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Review for the current performances for Machine Visions in Industrial Robotic welding and drilling tasks

Hamza Alzarok[*1], Simon Fletcher[2], Naeem S. Mian[2]
[1](Department of Electrical and Electronic Engineering/ Faculty of Engineering/Bani Walid University, Libya)
[2](Centre for Precision Technologies, School of Computing and Engineering/ University of Huddersfield, England)

Abstract:
Industrial robots have been more and more involved in the automation industry due to their capability to perform precise tasks, with an accuracy in sub-millimeters, tasks such as welding and drilling where a successful cooperation between the robots and the machine vision is necessary to end tasks within a demanded accuracy and in less execution time. The feedback from the machine visionsis used for enhancing the efficiency of detection, tracking and control of the robot motion by utilizing their visual information. The feedback, therefore, improves the safety of the system by preventing the robots from being damaged and operators from being injured which, in turn, saves the production time.
Robotic welding tasks is one of important applications for industrial robots where high temperatures can limit the ability of welding workers to monitor and control the process around the close proximity of the welding area. Here the use of vision sensors could significantly aid in terms of protecting the welded area and provide safety to the operators. Similarly for the drilling tasks where robots are widely used, visions systems has significantly improved their performance to achieve desired accuracy.
This paper targets these application areas and presents a review of the state-of-the-art equipment, methodologies and practices used within the associated research areas of robotic systems in the context of vision systems. It also examines the recent contributions of the vision systems in robotic tasks and highlights on their performance, the use of algorithms for image processing and calibration procedures adopted, and their contribution towards the effectiveness of robotic positioning resolution and accuracy.
Keywords:*Vision Systems; Industrial Robots; Trajectory Tracking; Machine Vision; Robotic Welding; Robotic Drilling.*

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I. Introduction

Industrial robots have been widely used in the automation industry such as for object handling or automatic grasping [1], peg-in-hole assembly [2], seam welding [3], they have been preferred due to their capability to change their position repeatedly with a small repeatability error in the sub-millimetre range (±0.3 mm,[4]), but their absolute accuracy can be in the order several mms (±5–10 mm, [4]; ±0.5–1.8 mm [5]) because of mechanical tolerances, elasticities, temperature, etc. [6]. These error sources can lead to a significant offset to the robot end-effector. Therefore, it is very important for applications that need an absolute accuracy to measure the end-effector position and orientation in Cartesian space [7].

The advantage of using the articulated robots in the industry is because of their freedom of movement in the environment and also for their ability to perform tasks without being fixed to one physical location. In fact, there is a high demand for using mobile robots in unprepared environments and hard-to-reach or hazardous areas [8]. In such scenarios, robots are often operated from a safe distance. In order to ensure an error-free performance of mobile robots, monitoring systems must be installed to keep track of the motion parameters programmed within mobile robots. The performance of mobile robots can be further enhanced by using the feedback from the installed sensors which can help robots to perform complex tasks by acquiring information such as, the robot location. In the past research, reviews have been conducted which highlighted the sensory techniques used for robots such as Cork et al. [9] provided a good review on the fundamentals of inertial and visual sensors which was followed by an intensive review from Kiang et al. [10] about the sensor systems that can be used in a specific kind of robot (flexible manipulators). However, the research or literature for the applications of sensory techniques within the industrial robots was not area does not address the current practices of vision sensors used within the areas of both applied and research oriented solutions for monitoring or improving industrial robot performance which has become the main motivation for this article. This paper provides a comprehensive review of the current contributions of these systems for detecting and tracking of industrial robots and also the challenges toward achieving the demanded manufacturing performance.

There are two common solutions for measuring the robot position. The first solution is to use embedded sensors for measuring the position of the articulated robot, such as by using accelerometers [11] and joint sensors [12, 13] for measuring the angular position and velocity as well as the Cartesian position, orientation, and the linear velocity of the robot end-effector. The advantage of these methods is the ability to provide good short term position estimates. However, they suffer from errors accumulating over time because of the integration of minute increments measurements (e.g. inertial) to obtain the final estimate [14] or from errors outside of the control loop such as deformation of the links either from time varying or finite stiffness effects. The second solution is to measure the robot position globally using external sensors such as laser trackers, vision systems or and intelligent global positioning systems (iGPS) [15].

