Scope and Prospects of Non-Invasive Visual Inspection Systems for Industrial Applications

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Abstract

This research has been done to facilitate the industries and researchers with a new concept and emerging trends in the field of non-destructive visual inspections. Visual inspection is a process of determining the degree of deviation from a given set of specifications. And, visual inspection system (VIS) is a method of data acquisition, data analysis, quality control, electrical system control, and process control for a particular product, system or process. The main processes involved in a visual inspection system are: image acquisition, image de-noising, image enhancement, image segmentation, image feature selection and extraction, image classification, feature matching, decision making, display of results, and generation of controlling signals according to set values and parameters. The major challenges were identified while the designing and implementation of VIS are: illumination intensity, illumination angle, camera angle, selection of resolution of camera, selection of type of camera, setting of image acquisition rate, development of segmentation algorithm, and selection of an appropriate image processing techniques for a particular system. According to survey it is found that off line VIS based analysis is mostly being applied to analyze the quality of product. Although, non-conventional methods have got higher popularity than conventional methods but non-conventional methods are generally developed for particular applications and it is not flexible enough to be used for other similar inspections, on the other hand, the conventional methods such as: statistical approach and neural network based approach are reliable, flexible, and generalizable. The main categories of VIS were identified as On Line, Off Line and Real Time Visual Inspection Systems. The main area of VIS applications are: space craft inspection, railway track inspection, road traffic density inspection, rain forecasting, real time monitoring and controlling of automotive vehicles, inspection of turbines, and patient action monitoring.

Keywords: AVIS, CCD, CMOS, SVM, Threshold

1. Introduction

The visual inspection systems (VIS) are integrated with automated plants, in line process, manufacturing, and assembling units to inspect and monitor the inclusion of in correct parts, defects in products, and also in real time sorting. These system works on non-destructive and non-invasive techniques. Based on applications, the visual inspection systems have different names viz. real time visual inspection systems (RTVIS)\(^1\)\(^-\)\(^3\) on line visual inspection systems (OLVIS)\(^4\), off line visual inspection systems\(^5\)\(^-\)\(^6\), automatic optical inspection systems (AOIS), automatic visual inspection systems (AVIS)\(^7\)\(^-\)\(^13\), and remote visual inspection systems (RVIS).

The inspection, in the sense of product analysis, may be defined as the process of determining degree of deviation from a given set of specifications. It involves measurement and detection of part features from the specimen or image data. The need of on line visual inspection systems becomes more demanding, if, 100% qualities with zero defects are prime requisite of the industry. Although, visual inspection system has been applied to a large range of industrial applications, but inspection accurateness remains an exigent issue

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due to the intricacy involved in industrial inspection applications. In some cases, the controversies over the replacement of human inspector by VIS still exist. The repetitive and demanding nature of inspection makes a human inspector to feel visual fatigue; as a result, it becomes very hard to maintain the concentration over the job. But in contrast, VIS has high consistency, repeatability, and not affected by fatigue factors. Also, the miniaturization of components, variety in size and shapes, and complex circuitry reduces the efficiency of human inspectors up to a great extent.

In this paper, an attempt has been made to explore the soft computing adaptation techniques in the visual inspection systems during the last three decades. The outline of this paper is as follows: Section 2 presents a review of the techniques, methods, and application areas of VIS. Section 3 provide the proposed VIS and with algorithm and section 4 explores the major challenges being observed while the designing of VIS. Section 5 contains the conclusion.

2. Noninvasive Visual Inspection Systems: A Review

The visual inspection system is an analysis technique being employed in industries to evaluate the properties of a material, component or system without causing it to damage. To protect plants, switchgear systems, electrical appliances, and electronic devices, the non-invasive sensors and controllers play significant roles at the time of integrated faults or catastrophe and therefore, the uses of visual inspection system for such systems enhances efficiency and prove to essential. This technology improves the productivity, reliability, and quality of products to a great extent.

An automatic visual inspection system involves a number of process viz. image acquisition, image enhancement, image segmentation, image feature selection, feature classification, and feature matching. In this paper, we have tried to investigate the inclusion of soft computing techniques in each process of VIS.

