REVISIÓN DE TÉCNICAS DE SISTEMAS DE VISIÓN ARTIFICIAL PARA LA INSPECCIÓN DE PROCESOS DE SOLDADURA TIPO GMAW

STUDY ON THE ARTIFICIAL VISION SYSTEMS TECHNIQUES FOR INSPECTION OF GMAW WELDING PROCESSES

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Resumen: El proceso de soldadura GMAW es ampliamente estudiado debido a su alta productividad y bajo costo. En este trabajo se han revisado las investigaciones orientadas a la inspección del proceso de GMAW a través de sistemas de visión artificial con el objetivo de establecer los principales elementos utilizados en estos sistemas destacando dos categorías: métodos computacionales (software y algoritmos generales), materiales y modelos matemáticos (métodos estadísticos y numéricos). Estas categorías se traslapan en el estudio y se han utilizado para evaluar el costo en términos de recursos humanos y recursos económicos. Las investigaciones revisadas se desarrollaron en la última década, con la excepción de algunas investigaciones que desempeñaron un papel principal en el desarrollo de los sistemas de inspección de los procesos GMAW. Finalmente, se han destacado los posibles campos de investigación para aquellos que intentan explorar sistemas de visión artificial para inspección de procesos GMAW.

Palabras clave: GMAW, soldadura, visión artificial, inspección.

Abstract: The GMAW welding process is widely studied due to its high productivity and low cost. In this paper we have reviewed the research oriented to the inspection of the GMAW process through artificial vision systems to classify them and establish the main elements used in these systems highlighting three categories: technology (hardware), computational methods (software and general algorithms) And mathematical models (statistical and numerical methods). These categories overlap in the document and have been used to assess the cost in terms of human resources and economic resources. The reviewed research was developed over the last decade, with the exception of some research that played a major role in the development of GMAW process inspection systems. Finally, potential research fields for those attempting to explore artificial visual systems for inspection of GMAW processes have been highlighted.

Keywords: GMAW, welding, artificial vision, inspection.

1. INTRODUCCIÓN

Gas Metal Arc Welding is a very complex process which uses many engineering and scientific disciplines in order to study techniques which may lead to the best possible mechanical properties of the resulting piece. GMAW process is widely used because of its low cost and productivity if comparing with GTAW (gas tungsten arc welding) and other processes. In spite of these advantages, the fume and spatters produced in the process due to the liquid metal transfer complicate the process (Wang, et. al, 2016), requiring high accurate inspection in order to achieve the mechanical and physical properties needed in industry tasks. In consequence the monitoring systems required for the inspection of GMAW processes have evolved because the human eye cannot detect imperfections due to different variations in the principal parameters involved in the process. For this reason, artificial vision is used in almost every monitoring system for inspection of GMAW processes.

The principal purpose of this work is to provide a constructive analysis of the researches in some of the principal techniques involving artificial vision, its properties, goals, benefits, disadvantages, weaknesses, costs and finally relate and classify them in terms of the usability, accurate inferences about the state of different parameters and measures of the geometric variables of the weld bead in the last fifteen years, as well as to determine and classify the mathematical models used to evaluate the image data obtained in inspection process. This work will help to choose the direction of the artificial vision research through the identification of the topics where the techniques have not gone forward, recommending new research areas.

2. PROBLEM STATEMENT

The artificial vision is a non-destructive testing method for visual inspection in GMAW welding process in order to detect faults, irregularities and external defects, such as grooves, incomplete fill groove, misalignment or partial penetration (Dávila, López, Méndez, Osorio and Lefranc, 2016). Inspection can be done registering a welding process picture by picture, but this is not a simple technique; it is a process involving different technologies, techniques and computational methods to registered image information, such as

algorithms to process digital images (Sobel, Canny, Gauss filter) or sophisticated mathematical and statistical models such as Multivariate analysis, Artificial Neural Networks, Taguchi Method (Pinto, Mota and Alfaro, 2016).

The wide range of techniques involved in artificial vision are focused on obtaining visual and sensing information in order to monitor and real-time feedback control of seam tracking, measure geometric parameters such as weld penetration, pool shape and seam forming to infer weld quality features (Áviles, Lopez and Rios, 2015).

3. COMPUTATIONAL METHODS

Detection of the geometrical features of the weld bead is one of the principal and more difficult tasks in artificial vision due to some aspects of the GMAW process such as the fumes expelling, lighting produced by the arc and spatters. The light produced by the electric arc does not allow capturing high quality images (Wang, Ma and Zhang, 2011) making difficult the image analysis to measure the parameters of the weld bead.