Large metrology systems such as laser trackers and iGPS provide higher positioning accuracy than other sensors, and have the capability to be used for measuring the position of the robot end-effector in small and large measurement volumes. However, in order to achieve a sub-millimetre accuracy by these sensors, the hardware cost will increase.

In order to balance between the hardware cost of the measurement system and its capability to provide sufficient information about the robot, vision sensors have been introduced, the distinguishing point of these sensors is in the reduced hardware cost, the easiness to install and use, and also for their applicability in both small and large measurement volumes. In industrial robotic applications, vision sensors have be intensively employed with the robots as tracking systems, trends of using these systems have significantly increased over thepast decade (as shown in Figure 1), particularly in four popular applications which are welding, drilling, pick-place, and assembly. The contribution and challenges of the vision sensors in welding and drilling applications will be the scope of this paper, also, this paper will also highlight on the challenges of applying these sensors and the efforts made by researcher to cope with them, and the paper is organized as follows. Section II highlights on the possible configurations of the vision sensor, Section III and section IV reviews the use of vision systems in robotic welding and drilling tasks. Section V discusses the associated challenges which may affect the applications of the vision system in the industrial robotic fields followed by Section VI which outlines the conclusions drawn from this work.

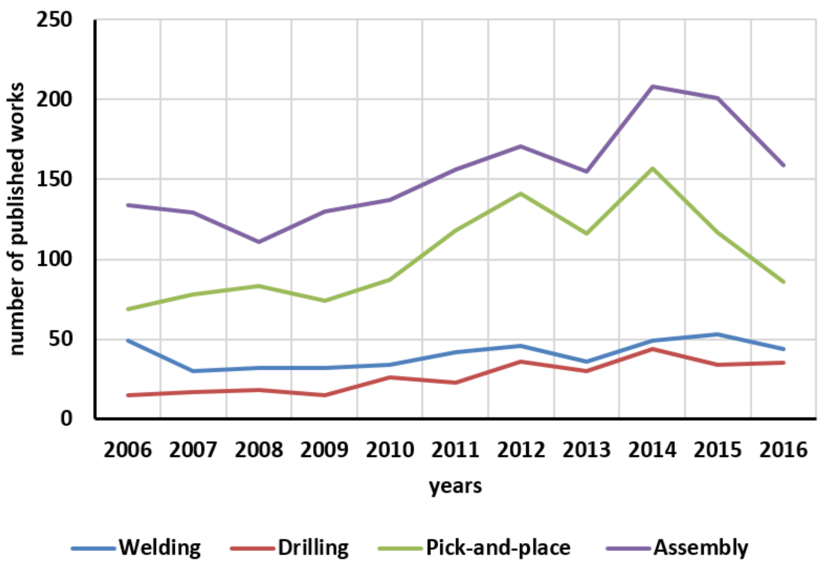

Figure 1: Trends in the use of vision system in robotic manufacturing tasks between 2006 and 2016

II. Vision sensors

Vision-based tracking sensors have been intensively used in industrial robotic applications, such as in grasping [16, 17], assembly [18, 19], welding [20] and drilling tasks [21]. In the aforementioned tasks, there are two possible configurations to set up a vision system (see Figure 2) namely eye-in-hand and eye-to-hand [22-28]. The eye-in-hand camera configuration (ENH) involves visual systems that are usually used by composing two or more cameras that can be rigidly attached to the robot end-effectors, whereas the eye-to-hand camera configuration (E2H) involves the vision systems that are fixed in the workspace [29]. The ENH camera method enables the robot to view the workspace more flexibly, but with restricted field of view (FOV) [22]. However, E2H camera ensures a panoramic view of the workspace, but typically produce lower resolution images[30].