2.1 Image Acquisition

The image acquisition techniques plays key role in the visual inspection systems. The quality of image enables VIS to work efficiently and accurately. The quality of image depends upon the type, position, number of cameras, and the illumination system. The illumination system enables the VIS to explore inherent characteristics of object under test. For this purpose, Ko and Cho have designed a three-color tiered illumination system, which consists of three colored circular lamps (Red, Green, and Blue), and a CCD camera. To acquire color pattern of different slopes they arranged the lamps with different incident angles: the blue lamp to 20°, the red lamp to 40°, and the green lamp to 70°. Vora et al. have used standard (1st order) direct illumination and an Open GL spotlight to provide a “virtual flashlight”. The flashlight’s position and orientation were obtained from the 6 degree-of-freedom electro-magnetically tracked “flying mouse” from Ascension. Pernkopf and O’Leary suggested various illumination techniques for the visual inspection of metallic surfaces that includes a geometrical technique for illumination viz. front lighting, back lighting, and structured lighting to acquire the three-dimensional shape of an object.

Initially, one or two camera based image acquisition systems were developed and thereafter, the line scan cameras came into existence for image acquisition in VIS because these cameras have capability to capture the images of moving objects very precisely. These cameras are also useful in the collection of one dimensional line data to produce a two-dimensional image. But, these cameras cannot generate a complete image at once. It requires hardware to develop images from multiple line scans. It can be replaced by an array of area scan camera. The line scan and area scan cameras may have charge-coupled device (CCD) or CMOS photo sensors. Scanning electron microscope (SEM) is used for image acquisition of semiconductor wafer sample in their inspection system.

Many visual inspection systems require video images for the monitoring and analysis. It utilizes CCTV footage connected through local area network (LAN) and wide area network (WAN) for the further analysis. An online, real-time, or automatic visual inspection system requires webcam to acquire video streams or still images. In few applications, X-ray images are also being considered as an input for VIS. Generally, X-ray imaging method is applied to visualize the hair cracks or flaws in a specimen. This noninvasive method is used to detect inner defects of shielded sample or object. The X-ray images are used to measure focal distance, specimen dimensions, position, image size, and scale factors. Huang et al. had developed
a template model for defect simulation in which the simulated long crack is created by superimposing several single cracks onto a real X-ray image.

2.2 Image Enhancement

The image enhancement techniques are applied to raw images to improve the quality of image features for further analysis. The various techniques developed for the image enhancements are explained in 15,34-36. The common method for image enhancement is edge enhancement through threshold1. The edge enhanced image is thresholded to segment out the object edges19. Cho et al.22 applied thresholding technique17 to enhance the fabric images and Prabuwono et al.33 have used threshold based image enhancement in intelligent visual inspection system (IVIS) for bottling machine. Jaffery and Dubey2 have used threshold based image enhancement for real time visual inspection system to calibrate mechanical gauges.

2.3 Image Segmentation

Image segmentation25,31,36 is a process of portioning an image into group of homogeneous pixels. The adjacent group may be heterogeneous. In many VIS applications, thresholding based image segmentation method is being used1,22,37 because it is easily realizable. The other methods of segmentation employed in VIS are Hough transform19,28, Gabor filters38, and Vertical Sobel Operator17,32,39. To detect circular shape, Gonzalez et al.16 applied circular Hough transform for their VISUALISE system to detect circular road signs.

The modern wavelet based image segmentation techniques are getting popularity in the field of visual inspection system13 as image analysis and synthesis both are possible through the wavelets60. The learning vector quantization (LVQ) clustering and fuzzy rule-based boundary approach18 can be applied to segment and classify the desired object. Fuzzy c-means clustering is an emerging technique for the segmentation of desired portion from the raw images in visual inspection systems41. Otsu, wavelet-based multivariate statistical (WMS), and wavelet-based neural network (WNN) are very useful techniques for segmentation and recognition. The performance of these techniques was evaluated by42 and it was concluded that WNN has the highest recognition rate. Few other soft computing techniques for the segmentation are Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Coactive Neuro Fuzzy Inference systems (CANFIS), and Fuzzy Min Max Neural Network (FMMIS)10.

In the category of non-traditional techniques (NTT), Garcia11 had proposed a method which was based on an indirect estimation of the misclassification error rate (MER) for feature selection process. This method is applicable only when a Quadratic Discriminant Function (QDF) is used as the algorithm to discriminate between the classes of components12. Gaussian Mixture Models (GMMs) are statistically mature methods for clustering used in segmentation43. The erosion, max entropy threshold, ROI segmentation, roundness measurement, blob analysis, circle fitting, and gamma transformation were used by44 for segmentation and defect detection. Jaffery et al.45 claimed that statistical approach can also be used for image segmentation and analysis. They applied wavelet based techniques to explore the statistical features of an image.

In food industries, color mapping method is applied to segment the fruits from its background images39. Few other NTTs being used for image analysis and segmentation are Harris corner method49, background subtraction26, and BDCT46.