In order to overcome some of the issues mentioned above, some computational techniques have been developed in recent years: algorithms to transform images into readable pictures making easier to determine geometrical features for prediction of possible weld defects. In the following, some principal and widely used techniques are presented

3.1 IMAGE ANALYSIS ALGORITHMS

The principal purpose of image processing is to improve the information stored in an digital image for human interpretation, through the manipulation of the discrete quantities (x, y) which constitutes the object and refers to the intensity values or gray level of the image at that pixel (Gonzalez, Woods and Eddinds, 2004).

In capturing a digital image of a GMAW process, it turns necessary to measure the intensity of the arc and detect the lowest point of this to capture the image; the goal is achieved by capturing and measuring the signals of current and tension of the process through an Ethernet shield and synchronizes the camera shutter with the signal analysis determining the precise moment to take the picture avoiding the intense arc light due to the weld process (Cruz, Torres and Alfaro, 2015).

Also, in (Duarte, Franco, Chagas, Crisóstomo and Alfaro, 2007) a *short circuit monitoring system* was designed and implemented in order to avoid the noise present in capturing weld images.

Nevertheless, the synchronization process is not enough to capture high quality images. Once the images are obtained it is necessary to apply filters in order to eliminate the interference caused by the arc light intensity (Wang, 2016; Li, Wang, Xu, and Tan, 2010; Shao, Wang and Zhang, 2011; Guo, Shi, Liang and Wang, 2016).

Additionally, because of the hostile environments found in factories, many types of noise can alter the quality of the acquired images, as well as the workpieces which are cleaned and smoothed for the weld process creating a reflective surface over hiding partially the laser stripe (Huang and Kovacevic, 2012).

This means that despite the effort of avoiding the arc light it is not possible with the actual techniques to take completely clear images free from noise and light blurs or excess, being necessary to use algorithms for image processing.

3.1.1 GAUSS

One of the principal tasks in image processing is eliminating errors as a result of the image acquisition process which translates in pixel values different from the real intensities, as mentioned above. These errors are commonly known as noise.

The most commonly used filter is Gauss. The effectiveness of this filter in removing noise from images has been proved widely and it is more effective in smoothing images due to the fact that it is based in human visual perception system. It is usually defined by the equation.

$$H(x, y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu_x)^2+(y-\mu_y)^2}{2\sigma^2}} \quad (1)$$

Where μ_x and μ_y are the pixel value of the kernel center, σ is the standard deviation (Li, et. al., 2010), and a 5x5 order kernel, here mu_x and mu_y are the pixel value of the kernel.

In (Park, Kim, Lee, Jin and Kim, 2016) the Gauss filter was used to minimize possible measurement errors caused by incidents as explosions in the short-circuit metal transfer mode.

After eliminating noise, an algorithm must be applied to detect the edges of the weld pool. This can be achieved through algorithms such as Sobel, Canny, Roberts, Perwitt and Laplacian. Neverthless, Canny operator produce better results than other algorithms in accuracy and continuity of edge detection (Xu, Fang, Chen, Zou and Ye, 2014).

3.1.2 SOBEL AND CANNY OPERATORS

Next step, the Sobel filter is used to measure the intensity gradient of the image to find where the intensity of pixels increase. This is composed by two 3x3 order convolution kernels:

$$\begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \qquad \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix}$$

X-direction and Y-direction filters

the x-direction and the y-direction. These kernels are built to respond to vertical and horizontal edges, one kernel for each perpendicular axe. After applying the Sobel operator the horizontal and vertical lines detected will be highlighted by each of the kernels respectively (Shao, et al., 2011; Muhammad, Altunu and Abo, 2016; Wang, Huang and Zhang, 2013; Xu, fang, Chen and Zou, 2015).

Also, after applying the Gauss filter, the edges of the weld bead can be detected in order to measure the geometrical features of the weld bead and this is achieved through the Canny filter. This edge detector works within a multi stage process requiring the elimination of noise in the imaging and a simple 2D operator used to highlight regions of the image. The input is a gray scale image and the output is an image with the track intensity discontinuities (Shao, et al., 2011; Muhammad, et al., 2016; Wang, et al., 2013; Guo, et al., 2016; Xu, et. al., 2015; Shen, Wu, Lin and Chen, 2008; Gao, Zhong, You and Katayama, 2012).

