find a good compromise between costs and performance at the time when these experiments were performed.

According to Tables 1 and 3, each board has buttons of types A–C. If the quality assessment is performed with the aim of assessing the quality of each button of the board, 92 buttons per boards (see Table 1) have to be assessed. This case is mentioned as Full Control. In this case, the execution time estimation reported in the figure corresponds to a configuration for acquiring presenting views of type:

(A) 2 CCD cameras. Each camera takes two images in two different positions.
(B) 8 CCD cameras. It is not possible to acquire the whole 16 images in positions P1 and P20 with the

Table 3
Performance assessment/estimation on the basis of the algorithm execution time.

General parameters					Full control	Optimised version	
View type	Number of buttons per position	Number of positions (cameras)	Detection time per position	Processing time per position (det. + ass)	Time per board per view type (det. + ass)	Optimised Assessed buttons per board	Time per board per view type (det. + ass)
A	$P2(3+3)+P19(3+3)$	2 (2)	0.75	7.38	14.76	$P2(1+1)+P19(1+1)$	5.92
B	$P1(2+2+2+2)+$ $P20(2+2+2+2)$	2 (4)	0.50	4.92	9.84	$P1(1+1+1+1)+$ $P20(1+1+1+1)$	5.42
C	$P3(1+1+1+1)+P4(1+1+1+1)$ $+\cdots+P18(1+1+1+1)$	16 (4)	0.25	2.46	39.36	$P10(1+1+1+1)$	2.46
Processing time per board (detection + assess) in seconds					63.96		13.80
Positioning time in seconds					9.03		7.50
Total assessment in seconds					72.99		21.30

$Pi(j+j+j)$ means that at position i there are 3 CCD cameras that take images with j buttons each.

same cameras. They have to be oriented back and forward with respect to the board to take the back and front without rotating the board or changing position to the camera. Therefore, of these 8 cameras only 4 work together at the same time for each position of type B.

(C) 4 CCD cameras. Each camera takes one image for each position. 4 CCD cameras work at the same time to get 4 buttons for each position.

This configuration allows assessing all buttons of each board with 20 different positions in a time equal to 63.7 s plus the time to move the board in the positions. This processing time is not acceptable for the production constraints. In order to reduce the processing time while remaining in the condition of detecting any production problem, an optimized solution has been chosen.

The optimized solution (see Table 3) aims at reducing the execution time while assessing for each board the most relevant buttons for the board security and for the detection of incipient degeneration of button quality. When a tool for clinching has deteriorated, it begins to produce bad buttons. Sporadic problems are not possible since the metal is controlled. This allows a significant reduction in the number of buttons to be controlled by avoiding the assessment of all views of type:

A are produced by 2 clinching tools per board and are quite relevant for the security for the board. The tools produce 12 buttons per board. The assessment of buttons produced by the tools is performed twice for each tool per board, by using 2 CCD cameras.

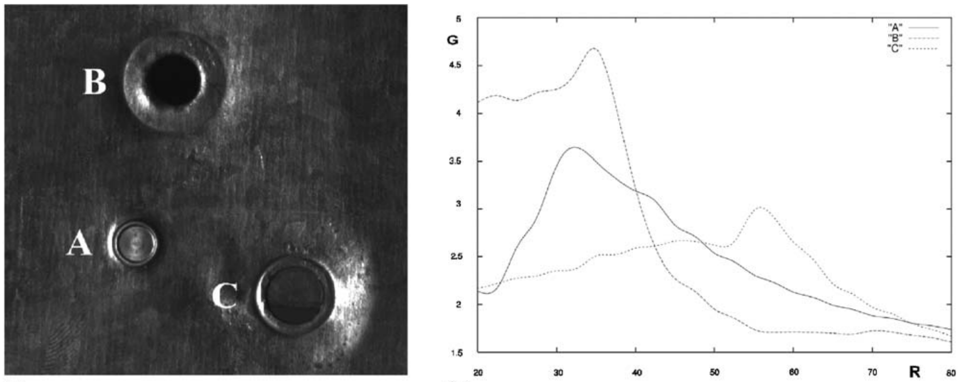
B are produced by 2 clinching tools per board and are moderately relevant. The tools produce 16 buttons per board and the assessment controls 8 of them: 4 on 8 in the front and 4 on 8 in bottom. The assessment of the buttons produced is performed twice for each tool per board. The assessment is performed by 4 CCD cameras with 2 local inspectors for the front and the same for the back.