As the single ENH camera moves away from the target object, the FOV of the camera is increased at the cost of reduced accuracy. Multi ENH configurations with different FOVs have beensuggested to address the deficiencies of a single camera and to increase the overall FOV and improve the overall accuracy. However, the visibility of the target object, and the common appearance of errors in the target object modelling (e.g., CAD modelling errors) are crucial for such configurations and strongly affects the overall robot pose estimation. According to Assa[31] there are a few methodologies introduced for addressing this problem such as one by Malis et al. [32] in which comparison was made between the precision of multi ENH camera to a single ENH camera. The authors found that the positioning accuracy was significantly enhanced with the use of multi-camera visual Servoing compared to the use of a single ENH camera.

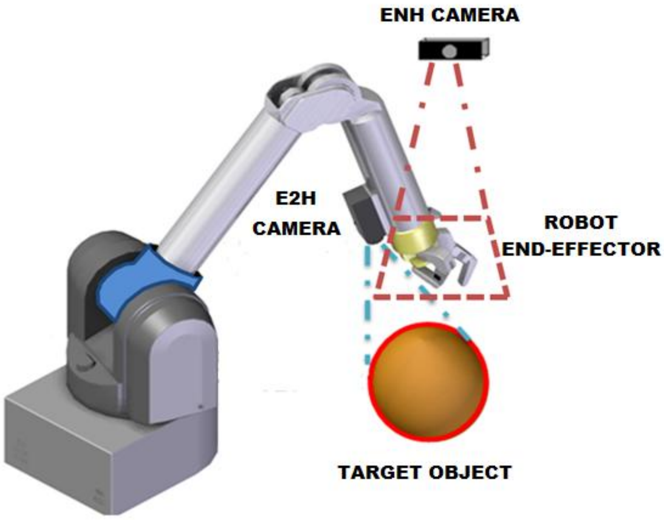

Figure 2: Possible Camera configurations

Another type of camera configurations which is less highlighted in the reviewed papers is the cooperation between two cameras, the first one could be considered as an E2H camera, and the other one as an ENH camera (see [33, 34]). The advantage of this cooperation is the ability to subdivide the tracking process into two tasks, the first is tracking the target and the second is knowing the position of the robot end-effector, with each task being performed with a single camera. In both tasks, image information is used to determine the error between the current location of the robot and its desired location. The image information that is used to perform the task is either i) two dimensional, described by using coordinates of the image plane, or ii) three dimensional where a camera or object model is employed to retrieve pose information with respect to the camera/world/robot coordinate system. The robot is controlled either using image information as two or three dimensional which classifies the visual servo systems additionally as: Position-based visual servo systems, Image-based visual servo systems, and the third is a cooperation of the previous two approaches [35], called 2 ½ D visual Servoing. This approach provides an advantage in not requiring any geometric 3D model of the object in comparison with position-based visual Servoing. Furthermore, the 2 ½ D visual Servoing ensures the convergence of the control law in the whole task space which is not available in the image-based visual Servoing. However, the 2 ½ D visual Servoing is more sensitive to image noise in comparison with 2D visual Servoing, and that refers to the third approach which directly uses visual features as inputs of the control law without any additional estimation step [36].

The cooperation between ENH/E2Hcameras is introduced as suitable option in the case where the employed stereo vision system either cannot provide precise information or can provide precise information about the actual position of the robot but with long time delay. In this case, each task is performed with a single camera i.e. the ENH camera can perform the tracking of the target and the fixed camera can measure the position of the robot arm in the 3D space. Moreover, while complex artificial vision algorithms are required by the stereo vision system, an ENH/E2H camera cooperation could be performed with easier image processing [37].