In (Shao, et al., 2011), after several experiments, excellent results were obtained involving both operators: the Sobel algorithm is used to detect edges in the brighter areas of the image and the Canny operator is used in the darker ones.

In order to detect the edges of droplet to study the metal transfer, Sobel and Canny operator were used in (Wang, 2016) and it was difficult to distinguish the edges of the droplet. Similar results were obtained with the graph cut-based method Results by gray level co-occurrence matrix based. method showed it is very time consuming, which is a great disadvantage for real-time detection purposes.

As an alternative, a novel method is proposed choosing a Region of Interest (ROI) and applying a band-pass filter formulated as

W(f_x,f_y)={((f_x–f_{cx})^2+(f_y–f_{cy})^2)^{0.25}   if   f_{xcl}<f_x<f_{xcu}, f_{ycl}<f_y<f_ycu

$$W(f_x, f_y) = ((f_x - f_{cx})^2 + (f_y - f_{cy})^2)^{0.25} \quad (2)$$

With the restriction $f_{xcl} < f_x < f_{xcu}$ and $f_{ycl} < f_y < f_{ycu}$

Or 0 else f_x

Where f_x, f_y represent the frequencies, and f_{xcl}, f_{xcl} represent the lower cut off frequency in the f_x direction and f_y direction respectively.

After the image processing with filter in equation (**) the edge detection is carried out.

Canny algorithm is not as effective as expected when it is used to detect V-grooves in a weld bead due to the fact that judgment conditions must be based on prior knowledge. Also, application to V-grooves detection often produces false edges resulting in a low accuracy of the image processing. In order to overcome this shortcomings an improved Canny algorithm is proposed in (Guo, et al., 2016), and through this algorithm, possible weld deviation can be detected.

3.1.3 HOUGH TRANSFORM

In order to process digital images it is necessary to reduce the amount of data and to preserve the important and structural information. The Hough transform was developed initially to detect and highlight lines and then evolved to recognize arbitrary shapes.

Together with pattern recognition and line fitting, Hough Transform is used to detect feature points of the weld bead or the baseline of the stripes on the surface of the weldment. Li et. al, (2010) used the Hough transform to calculate the bead dimensions. It is also used after applying a segmentation method which identifies the image pixels composing the weld line. The Modified Hough Transform is able to find the coordinates which best represents the weld line (Carvalho, Luciano, Freire, Molina and Freire, 2009). Muhammad et at, (2016) used this transform to detect laser stripes orientation and use it as a reference line. Ranjan, Khan, Parikh, Jain, Mahto and Pal (2016) offer a complete explanation of the application process; here, the Hough transform is used to classify defects on the weld bead into voids, grooves, cracks, flash and key-hole defects.

3.1.4 FURTHER APPLICATIONS

3.1.4.1 DROPLETS DETECTION

The solid to liquid metal transfer in GMAW is a complicated process due to the fumes and spatters it expelled during the procedure. Also, the amount of material used in the process determines the time and economical resources, justifying the need to understand and control the metal transfer in order to improve stability, quality and energy consumption.

Some experiments have been developed in [49] to study the analysis of metal transfer by capturing images of the process. Gauss filter was used to reduce noise and an algorithm using a double-threshold method is proposed for better results. The histogram distribution and the gray-scale was used to calculate the slope difference in order to find both thresholds approximations.

Using double-threshold segmentation method has some advantage in comparison with other threshold methods: the accuracy in processing fuzzy images, easy to handle and the cost of the elements involved.

To study the metal transfer it becomes necessary to study the droplet. This is usually like an ellipsoid and there about two oscillations before it falls on the weld pool. Additionally, approximations of the surface tension and the period of the droplet need to be determined in pursuance of understanding the weld bead formation and control the geometrical features and in consequence the mechanical properties of the weld bead

Investigation to understand the droplet size, droplet shape and speed of droplet when falling into the plasma are explained and developed in (Chapuis, Romero et al., 2013; Chen et al., 2016). Furthermore, some results are discussed by comparing two different shield gases: pure argon and CO2.

When capturing images of the metal transfer from high speed videos, the geometry of the droplet is analyzed through edge detection (Chapuis *et al.*, 2013). This allows measuring the surface tension of the droplet by analyzing the oscillations during the free flight. It was demonstrated through metal transfer analysis that higher speed is obtained with argon.