2.4 Image Feature Selection

The image feature selection is also known as variable selection, feature reduction, attribute selection or variable subset selection. It can be obtained by removing redundant and irrelevant features from the data. It helps to improve the performance of visual inspection system by alleviating the effect of the curse of dimensionality, enhancing generalization capability, speeding up learning process, improving model interpretability etc. It has two categories: feature ranking and subset selection47. The feature ranking ranks the features by a metric and eliminates all features that do not get an adequate score whereas the subset selection looks for set of possible features for the justified subset. The shapes features are extracted from raw images for classification1. Edge extraction, straight-line extraction, and straight-line grouping are few geometrical features being used for feature selection19. The geometrical characteristics33 are very suitable for feature extraction of wood defects19. The first order statistics known as feature difference is used for visual characterization of the texture for feature extraction38. The mean value filter and erosion algorithm based statistical values may be utilized for the feature extraction22.
Sobel edge operator kernels based contour extraction technique having contour linking or edge-linking can further be classified into two categories like as: local edge linkers group points and global edge linkers. The contour labeling is used to mark and calculate objects within the frame. Vertical Sobel Operator (VSO) based edge detection methods had a remarkable efficiency.

Ibrahim and Al-Attas have applied wavelet based feature extraction technique for PCBs inspection, Acciani employed wavelet transform and geometrical characteristics, and Lin firstly utilizes the wavelet transform to decompose an image and then applied wavelet characteristics as texture features to describe surface texture properties and thereafter, he applied multivariate statistics of Hotelling T², Mahalanobis distance D², and Chi-square X², respectively, to integrate the multiple texture features and judge the existence of defects. Haar wavelet transform was applied by Lin to decompose a chip image and extract at least four wavelet characteristics for wavelet-based neural network (WNN) and wavelet-based multivariate statistical (WMS) approaches. Edinbarough et al. applied neural network for feature extraction in their on-line inspection monitoring system for electronic manufacturing. Garcia et al. have explored various feature selection related problems that arises in the development of AVI algorithms using multivariate stepwise discriminant methods (MSDM).

The support vector regressions (SVR) have highest success rate (99.17%) than Artificial Neural Network-back propagation (ANN-BP), Hidden Markov Model (HMM), and Support Vector Machine SVM as claimed by. Kumar suggested that the combination of statistical, spectral and model-based approaches can give better results than any single approach for feature extraction and detection. He also mentioned that texture features extracted from fractal dimension (FD), first-order statistics, cross correlation, edge detection, morphological operations, co-occurrence matrix, Eigen filters, rank-order functions, and many local linear transforms may be categorized into this class. The statistical approach is becoming trendy for feature extraction in visual inspection systems due to its high reliability as compared to geometrical approach. The ROI based feature extraction method is appropriate for on line visual inspection systems. Hough transform is very popular feature selection algorithm. The circular Hough transforms and Max-Margin Hough transform are the modified form Hough transforms being utilized to detect the object from image. The circular Hough transforms have capability to detect objects from the noisy image also. Some visual inspection systems use color matching techniques for feature selection algorithms. Histogram of Oriented Gradients (HoG) and Histogram of Gabor Coefficient (HGC) are the two special feature extraction technique used in Off Line VIS. Log Gabor Filter, Discrete Wavelet Transform, and Discrete Cosine Transform are also useful image feature extraction techniques.

2.5 Image Feature Classification Techniques

The choice of an appropriate classifier technique varies according to the need and availability of computational and storing power. Generally, a researcher develops his own classifier for the VIS application because of change in the characteristics of database and features.

A non-conventional tree classifier is initially developed for the real time visual inspection system. But, when soft computing techniques came into existence, tremendous changes were observed into the development of classification and recognition systems. For on line systems, fuzzy logic, Neuro-Fuzzy Algorithm, CANFIS, and ANFIS based classification systems were employed. The learning vector quantization (LVQ) neural network is used by for pattern classification because of its fast learning characteristics. The LVQ neural network clusters the inputs based on the Euclidean distance between the input and the weight vectors connected to the output neurons. A recurrent fuzzy coupled cellular neural network (RFCCNN) includes structure learning algorithm and parameter learning algorithm and the parameters are determined using real-time recurrent learning (RTRL) scheme. For feature selection, multivariate stepwise discriminant and Wilks’ Lambda method are the good option. Gabor filter based classification and detection is also one of the best methods for classification. For vehicle detection, Atkociunas et al. have used lane masking, background elimination, noise and blobs filtration, contour extraction, Laplacian of Gaussian (LoG) detection, contour linking, and contour labeling based classifier. The wavelet based extraction algorithm was developed by Ibrahim and Al-Attas for VIS applications, they claimed that higher level wavelet based inspection system takes less time to respond than a low level and non-wavelet based systems. Lin initially
applied the wavelet transform to decompose and wavelet characteristics as texture features to describe surface texture properties of an image and then he applied multivariate statistics of Hotelling $T^2$, Mahalanobis distance $D^2$, and Chi-square $X^2$ respectively to integrate the multiple texture features and judge the existence of defects and concluded that the Hotelling $T^2$ algorithm have highest 93.75% detection rate. Lin et al. tried to justify the best methods for defect detection through the receiver operating characteristic (ROC) plots among Otsu, wavelet-based multivariate statistical (WMS) and wavelet-based neural network (WNN) methods. A single layer neural network with multiple neurons is also used to classify the defects in electronics industries. Marino et al. have designed wavelet-based multilayer perceptron neural classifiers (MLPNCs) and concluded that it worked successfully with 99.6% success rate.