In the case where anadditional visual information about the tracked targets is required during the execution of a certain robotic task, the use of multi camera systems is often a more suitable choice compared to single or stereo camera configurations [38]. However, the downside of using multi-camera systems is the need for matching across multiple views that are captured from different cameras having different perspectives, which is usually a time consuming and non–trivial problem. Therefore, servo systems that use more than two cameras for controlling a robot are uncommon [35], in addition to the matching problem, and the additional hardware cost as main factors affecting the use of multi-cameras. The E2H cameras are widely preferred in robotic grasping [39]and in assembly tasks[40] due to the importance to track both the target to be grasped or assembled and also to recognize the position of the robot end-effector, this kind of setups provide a wide field of view of the workpiece. However, in robotic welding and drilling tasks, vision sensors are often used in a single ENH setup, due to the nature of these tasks which require the camera view to be closure to the weld seams in order to keep the seam trajectory or to ensure the perpendicularity between the drill-end effector and the workpiece surface[41, 42].

In the next sections, the practical use of vision systems as tracking systems with the robotic manipulation in robotic welding and drilling tasks will be highlighted, and their challenges towards achieving the desired accuracy for the two aforementioned tasks will be discussed.

III. Robotic welding tasks

Welding has been widely used in many industrial applications but the automation level is still low at the current stage. More than 90 % of the welding tasks are executed manually [43, 44], and that might refer to the cost which is often cheaper compared with using robotic welding [45]. Although in some welding tasks, industrial robots have been adopted and used in the factories but most of them operate in the teaching-and-playback mode [46]. Huang and Kovacevic[47] defined this mode as “In which the position and motion path of the welding torch are predefined and taught point by point”. This mode has special requirements for the shape and the position of the weldments, which limits the applications of the welding robots and reduces the quality of welding [46].

However, some welding processes such as based on semi-automated welding methods require manpower to monitor and guide the welding system during the welding process. Since high temperatures are involved during the welding process and the requirement to protect the welded area using gas, and where the health and safety cannot be compromised, welding operators are abstained from entering inside the welding vicinity to monitor and control the process. Error caused by the human operation and the welding environment lead to errors in the coordinates of the weld seam which affect the welding quality. To cope with these problems that consumes time and manpower, vision systems was suggested [48].

In the welding automation field, there are three aspects in which the vision sensor can be utilized, the seam tracking [49, 50], the weld pool control [51, 52], and the initial weld point positioning [53, 54]. Vision sensor system has become a vital part of the robot welding detection system as it performs many functions such as welding environment identification, initial welding seam guiding and welding seam tracking.

Vision sensors in particular have gained popularity among researchers mainly because it is a non-contact sensing system with high measurement accuracy [46]. Also, for its very low hardware cost compared to laser sensors. For example, the cost of a visual sensor (including CCD camera, lens, data acquisition, etc.) is approximately $1.500 whereas the cost of production of a laser sensor is 15 times higher than the visual sensor (Meta vision systems) [43].

Vision sensors were used to view the laser structured light projected onto the groove to detect the groove position [55], groove size [56], and weld deviation [57]. This laser vision sensor is useful for seam tracking. However, the laser vision sensor still has several limitations. First, the detected position must be placed at a distance (30–100 mm) ahead of the weld pool [58]. Although the detected position of grooves can be recorded, the distortion between the detected position and the weld pool caused by the strong thermal effect leads to an error. Second, it is difficult to detect the projected laser structured light when working with shiny surfaces. Third, the laser vision sensor is applicable only to seam detection and cannot be used for viewing arc and weld pool [59].

To solve these problems, many researchers used only a vision sensor to capture welding images without structured light in gas tungsten arc welding [43] and gas metal arc welding [60].

The employment of optical filters with the vision sensors is another issue, although that the optical filters are employed in front of the lens in order to filter out an arc in a certain wavelength range and can reduce the arc’s interference with the imaging, they can also result in the loss of some useful information because useful image information on the wire, arc, weld pool, and groove is distributed in various wavebands of the spectrum; thus, the image quality declines and image edge blurs, which brings trouble to the subsequent image processing. therefore, the use of only a wide dynamic range (WDR) camera without employing any external light source or filter is suggested [59].