Also, it is possible to use a low power to detach the droplet at a desired size that best suits for the control of the weld pool. This is achieved by edge detection of the droplet in a laser-enhanced GMAW process and this is used to derive the boundary of the droplet, where Sobel and canny operators were used in different parts of the same image as mentioned in last section, in order to obtain better results. (Kiran, et al., 2016)

The image processing methods allows to study, as mentioned, the geometry of the weld bead and the droplet. This information let us infer the amount of material used in the process, wasted material and the mechanical properties of the resulting piece, which is important for industrial purposes.

Also, through detection of the edges of the weld bead is possible to identify defects in GMAW process. This subject has been studied widely (Alfaro, Vargas, De Carvalho and De Souza, 2015; Ali, Gsimalla and Dening, 2013; Chu and Wang, 2016; Gomes, Costa, Paiva and Balestrassi, 2012; Huang and Kovacevic, 2011; Senthil, Natarajan, Veerajan and Ananthan, 2014; Squillace, Prisco, Ciliberto and Astarita, 2012; Wang, Zhang, and Wu, 2010) and is almost the main purpose in visual inspection of robotic GMAW process.
Weld defects means low quality of the welded structures and risk of part fatigue due to the resulting mechanical properties (Alfaro, *et al., 2015*). For this reason there are several methods for detecting weld defects.

3.2 SOFTWARE

One of the costs that must be included in the budget for visual systems is the software, LabVIEW and MATLAB being the most commonly used. Nevertheless, MATLAB (Rodríguez O et al., 2012) is on the top for image processing and analysis tasks being used in to detect weld defects (Chokkalingham, et al., 2012; He, Xu, Chen and Chen, 2016; Reisgen et al., 2014; ummenhofer and Medgenberg, 2009) to study the metal transfer through droplet detection and build 3D determining concrete features of the weld profile (Sreedhar, Krishnamurthy, Balasubramanjam, Raghupathy and Ravisankar, 2012; Wang et al., 2010; Ramos et al., 2013;).

LABVIEW is a graphic-language based software flexible and ease-of-use platform which sometimes is used together with MATLAB.

An algorithm was developed by Sreedhar *et al.,* (2012) in order to process IR thermal data in real time for weld defects detection. In this research, some algorithms for image registration, such as image angle correction, circumferential location and generation of cooling curves, were developed in MATLAB, and then the algorithms were assembled in a single piece as an automatic IR image analysis software using LabVIEW.

This tool has been also used to develop systems for multi-purpose tasks: geometrical features measurement, seam tracking and 3D profiling, processing successfully a complete image in just 3ms and a high efficiency and simple programming if a different configuration is required. According to (Reisgen *et al,* 2014) *t*he most common use of this tool refers to data acquisition and image processing.

This matrix-based language allows expressing computational mathematics. Its high performance language makes possible algorithm development, data analysis, visualization, application development, Graphical User Interface building.

The MATLAB Image Acquisition and Image Processing toolboxes are used commonly in visual inspection. Additionally, it is used for prediction through Neural Network Toolbox with the transfer, training, learning and performance functions included in the toolbox. It is possible to establish relationships between the welding input parameters (weld speed, voltage, current) through ANN with this tool (Sreeraj, Kannan, & Maji, 2013;), as well as trace a 3D profile of the weld bead. In a research developed by (Ramos *et. al.,*(2013) the signal of the GMAW process were acquired with LabVIEW and the images were processed with MATLAB to determine the oscillation of the weld pool showing that the arc applies some pressure on the pool, oscillating in a regular state.

4. HARDWARE

Most of the artificial vision systems for welding inspection, used in research purposes, are very expensive systems due to the high quality of inspection required: an LDI SLP Laser Scanner, a portable 3D laser scanning system with high accuracy, costs from US$16.900 to US$22.900. The ViALUX z-Snapper 3D Camera price varies from US$25.000 to US$50.000; this is a LED-based DLP projection 3D camera. While the Surphaser HSX Laser Scanner price ranges from US$90.000 to US$150.000 depending on the accessories and post-processing software included. This hardware is known by its speed, unsurpassed accuracy and ease-of-use. The associated software is able to export 3D datasets with little noise for post processing purposes. However, it is possible to use a cheap visual system for inspection when using the right algorithms and software for research purposes.

A visual system for GMAW inspection was developed by Huang and Kovacevic (2011) with a total cost of US$2.500 in 2011, where specific features and prices can be found. This includes a license for LabVIEW to develop image processing.

The system developed results efficient for industrial purposes in terms of cost, time cycle and on-line image processing capabilities.

