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A Review on some commonly used sensors for Robotic applications

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Abstract: *Over the last decades, mobile robots are increasingly becoming an integral part of many modern manufacturing processes. This is because of robots' ability to perform repetitive tasks with an accuracy that meets a wide range of industrial demands, they have been involved in very wide range of applications, such as for manufacturing processes due to their capability to work in unstructured environments. They can execute tasks with high repeatability, although their low positioning accuracy that is often in the range of several millimetres can cause a significant offset to the robot end-effector (gripper). Therefore, for many industrial applications it is necessary to accurately estimate the position and orientation of the robot end-effector in Cartesian space, in order to perform accurate and reliable automated manufacturing operations involving the interaction between the robot end-effector and objects in the working area. The uncertainties in either the end-effector position or the target position can lead to failure of the operation or restrict the scope of applications for which the robot can be used. In order to cope with this problem, a combination of a reliable and robust sensory technique integrated with the robot is important. Many sensory techniques have been introduced and used for positioning measurement of the end-effector and its target, these sensors play a critical role to provide the mobile robot its capability in observing the environment and developing plans for decision making. The continuing developments in electronics technology is assisting drive down the cost of sophisticated sensors to affordable range for many robotic applications such as for grasping, pick-place and assembly tasks. A successful accomplishment of these tasks is heavily dependent on the feedback from the sensors to enhance the efficiency of detection, tracking and control of the robot motion by utilising their information. This paper presents a review of the state-of-the-art equipment and methodologies used within the associated research areas of robotic systems in the context of sensory technologies. It also highlights on their performance and their contribution towards the effectiveness of robotic positioning resolution and accuracy.*

Key Words: *Sensors, Object Tracking, Pose Estimation, Industrial Robots, Localisation, Obstacle Avoidance.*

1. INTRODUCTION:

Mobile robots have been widely used in the industry due to their freedom of movement in the environment and also for their ability to perform tasks without being attached to one physical location. In fact, there is a high demand for using mobile robots in unstructured environments and hard-to-reach or hazardous areas (Zhang, Lim, Chen, & Karimi, 2014)[1]. 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 (Corke, Lobo, & Dias, 2007)[2] provided a good review on the fundamentals of inertial and visual sensors which was followed by an intensive review from (Kiang, Spowage, & Yoong, 2015)[3] about the sensor systems that can be used in a specific kind of robot (flexible manipulators). (Alzarok, Fletcher, & Longstaff, 2020; Alzarok, Fletcher, & Mian, 2020)[4, 5] reviewed the contribution of vision sensors for improving the performance of industrial robots in four machining tasks, which are grasping, assembly, welding and drilling tasks. They also discussed the current challenges that can heavily affect the detection accuracy and time-efficiency for this type of sensors in the aforementioned tasks. In the industrial applications where robots are required to perform predefined tasks and follow programmed trajectories, sensors can be used for tracking the robot's motion and thus evaluating the trajectory performance. The research or literature within this area does not address the current equipment, methods and practices used within the areas of both applied and research oriented solutions for monitoring or improving industrial robot trajectory which has become the main motivation for this article. This paper provides a comprehensive review of some popular sensors used for tracking of industrial robots, and also for enhancing their positioning accuracy and safety during the performance of difference tasks. The performance of mobile robot tracking relies on the quality of parameters obtained through extraction, detection, identification, and tracking from its environment to acquire the related motion parameters such as position, trajectory, velocity, and acceleration. In many applications for mobile robots, the robot should know its motion parameters in order to complete some typical tasks, for example, it is crucial for a traction control robot to know its motion parameters before changing its speed and moving direction in order to walk in a specified trajectory.