The use of camera without any filters was also preferred for narrow welding seam, Chen et al. [3] have not employed any filters with their proposed vision system due to the reason that the camera cannot recognize a narrow seam feature properly in the presence of a filter. Moreover, since the main goal of using filters is to avoid obtaining noisy images, researchers such as Xu et al. [61] proposed an image processing technique for extracting the seam line from the noisy images, the technique is a combination of profile extraction, Hough transform, and least square fitting was. The results obtained showed that the seam tracking errors, measured according to the image errors, were within 0.4-0.72 mm.

laser vision sensors have been preferred by researchers in different welding tasks such as [62] by Sung et al. [63] for joint tracking in high-speed welding with a maximum tracking error of 0.6 mm, and by Gu et al. [57] as an automatic seam tracking system of multi-pass metal active gas (MAG) welding with tracking errors in all their experiments within the range of 0.3 mm.

The authors introduced a calibrated active vision system which can automatically identify welding seams and then measure their 3D coordinates in order to be used for an industrial robotic arc welding system. However, according to Chen et al.[3], the active visual sensor may not be a practical solution in tracking the narrow seam because of the hardness of capturing and recognizing the deformed laser light stripe for narrow seam during the welding. To address this issue a passive vision-based robotic welding system was suggested.

a Passive vision based seam tracking system was developed by Xu et al. [43] and Ye et al. [60] for Gas Tungsten Arc Welding (GTAW) task. Ye et al stated that the accuracy of the weld seam tracking was affected by the following factors, 1) image processing error, 2) calibration error, and 3) the time delay produced from capturing and processing images and sending the data to the robot. Although the modified formula of weld pool centre reduced the tracking error caused by the delay, however the formula cannot eliminate the error completely due to the fact that time spent on capturing and processing images was variable.

Passive vision sensors have also been preferred for another kind of seams welding named closed-gap butt of thin plate. Ma et al. [64] justified the use of passive sensors instead of active sensor because of the difficulty to use the later for this kind of seams welding (closed-gap butt of thin plate), where there is no depth variation in scanning across the seam.

Xu et al. [65] proposed a tracking system based on a circular laser vision sensor for weld seam location and seam tracking in Gas Tungsten Arc Welding (GTAW). A 6-DOF welding robot (namely IRB2400) was used to hold the camera and the welding torch while it moves along the weld seam. Order statistic filter method was proposed in order to obtain perfect circular laser trajectory and for minimising the random noise without blurring edge.

Shen et al. [66] dealt with two challenges during the use of their proposed a passive vision system during the square-wave AC GTAW. The first challenge is how to reduce the computational cost, and the second is how to obtain clear images. In order to cope with the first challenge, they used two small windows instead of using full resolution images and in order to obtain clear images and extract the seam edges, a median filter, edge detection and thinning algorithms were used with the captured images.

In addition to the GTAW process, passive vision systems have also been introduced for real time seam tracking in robotic Gas Metal Arc Welding (GMAW). According to Xu et al. [67], passive vision systems were preferred due to their low hardware cost compared to the active systems and due to their ability to provide rich seam information which can cope with the problem of laser tracking system [66].

The main difference between the passive and active vision systems is in the source of the imaging light, in active systems, devices such as laser light source was used for producing high intensity light. However, the arc light illumination was used in the passive systems for capturing the images[67].

Xu et al. [67] used a passive vision technique for real time tracking of the weld seam and controlling the quality of the weld in robotic gas metal arc welding (GMAW). The low hardware cost was the reason for using a camera with low image capturing rate and low frequency. despite of that, the obtained results showed that the tracking accuracy of the robot welding system was within ±0.3 mm which meets the requirement of the real time seam tracking.

The existence of the welding operator might be necessary for the performance of some welding tasks, especially when the welding task is executed in complex and poor environments, Plasma Arc Welding (PAW) as an example of the welding tasks that require use of operators for monitoring the computer system. In the event of some unexpected result, the program will send a message on the computer screen to alarm the operator to adjust the workpiece manually [68].

Vision sensors in the reviewed works in the robotic welding tasks are often used in a single ENH setup, due to the nature of these tasks which require the camera view to be closure to the weld seams in order to keep the seam trajectory in the FOV of the sensor [69]. Moreover, a single ENH camera can be used for acquiring the 3D coordinates of the welding seam [70]. The use of a single camera instead of multi camera was justified by Chen et al. [71] because of the convenience in the single camera setup than using two ENH cameras. However, a practical comparison between the two methods needs to be done in order to evaluate which one is more efficient.