C are produced by 4 clinching tools per board and are marginally relevant. The tools produce 64 buttons per board. For this reason the assessment of the produced buttons is performed only once in the middle of the board. This operation is performed in parallel by 4 CCD cameras with 2 Local inspectors.

In this way, only 5 positions are considered and for each position we have from 2 up to 4 Local Inspectors processing the images at the same time. In this way, the processing time is lower than the 30 s. Please note that in the estimation of the processing time, also the time lost for moving the board is required. This time cannot be drastically reduced with the reduction of positions since the time is mainly consumed in moving the board, and in any case the board has to pass along 3.60 m of the VISICON system.

5.2. Button detection

Both detection and quality assessment of joint buttons are based on the G Transform. Detection is obtained by transforming the acquired image with the radius R supposed on the basis of the configuration. This process is performed without filtering and directly performing Greedy searches for local maxima, starting from a grid of points in the image segment (see Fig. 9a). All maxima above a given threshold are considered as candidate buttons. If the distance between two maxima is less than a button diameter, only the greater one is considered, by following a procedure which scans maxima from the highest to the lowest. See for example Figs. 11a and b, where a reference image is presented with some circular structures and among them only one



(a) (b)

Fig. 11. (a) An image containing different circular structures. Only A is a button, these letters have nothing to do with the letters of the view type. (b) Behaviour of G value as a function of R. The spike is always in correspondence of that of the real circular structure size. The trend as a function of R depends on the geometry of the gradient on the circular structure boundaries.

Table 4
Example of the detection process

View type	Processing conditions		1st-stage detection			2nd-stages detection		
	Batch	# Targets	# False positive	# True negative	Success %	# False positive	# True negative	Success %
A	Overall	372	0	0	100.0	0	0	100.0
B	Camera 1	62	1	1	96.8	0	0	100.0
	Camera 2	62	4	1	91.9	0	0	100.0
	Overall	124	5	2	94.4	0	0	100.0

is a button. The graph reported in Fig. 11b depicts the behaviour of G as function of R (parameter of G) in the buttons reported in the left side of the figure. It can be noted that the trend and the values can be used for distinguishing the button from simple holes or any other circular structures.

This detection method (labeled ‘‘1st-stage’’ in Table 4) provides optimal results (100%) only on views of type A, characterized by circular and high-contrasted buttons in a context very poor of other features. Nevertheless, these views are highly affected by reflection and lightning variations, as those caused by improper curtain closing. The algorithm was able to deal with them successfully even when the same set of parameters (radius, threshold) was adopted for both CCD cameras, with no fine-tuning of distance, focus or diaphragm.

A lower result (94.4%) has been obtained for type B views, where the context is richer in terms of disturbing features and buttons are slightly elliptical, because CCD cameras are slant and no aspect correction was applied (in order to keep the computational costs low).

Another method of detection (labeled ‘‘2nd-stages’’ in Table 4) has been implemented to achieve a higher performance. The first stage of this method is similar to the previous one, but with a lower threshold, so as to set to zero the number of true negatives. The second stage considers the resulting candidate buttons and discards the false positives by evaluating the generalized G transform on a set of six concentric disjoined annuluses, the union of which covers the image segment which is supposed to contain the button. The candidate is confirmed as a real button if the logistic function of the weighted sum of the resulting values is over one half. Weights have been estimated by applying logistic regression to a wide set of true and false positives. This method resulted in optimal (100%) performance on both types A and B views, with only six different metrics for a test set, which is more than ten times larger. At run time, the same approach has been used to estimate a quality for each button with a different set of weights as described in the next section.

The values of weights to complete the model have been estimated by using a logistic regression method on selected cases, provided by NUOVACETASS. A total of 81 measures have been considered by a group of 5 experts who assigned to each button a simple score 1 or 0 if detected or not. The obtained model is based on 6 weights resulted to be statistically significant as demonstrated by traditional tests obtaining a value of 0.000 for the Deviance of McCullagn and Nelder, R^2 of Cox and Shell is equal to 0.664, and the R^2 of Nagelkerke is equal to 1.000. In addition, the p-values of the coefficients are 0.000 and the significance of the coefficient ranges from 0.992 to 1.000.