There are two solutions introduced for tracking indoor mobile robots. One is to start at a known location and track the position of the robot locally using methods such as odometry or inertial navigation (Chong & Kleeman, 1997)[6]. The advantage of these methods is the ability to provide good short term position estimates. However, they suffer from the growth of unbounded error because of the integration of minute measurements to obtain the final estimate (Borenstein, Feng, & Everett, 1996)[7]. The other solution is to estimate the robot position globally using external sensors such as global positioning systems (GPS). GPS provides a sufficient and reliable way to track mobile robots, but it cannot be used indoors (Zhang, et al., 2014)[1]. This has led to new innovations in indoor GPS (iGPS) (Z. Wang, Mastrogiacomo, Franceschini, & Maropoulos, 2011) [8]. This paper reviews the use of sensory techniques in industrial robotic applications, the paper is organized as follows. Sections 0 and 0 review the recent developments of vision sensors and Positive Sensitive Detectors (PSD) in tracking of the motion of industrial robots and detecting the poses of their end-effector. Sections 0, 0, 0, 0, 0 and 00 review the use of other sensors including Ultrasonics, Range sensors, Kinect sensors, Encoders and joint sensors in mobile robot applications. Section 0 summarised the contributions of reviewed sensory techniques and their associated challenges which may affect their performance in the robotic fields followed by Section 0 which outlines the conclusions drawn from this article.

2. CAMERA SYSTEMS:

In mobile robot applications, there are two main kinds of imaging sensors which are the Charge Coupled Device (**CCD**) and Complementary Metal Oxide Semiconductor (**CMOS**), both sensors have been intensively used in mobile robot applications due to their distinctive features (Hefele & Brenner, 2001)[9]. They have two possible configurations to set up which are namely eye-to-hand (E2H) and eye-in-hand (ENH) (Bishop & Spong, 1999; Carelli, Nasisi, & Kuchen, 1994; Chaumette, 1998; Cheah, Hirano, Kawamura, & Arimoto, 2003; Chen, Dawson, Dixon, & Behal, 2003; Deng, Janabi-Sharifi, & Wilson, 2002; Espiau, Chaumette, & Rives, 1992)[10-16]. The eye-to-hand setup (**E2H**) includes the camera systems that are fixed in the workspace or mounted above its ceiling, whereas 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 (Hutchinson, Hager, & Corke, 1996)[17].

2.1. E2H (Fixed near the target):

(H. Wang, Liu, & Chen, 2012)[18] used a fixed camera (a Point Grey camera) mounted near a 3-DOF robot for tracking its motion. A new controller was proposed for controlling feature points on the end-effector of the robot to trace desired trajectories (circular trajectory) defined on the image plane of the camera, the proposed work was an extension of their previous work (H. Wang, Liu, & Zhou, 2007)[19]. The main difference between the previous and current is that in the previous work, the controller can only guarantee semi-global stability, however in the proposed work, the developed controller can provide a global stability of the system. Another advantage of the new algorithm is in its ability to cope with the unknown feature positions. The intrinsic and extrinsic camera parameters of the camera were assumed unknown, and position of the features were also considered unknown. The used camera provides a video signal with 120 fps. Due to this, the performance of the presented controller for trajectory tracking of features on a 3-DOF robot was demonstrated only by the simulations in their work. It should be noted that the measurements of the position errors (the difference between the desired and actual trajectories) were simulated in image coordinates (pixels) instead of the world coordinates (e.g. mm) which makes the evaluation of tracking performance for the proposed technique a difficult task.

(Hollinghurst & Cipolla, 1994)[20] and (Hollinghurst, 1997)[21] described an inexpensive vision system that combines two stereo CCD cameras placed 2 m to 3 m from the workspace of the robot to enable locating a 5-DOF robot (namely Scorbot ER-7 robot arm) to reach and grasp polyhedral objects. An affine stereo algorithm was used by the proposed vision system to estimate positions and surface orientations of the objects of the target. Four reference positions of the robot were observed in order to perform the calibration. The feedback is obtained by an affine active contour model which tracks the motion of the robot gripper across the stereo images. Although the grasped objects had a simple geometrical shape and an overall planar constraint was used, the advantage of the introduced work is the automatic estimation of the object pose. The user points to the object to be grasped by the robot and the proposed vision system computes its pose.