4.1 3D PROFILING TECHNIQUES

Line Structured Light Vision Sensors (LSLVS) are used in 3D profiling techniques of the weld bead in GMAW process. An LSLVS is constituted by a camera and a light plane projector used to generate a structured light over the weld surface; then, the reflected structured light is captured with a CCD camera (Guo et al., 2010).

4.2 INFRARED CAMERAS

Laser illumination and monochromatic imaging is used to measure the weld bead [30] in order to overcome the arc lighting. Other methods used to avoid lighting are infrared cameras (Shengqiang, et al., 2011) and the analysis of thermal images captured through thermovision techniques. An algorithm was developed by (Squillace*et al.,* 2012) to compare radiographic and thermographic data from the weld bead to identify defective weld regions detecting defects automatically.

Infrared thermography consists in capturing the electromagnetic waves in the infrared spectrum in a body at certain specific temperature through the Planck's Law.

Once images are captured it is necessary to reduce the noise present through filters such as Gauss filter (Rios, America, Morales, Aviles, Nas and Lopez-Juarez, 2016)

These methods often are related to image analysis and processing (Ummenhofer & Medgenberg, 2009) in order to transform the image data into images where the welding process features, such as geometry of the weld bead, can be measured and analyzed.

The technology required in monitoring systems includes different types of cameras, filters, Ethernet shields (Ogawa, 2011). The different models of the apparatus used in each process depends on the space where the process is to be developed, the parameter that is going to be measured, the technique applied and the principal purpose of the research.

5. MATHEMATICAL MODELS

Despite the amount of techniques and algorithms built to infer the geometrical features of the weld bead with specific input parameters, there is still a gap in mathematical models to predict bead geometry over a wide range of welding conditions (Park *et al.,* 2016). Nevertheless, there are some models oriented to analyze and predict specific geometrical features, such as width bead or height (Caballero A. et al., 2013).

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5.1 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are biologically inspired techniques (Sreeraj *et al.,* 2013), which simulates an interconnected parallel computational structure with some individual processing elements. Some areas where ANN are applicable are classification, associative memory, clustering or compression, generation of sequences or patterns and control systems (Cruz *et al.,* 2015). These powerful tools have been used, even to develop smart home control by voice (Camargo, Coronel and Calderón, 2014).

ANN were used in by Campbell, Galloway & McPherson (2012*)* to find the most influential input parameter in the geometrical features. In this process two different shielding gases were provided at a given constant frequency. The model used can predict penetration, length and thickness for a given set of weld parameters. It was found that travel speed is the most influential input parameter in predicting the geometry of the weld bead.

Defects on GMAW process can be classified to ampere defects, travel speed and gun defects were used to distinguish welding defects obtaining 80% success in poor quality weld bead recognition and 90% success in high quality weld bead, establishing the ability for ANN in classifying weld beads.

Frequently ANN are used together with some other tools due to the fact that ANN has some limitations in predicting processes. According to Akkas, Karayel, Ozkan, Ahmet and Topal (2013) it was possible to model the relationship between the input parameters using ANN and a neurofuzzy approach; Xiong, Zhang, Hu and Wu (2014) predicted the weld bead parameters through ANN and a second-order regression analysis in robotic GMAW process, obtaining a better performance with ANN rather than the second-order regression model because of the ability of ANN in approximating nonlinear processes.

Many ANN have been proposed for ANN network algorithms but Back Propagation algorithm is actually considered the best algorithm for prediction task using ANN (Sreeraj, Kannan and Maji, 2013).

5.2 ANN and Genetic Algorithms

Genetic Algorithms (GA) techniques, inspired in biological evolution, can be integrated with ANN (Sreedhar *et al.,* 2012) in order to determine optimal input parameters to get high quality dilution of materials in GMAW process (Baskoro et al., 2009; Kim et al., 2005).

To carry out the analysis of image data and determine the number of experiments some mathematical and statistical models are needed. For example, the Pareto frontiers (Gomes *et al.,* 2012) are used when the effect of many parameters (different aspects of the welding process as productivity, amount of material used, cost, weld bead geometry, mechanical properties of the result) need to be optimized; the Taguchi method and Grey relational analysis (Kiran *et al.,* 2016) have been used to estimate the values of the parameters that optimizes the parameters of the weld bead geometry in TIG welding process. Other statistical models as the Mahalanobis Distance (Shengqiang *et al.,* 2011) have been used to analyze welding faults due to the variation of parameters such as wire feed speed or ampere defects.