Table 5
Example of the classification process

View type	Processing conditions		Classification performance			
	Batch	# Targets	# True targets	# False positive	# True negative	Success %
A	Camera 1	93	78	0	0	100.0
	Camera 2	93	57	9	13	76.3
	Overall	186	135	9	13	88.2
B	Overall	62	28	4	2	90.3

The model obtained with the data provided by the experts has been used for detecting the large amount of buttons on the production pipeline. The percentage of success (called also classification correctness) resulted similar to the one estimated in the phase of weight estimation.

5.3. Quality assessment of buttons

The same regression-based decision-making procedure used in the above cases has been adopted to distinguish between good and defective buttons (see Table 5). Values computed in the second stage of the detection are combined by using a specific set of weights, which have been estimated by applying logistic regression to buttons classified as good or faulty by Ediltavole operators. A total of 81 measures have been considered by a group of 5 experts who assigned to each button a quality score in a range from 0.0 to 1.0. The estimated model is also based on 6 weights. The model resulted to be statistically significant as demonstrated by the value of 0.000 for the Deviance of McCullagn and Nelder, R^2 of Cox and Shell is equal to 0.587, and the R^2 of Nagelkerke is equal to 1.000. In addition, the p-values of the coefficients are 0.000 and the significance of the coefficient ranges from 0.984 to 0.999.

Results turned out to be relatively variable on the basis of the different views, covering a range going from 75% to 100% of recognition of good and bad buttons. This wide range can be explained if considering that defects collected within the same view are similar, since they are due to the same tool breakdown, but different breakdowns may lead to defects, the evidence of which is quite different. Apart from slantness, which has a strong impact on the shape of reflexes, most of the defects collected within type B views are visually evident also for an unskilled operator and this fact allowed a rather good (90.3%) performance on those views.

In Table 4, some examples of classification performance are detailed by view and data batch. Each data batch has been processed with a different set-up.

However, provided that the purpose of the quality assessment process is to assess the quality of a whole board, the precision of classification correctness in the worst case (76.3%) seems to be enough, since each clinching tool clinches a minimum of four buttons for each board. By assuming the approximation that buttons clinched by the same tool share the same quality, it is possible to bound the error below 6% (obtained with (100−76.3)/4).

Please note that in the above example, the percentage of false negative is in the order of 5% while the percentage of false positive is about 7%. Also in this case, the real performance has to be scaled according to the number of buttons on the board, while avoiding the inspection of all the buttons that are produced by the same clinching tool. In fact, when a defect in the button is registered, it is typically due to the degeneration of the clinching tool, and therefore even if buttons are not inspected exhaustively, the defect detection will be carried out all the same. This is obviously a compromise between velocity of detection and precision and costs. In fact, a complete inspection of all buttons could be feasible by using VISICON architecture and thus by increasing the number of Local Inspectors.

6. Conclusions

VISICON is a general-purpose distributed quality control system based on computer vision. The VISICON architecture allows the real-time evaluation of boards with multiple clinched areas, by delegating to a variable number of industrial PCs the image processing aspects, together with the corresponding computational cost. This allows scaling the system on the basis of the production line speed and end-user's quality requirements. The developed architecture is strongly modular and easily customisable to other industrial applications. The number of Local Inspectors may vary depending on the board model and production line speed, so each customer can scale the system on the basis of his needs. Image acquisition is performed under controlled conditions, inside a dark tunnel enclosing sources of diffused light. A specifically defined transform detects radially symmetric shapes like joint buttons. Its calculation can be performed in real time for both the effective joint point detection and quality assessment.