(Wen-Chung Chang, 2007)[22] described an enhanced technique for 3D trajectory following tasks using E2H binocular visual servoing. A binocular camera was used for a 3D trajectory construction without prior knowledge of the environment. The robot manipulator was guided to follow the constructed 3D trajectory by using vision information only (Wei-Che Chang, Cheng, & Tsai, 2013)[23]. The researcher proposed a strategy which is based on implementation of the path tracking control in the absence of correspondence information between the two cameras about the required trajectory.

(Wen-Chung Chang & Wu, 2012)[24] presented two vision-based control approaches for a robotic assembly task. The task involved the use of a 6-DOF robot to install the back shell of cellular phones while the end-effector of the robot was equipped with a vacuum absorption device. The task can be divided into two main stages (see Figure 1), 1) driving the robot for grasping the back shell, and 2) positioning the back shell into the phone. This task required using of a cooperation of both camera configurations in order to track the relative positions and orientations of the cellular phone and its back shell. Images extracted from the cooperation setup were used for measuring the objects in 3-D space by detecting corner features and thus computing the positions and orientations of the cellular phone and its back shell. The two control approaches used are the look-then-move open-loop approach and look-and move closed-loop approach. According to the authors, if precise calibration can be performed then the look-then-move open-loop approach can be adopted with the calibrated cameras and hand-eye relation for completing the task with a resolution up to individual pixels. However, if the calibration process cannot be precisely completed, the closed-loop approach can be used without precise calibration to complete the task with accuracy up to a pixel resolution. This advantage makes the closed-loop approach more suitable than the open-loop approach for industrial applications.

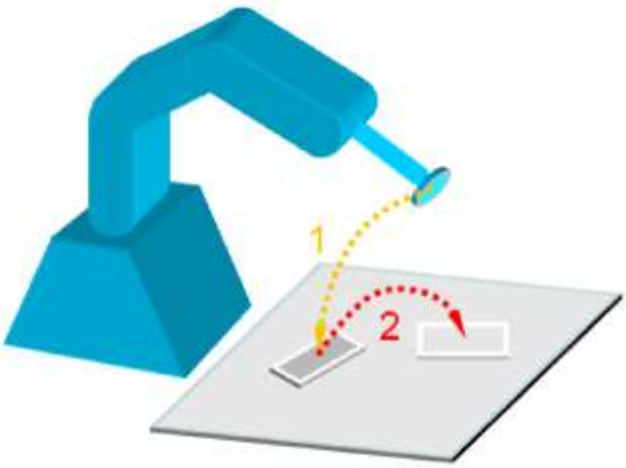


Figure 1. The stages of the robotic assembly task [24].

(Wen-Chung Chang & Chai, 2003)[25] used a fixed single camera (E2H) for another robotic task, the task required the use of the camera to drive the spot of the laser in order to follow a visually arbitrary planar contour., A Sony XC-55 CCD camera was fixed near a 6-DOF robot (namely Mitsubishi RV-E2). Only two of revolute joints of the robot were used to perform the 2-DOF rotational motion (pitch and yaw motion). A laser pointer was mounted on the end-effector of the robot whereas the camera was used for tracking the spot of the laser and geometric features of the laser pointer (i.e., the centre). The reference trajectory of the vision system was obtained from the fixed planar contour. In the performed experiments, the tracking error measured was less than 4 pixels.

(Chien & Huang)[26] used an E2H system where the camera was fixed above the workspace of the robot and can capture images throughout the robot workspace. The aim of the work was to move the 2-DOF planar robot end effector to follow a desired circular trajectory in the Cartesian space via the observation from the camera located at the end effector position in the image space. The Function Approximation Technique (FAT) was proposed to deal with time uncertainties. The proposed controller does not require knowledge about the robot parameters which is often required in most adaptive designs for visual servoing systems.