Acciani et al. have compared the performance of three different classifiers: a multilayer perceptron (MLP), a linear vector quantization (LVQ), and a K-nearest neighbor (KNN) classifier and suggested that the MLP network fed with the Gabor-Wavelet (GW) features has the best recognition rate. Gleason et al. had tested k-Nearest Neighbors (k-NN), Random Forests (RF), and Support Vector Machines (SVM) based classifiers and concluded that the SVM classifier have good success rate in visual inspection based applications. Sun et al. modeled a visual inspection system for electric contacts inspection. The summarized view of various techniques and methods being applied in the visual inspection systems is shown in Figure 1. In this, the VIS is broadly classified into three main categories: On Line VIS, Off Line VIS and Real-time VIS. This classification is based on the type of image input.

### 2.6 Applications of Visual Inspection Systems

The VIS applications have been categorized according to the field and process of the industries. The application of visual inspection system is not limited to only one kind of field. In present scenario, it is replacing the need of supervisors in various fields of engineering, technology, industries, transports, and in agriculture also up to 40%. The main reasons behind the success of VIS are its reliability, flexibility, adaptability, and accessibility. The summarized views of applications of VIS are shown in Table 1.

### 3. Proposed Visual Inspection System

The basic block diagram of proposed visual inspection system is shown in Figure 2 and its algorithm in Figure 3. The VIS shown here is to explore the idea behind the system. Now, the VIS is not limited to any one field application. It has versatile and multi utility applications as mentioned in the proposed diagram ranging from analysis,
| S. No. | Type of Industry                  | Object/Process under Visual Inspection                                                                 | Type of Camera | Image Processing Methods                                                                 | AI Techniques          | References          |
|-------|----------------------------------|----------------------------------------------------------------------------------------------------------|----------------|------------------------------------------------------------------------------------------|------------------------|---------------------|
| 1.    | Electrical Industries            | Cable Crimping                                                                                           | CCD            | Background subtraction, ROI based segmentation, Color comparison etc.                    | None                   | 37                  |
|       |                                  |                                                                                                           |                |                                                                                          |                        |                     |
|       |                                  | Electrical Contacts                                                                                      | CCD            | Minimum Residue Thresholding, Median Filter, and Erosion, Blob Analysis, Gamma Transformation, ROI Segmentation, etc. | GA                     | 44                  |
| 2.    | Electronics Industries           | IC lead defects, PCB, Solder Joints, Semiconductor Wafer, SMD components, surface barrier layer (SBL) chips of ceramic capacitors, Solar Cells, LED etc. | CCD            | Energy, Correlation, Diffusion, Fenergy, Blob, Texture, Thresholding, Log-Gabor Filter, Wilks' Lambda, Hotelling $T^2$, Mahalanobis distance $D^2$, and Chi-square $X^2$ etc. | Artificial Neural Network (ANN), Self-Organizing Neural Networks (SONNs), Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), wavelet-based neural network (WNN), wavelet-based multivariate statistical (WMS), k-NN, WT, Back-Propagation Neural-Network (BPNN), Radial Basis Function Network (RBFN). | 4, 12-14, 23, 24, 26, 30, 35, 41, 42, 48-50 |
| 3.    | Measuring Instrument Manufacturing Industries | Testing, Calibration and Monitoring of Gauges etc.                                                      | CCD, Web Camera | Hough, Sobel, Canny, Roberts, Threshold, ROI based Segmentation etc.                       | Wavelet Transform, Fuzzy Logic | 2, 8, 58-59        |
| 4.    | Mechanical and Production Industries | Hot Steel Slabs, Metallic Surfaces, wood defect Classification, Inspection of Strongly Reflected Metal, Rapid Prototyping (RP) Part Quality Inspection, Defects in MIG Welding Joints etc. | CCD, CMOS      | Threshold, Euclidean distance, Otsu's Method etc.                                        | MLP neural network, Fuzzy Min–Max Neural Network, Multi-Class SVM, Discrete Wavelet Transform (DWT), Back-Propagation Neural Network (BPNN), ANN | 1, 5, 7, 9, 10, 17, 20, 21, 32-33, 46, 51, 55, 57-61 |
| 5.    | Automobile and Aviation Industries | Railway Maintenance, Traffic Signs and Panels Inspection, Road Traffic Analysis, third eye monitoring and controlling of fuel, temperature, and speed governors of aircraft, vehicles and trains etc. | line-scan camera, CCTV Cameras | Prediction Algorithm Block(PAB), Circular Hough, Canny, Histogram, Threshold, Laplacian of Gaussian (LoG), Edge-Linking, Kalman Filter etc. | Multilayer Perceptron Neural Classifiers, K-NN, Discrete Wavelet Transform | 3, 16, 27, 31, 39, 43,60 |