Dinham and Fang [45] indicated some challenges resulting from the use of computer vision system in robotic welding. These involve reflections and imperfections on the surface of the material, for e.g., due to the scratches which could have adverse effects on the edge identification. Another difficulty arises if the surfaces of the steel from a computer vision side are largely textureless and do not provide unique feature points which will make stereo matching difficult.

In summary, Table 1 shows a sample of vision tracking algorithms applied by researchers in different welding tracking tasks and their achievable positioning accuracy.

Table 1: Examples for various algorithms for welding tasks with the achieved accuracy

Authors	Detection algorithm	Welding Tracking task	Achieved accuracy
Sung et al. [63]	template matching method	High speed joint tracking	0.6 mm
Gu et al. [57]	feature extraction algorithm	GMAW	0.3 mm
Ye et al. [60]	Sobel operator	GMAW	±0.5 mm (straight)& ± 1 mm (curve)
Xu et al. [43]	enhanced Canny algorithm	GTA	±0.3 mm
Xu et al. [72]		GTA	less than 1 mm
Xu et al. [65]		GTA	less than 0.5 mm
Shen et al. [66]	an eight-bit grey level	GTA	±0.2 mm
Ma et al. [64]	edge	planar butt	±0.3 mm
Xu et al. [67]	Canny edge algorithm	GMAW	±0.3 mm
Chen et al. [70]	sub pixel edge detection based on Zernike moment		3 mm (S shape) & 4.5 mm (saddle)
Gao et al. [73]		fibre laser	less than 0.03
Xu et al. [61]	profile extraction, Hough transform, and least square fitting	narrow butt	0.4-0.72 mm
Chen et al. [3]	profile extraction, Hough transform, and least square fitting	narrow	0.3 - 0.4 mm
De Graaf et al. [69]		laser	0.1-0.5 mm (cur)
Dinham and Fang [45]	Hough transform	arc	±1 mm
Stoica et al. [74]	edge detection algorithm (square tool)		2 mm

IV. Robotic drilling tasks

Robotic drilling for aircraft structures with high accuracy has been a challenging task due to the difficulties involved with drilling large number of fastener holes on a variety of machine materials such as titanium and other composite materials [75]. Manual drilling is labor-intensive, time-consuming, may cause health problems to the operators and do not guarantee the desired quality [76]. Therefore, in order to perform a robotic drilling task with good quality that meets the task requirement, vision systems were introduced as a non-contact and cost effective system which can improve the positioning accuracy of the drilling systems by measuring the workpiece position, correcting the drilling position by comparing the actual and theoretical positions of the workpiece [75]. As the vision systems gained popularity, they were also prone to the measurement errors. The setup of the vision sensor in drilling tasks is often in an ENH configuration.

Zhu et al. [75] discussed the measurement errors associated with the vision system that occurred within the robotic drilling applications. These errors are due to the non-perpendicularity between the optical axis of the camera and the surface of the workpiece and wrong object distance between the lens of the camera and the surface of the workpiece. To counter this, the authors proposed a technique based on the use of four laser sensors for providing feedback information to adjust the camera pose with respect to the workpiece.

In drilling applications, when the robotic drilling system is operating, the drill-end effector has to be perpendicular to the workpiece surface and the distance between the drill bit and the surface is not variant, so obtaining the depth information by the vision systems is not important for the drilling system. Furthermore, obtaining the depth information of the monocular vision system is not an easy task due to the difficulty in calculation and the time consumption, therefore techniques for avoiding the calculation of the depth information were introduced. For instance, Zhan et al. [77] introduced a calibration method which indirectly obtains the relative relationship of the hand-eye vision from the relationship between the image coordinate system and the world coordinate system. The proposed method is simple and practical, and can also be used for achieving high positioning accuracy within 0.4 mm including the positioning error of the robot and the drilling end effector without the need to use expensive auxiliary calibration devices.