VISICON solution has been studied with respect to the actual industrial situation of several potential partners and with a special attention devoted to a real end user, like Ediltavole. It is a SME which produces boards for the frames of buildings in the centre of Italy. A typical factory has three clinching machines, working on three turns per day on 5 days per week, for a total production of about 15,000 boards per week. About 1–2% of these boards are defected by inaccurate metal sheets positioning or clinching machine failures, but about 95% of the defective boards can be corrected and delivered on the market by clinching them again with acceptable results but spending time and money. Thus, the wasted material can be estimated in about 11 boards per week. People charged with the task of detecting clinching defects, in time for stopping the production; do work several man hours per week. Therefore, time and costs related to these people can be saved as well, with the proposed solution. In addition, some man hours per week are spent to clinch again defective boards for recovering the 95% of defective boards.

A prototype quality-control system using four industrial PCs and 12 CCD Cameras has been tested on some thousands of boards on a real production line. It has successfully provided an on-line, continuous control of quality recognising defective boards with a better than 90% accuracy. Joint detection performance exceeded 99% and this result applies also to overall board quality control. In the case of a major fault it is very important to stop the clinching machine to avoid the production of other joints. The costs of a stopped production are lower than those faced when recovering errors on badly produced boards.

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References

[1] Booch G. Object-oriented design with applications. USA: Benjamin/Cummings Publishers; 1991.

[2] Nesi P. Managing object oriented projects better. IEEE Software July 1998. p. 50–56;
Braude EJ, editor. Software engineering selected readings. New York: IEEE Press, 2000.

[3] Neill CJ, Laplante PA. Specification of real-time imaging systems using the UML. Journal of Real Time Imaging 2003;9(2):125–38.

[4] Derganc J, Likar B, Bernard R, Tomazevic F, Pernus F. Real time automated visual inspection of color tablets in pharmaceutical blisters. Journal of Real Time Imaging 2003;9(2):113–24.

[5] Martinez J, Costa E, Herreros P, Sanchez X, Baldrich R. A modular and scalable architecture for PC-based real-time vision systems. Journal of Real Time Imaging 2003;9(2):99–112.

[6] Bellini P, Buonopane M, Montanelli M, Nesi P. Evaluating a flexible architecture for distributed control. In: ICECCS '99, Proceedings of the Fifth IEEE International Conference on Engineering of Complex Computer Systems, Las Vegas, USA, October 1999. New York: IEEE Press; 1999. p. 66–76.

[7] Nesi P. Real-time motion estimation. In: Laplante P, Stoyenko A, editors. Real-time imaging: theory, techniques, and applications. USA: IEEE and IEEE Computer Society Press; 1996. p. 27–57.

[8] Darscht P, Pereira CE. An object-oriented approach to handle complex real-time industrial automation projects. In: ICECCS '95, Proceedings of the First IEEE International Conference on Engineering of Complex Computer Systems, Ft. Lauderdale, FL, USA, November 1995. New York: IEEE Press; 1995. p. 302–5.

[9] Yuen HK, Princen J, Illingworth J, Kittler J. Comparative study of Hough transform methods for circle finding. Image and Vision Computing 1990;8:71–7.

[10] Yuen SYK, Lam TSL, Leung NKD. Connective Hough transform. Image and Vision Computing 1993;11:295–301.

[11] Leavers VF. The dynamic generalized Hough transform: its relationship to the probabilistic Hough transform and an application to the concurrent detection of circles and ellipses. Computer Vision, Graphics, and Image Processing: Image Understanding 1992;56:381–98.

[12] Guil N, Zapata EL. Lower order circle and ellipse Hough transform. Pattern Recognition 1997;30:1729–44.

[13] Atiquzzaman M. Coarse-to-fine search technique to detect circles in images. International Journal Advanced Manufacturing Technology 1999;15:96–102.

[14] Kavianpour A, Shoari S, Bagherzadeh N. A new approach for circle detection on multiprocessors. Parallel and Distributed Computing 1994;20:256–60.

[15] Davies ER. Radial histograms as an aid in the inspection of circular objects. IEE Proceedings 1985; 132(Pt D) (4): 158–63.

[16] Bruno I, Giotti A, Monsignori M, Nesi P. A distributed industrial application for quality control of clinched boards based on computer vision. In: SEKE 2002. Proceedings of the 14th International Conference on Software Engineering and Knowledge Engineering, Ischia, Italy, July 2002. New York: ACM Press; 2002. p. 715–8.

[17] Giotti A, A transform to highlight annular shape in grey-scaled images. Ph.D. Thesis of the University of Florence, under publication in 2004.