(Continued)
The basic block diagram of proposed visual inspection system is shown in Figure 2 and its proposed model of Visual Inspection System. The VIS applications have been categorized according to the field and process of the industries. The VIS applications have been categorized according to the field and process of the industries. The VIS applications have been categorized according to the field and process of the industries.

4. Challenges in VIS

The major challenges observed while designing of VIS are summarized as follows:

4.1 Illumination

An adequate preprocesses are required for the image to amplify features and to improve the efficiency and reliability of the VIS’ decision making process. The researchers as well as industries have the option to choose type of light source for illumination: such as LED, fluorescent light, IR or UV. It depends on the area, surface of object, size of object, quality and type of camera etc. Many researchers and industries have preferred LED illumination source over fluorescent light source due to the quick degradation of fluorescent lamp under frequent light changes. The LED based illumination system is very stable and can be easily controlled as compared to incandescent and fluorescent lighting. Another illumination technique is to project a pattern of light on an object by using a laser with a holographic lens or a white light source with an attached projection grid. These techniques are mostly employed for inspection of 3D objects such as engine blocks and PCBs etc. The major issue related with illumination is that the position of light source. The angle of lighting or focusing directly affects the accuracy of measurement.

4.2 Designing of Camera Angle

Camera angle affects the surface characteristics of the sample. Pernkopf and O’Leary have established schemes for camera positioning based type of image e.g. intensity, gray level intensity etc. They have also pointed out the effects of light sectioning on quality of image. Their single range imaging approach was based on light sectioning in juxtaposition with fast imaging sensors and the second approach was photometric stereo in which the shape of the object was prepared by the analysis of image intensity.
it was good enough for their real time application. Cho et al., have pointed out the problems associated with online image acquisition rate. They have developed a concept of dual buffer system in which one buffer is used for storing and processing the image and another for image grabbing. It was quite appealing approach to enhance the existing system speed. It may also be concluded that the line scan camera is appropriate for the inspection of a continuous rivulet of objects such as iron sheets, plywood, paper sheets, and fiber sheets etc. having a large size of image data. The selection of imaging technique depends on characteristics of the flaws, the nature of the surface and spatial resolution.4,9,19-22,31,32,34,38

4.4 Selection and Reliability of Artificial Intelligence (AI) Techniques

The success of inspection systems depends upon the functioning of AI techniques being applied. The technique developed for one process may not be applied directly to the other process. It needs further modification depending upon the following factors:

i) Type of input/output
ii) Type of product or process to be inspected
iii) Location of product in the process
iv) Type of inspection system i.e. ON LINE, OFF LINE, REAL TIME
v) Area of inspection
vi) Material of object to be inspected
vii) Dimension of object

5. Conclusions

The VIS has shown consistent progress in its application areas with adequate artificial intelligent systems. The tendency of using various AI techniques in modern VIS is shown in Figure 4 through the statistical approach. According to this graph, it may be concluded that off line VIS based analysis is mostly being applied to analyze the quality of product. The nonconventional methods have got higher popularity than conventional methods but, these are generally developed for particular applications and also not flexible to use for other similar inspections whereas the conventional methods such as: statistical approach and neural network based approach are much popular, reliable, and flexible. The main categories of VIS applications were identified as On Line, Off Line and Real Time Visual Inspection System. The future scope of VIS may be
extended for spacecraft inspection, railway line inspection, traffic density inspection, rain forecasting, and third eye real time monitoring and control of vehicles, and turbines etc.

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