Zhu et al.[41] developed a monocular vision system for improving the positioning accuracy in robotic drilling. Due to the effect of the noise and environmental disturbances on the vision measurements in the applications of robotic drilling. An elliptical contour extraction method named saliency-snake method was proposed, the performance of this method was compared with other detection techniques (e.g., Otsu algorithm and Hough transform method) on different noisy images taken at different exposure times. The introduced method succeeded in detecting reference holes in all images despite of the variation of the exposure time and the changes of burrs and dust flocks.

Bi and Liang [76] developed a robotic drilling system for titanium structures, the proposed systems composed of a workpiece holding fixture, a sensor system which comprised of a Kistler 9234 strain transmitter for measuring thrust force and an industrial camera (ENH) for measuring the location and identifying weld marks. A plane-based hand-eye algorithm was used for calibrating the vision system. The data collected from the measurements showed poor consistency due to the stiffness, corresponding to the configuration of the robot joint, differing at each target point.

Mei et al. [78] proposed an in-process robot based calibration technique using a 2D vision system. The used vision system consisted of an industrial camera (ENH) with a lens that has invariant focal length. An iterative measurement algorithm was used for positioning of the reference holes to avoid the errors of the measurement caused by the non-perpendicularity and object distance. Depth control with auto focus was integrated to measure the features in 3D space without the need for extra sensors. The experimental results showed that the rough positioning accuracy of the drilled holes was minimized from 4 mm to 0.6 mm after performing the calibration.

In summary, the main challenges in robotic drilling tasks and their proposed solutions can be summarized in Table 2.

Table 2: Drilling task Challenges and their solutions.

Type of challenge	Suggested solutions
non-perpendicularity between the optical axis of the camera and the workpiece surface	Feedback from multi laser sensors for the positioning adjustment [75]
	An iterative measurement algorithm for avoiding the measurement error[78]
the difficulty in the calculation of the depth information	a calibration method for avoiding the direct calculation [77]
poor consistency due to the robot stiffness	No solution presented [76]

V. Summary

The use of vision sensors in industrial robotic applications has gained increasing attention from researchers due to their robustness and ever reducing hardware cost compared with other measuring systems such as laser trackers. The literature review shows that vision systems can drive the robot to perform machining tasks with an acceptable accuracy for most general applications. In robotic welding and drilling tasks, the limitation of the camera’s FOV is not a problem due to fact that the camera is often used in an ENH configuration and required to cover only a small measurement area. In robotic welding tasks, There are many challenges that restrict the performance of vision sensors in these tasks, such as reflections and imperfections on the surface of the material, which could have unfavorable effects on the edge identification. Another difficulty arises if the surfaces of the steel from a computer vision side are largely textureless and do not provide unique feature points which will make stereo matching very difficult. However, in robotic drilling tasks, the main source of positioning errors is the non-perpendicularity of the camera optical axis to the surface of the workpiece. However, there are other sources of errors which effect the robotic welding such as 1) related solely to the camera operation such as the image processing error which is due to the quality of the captured images, 2) errors occur due to the use of improper calibration process for the camera 3) related to the performance of the extensions and algorithms used with the camera such as the effectiveness of the optical filters and feature extraction algorithms and 4) the effect of the illumination environment (lighting environment) which is present in other robotic machining applications too.

VI. Conclusion

Over recent decades,considerable progress has been made in developing of vision techniques into a very useful technology within industrial robotic applications. This paper has reviewed the contribution of vision sensors for improving the performance of industrial robots in machining applications, which are welding and drilling tasks. Each application area have been explored thoroughly with an insight to the related research work conducted. This paper also highlights the advancements in the field of vision sensors and image processing algorithms which can enhance the performance of an industrial robot. It is envisaged that progress in the vision technology and image processing techniques will further improve the precision of visual information extracted from images and reduce the computational and hardware cost. This development will further extend the potential of vision sensing technology and allow vision sensors to be used with robots more widely, probably in high-speed machining tasks.

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