6. CONCLUSIONS

Artificial Neural Networks and Genetic Algorithm constitute powerful tools to establish inferences about the behavior of the geometrical features of the weld bead when modifying input parameters: voltage, current and speed.

Despite the variety of algorithms and mathematical models built to inspect some of the geometry parameters of the weld bead, none of these are still capable of predicting the bead geometry in different welding conditions.
Inferences about the dependence between different parameters are still to be determined. Sophisticated tools such as ANN allow to infer some of these relations. As an example, the bead width is affected more than the bead height in different welding processes parameters.

A closed loop control system to study droplet features for GMAW metal transferring is required.

High accuracy measurements can be achieved with low cost vision systems using CCD cameras and LSVLS technique.
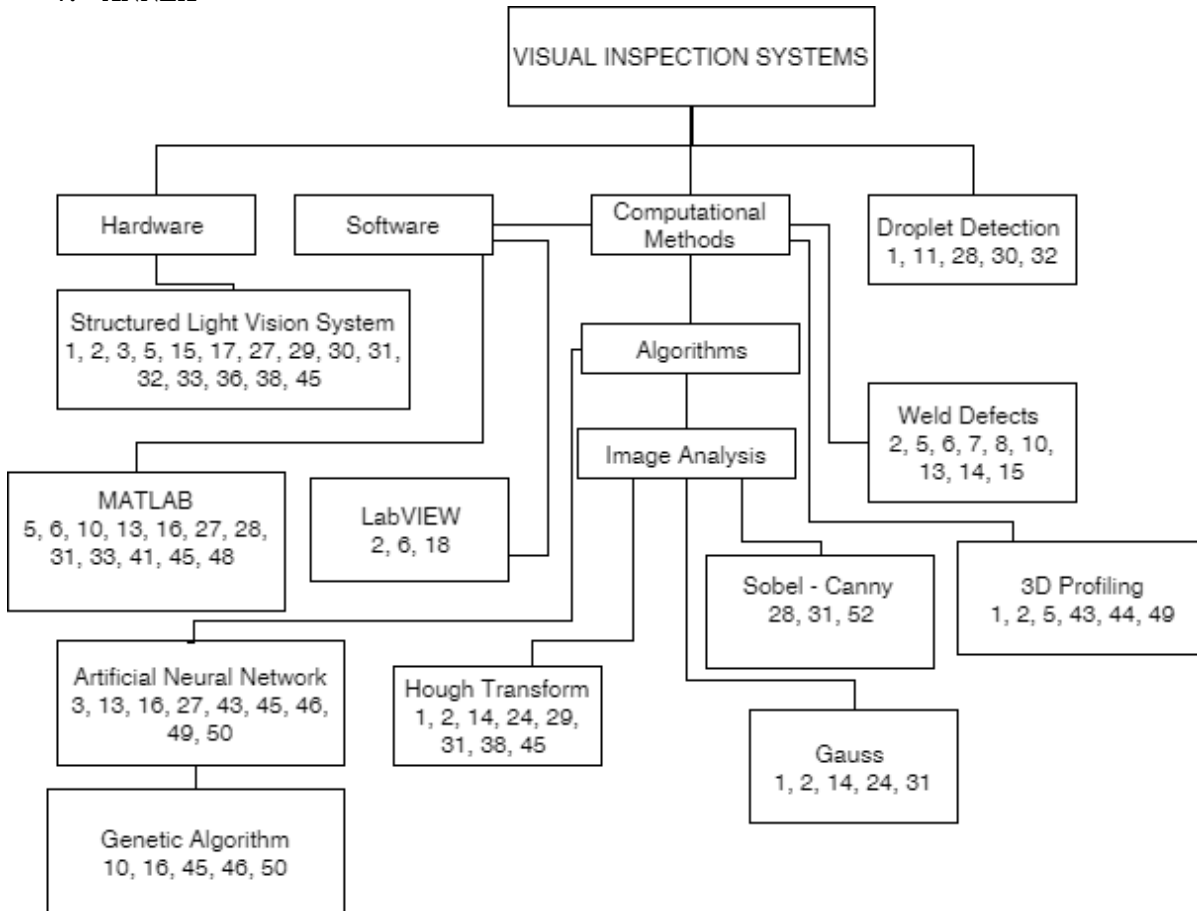
7. ANNEX

Figure 1. Visual inspection systems.

8. ACKNOWLEDGMENTS

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