(Grosso, Metta, Oddera, & Sandini, 1996)[27] also used a stereo vision system that combines two CCD cameras with a resolution of about 0.3 Megapixels to track the trajectory of a 5-DOF robot end-effector, namely Unimation PUMA260 robot which was controlled by a HP 743 VME board running RCCL (Lloyd & Hayward, 1993)[28]. Optical flow was used to obtain visual measurements that are used for controlling the robot. In all experiments executed, the cameras were kept static but their positions for each test were adjusted to cover the required work area. The proposed end-effector position estimation algorithm was based on velocity segmentation in the image space. The performance of the algorithm during the experiment was only appeared in simulations and was not available in numbers. Moreover, in order to increase the computational speed of the tracking system, original images were sampled down to 80×80 pixels. The robot spent approximately 9 seconds to reach the point of the target, during which, 43 frames were captured. The computation of the optical flow suggested to be kept limited in order to increase the computational speed.

(H. Wang & Liu, 2005)[29] used a vision system (E2H) which is mounted near a 3-DOF robot (Puma 560) to monitor its motion with the camera providing a video signal. The target object was set as a one feature point on the robot end-effector and was extracted from the images. The robot was programmed to move in two different trajectories (linear and circular). An adaptive dynamic controller was proposed for the image-based trajectory tracking of a feature point on a robot manipulator in an un-calibrated E2H setup. Simulation results showed that the tracking errors on the image plane for both trajectories had been significantly reduced along the tracking process time. However, the performance of the proposed controller could not be easily evaluated due to that the results of the trajectory tracking experiment were only available in simulations The ENH setup was proposed for future work in order to extend the applications of the proposed technique.

2.2. Pan-tilt-zoom (PTZ) setup:

This kind of cameras is built with mechanical parts that gives them the capability to monitor wide areas that require a 180 degree of view or more, therefore, it is often used for security issues, such as in airports and guard stations. Moreover, PTZ cameras are also preferred for robotic tracking tasks due to their capabilities to adjust their FOV to track moving targets automatically. However, they also have some disadvantages such as the high hardware cost compared with a single or multiple stationary cameras. Also, the lifespan of PTZ cameras is shorter than other cameras because of their motors which are prone to fail eventually. Many researchers used PTZ cameras for obtaining this purpose, for example, (Kim, Cho, Kim, & Lee, 2005)[30] proposed to use an active camera (Pan-Tilt-Zoom) and a single camera mounted on a robot for real-time tracking (as shown in Figure 2). The problem with using CCD cameras is that they are not very practical for tracking of very fast moving targets or objects such as a Pin-Pong Ball. Moreover, using one camera with pan-tilt motion cannot provide a good tracking for the robot end effecter, especially if the robot programmed to move in different directions not in the field of view of the camera.

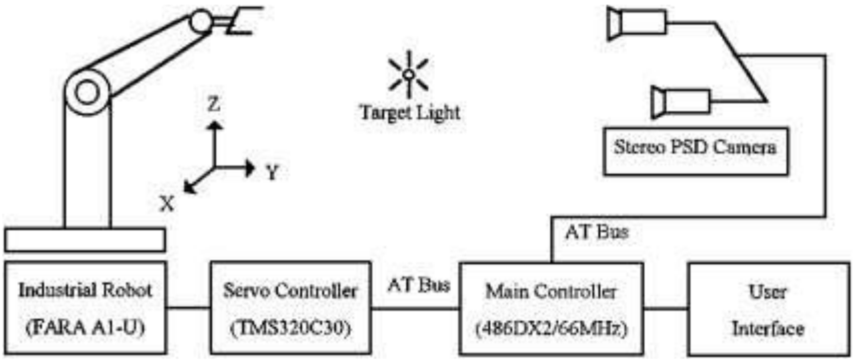


Figure 2. System hardware and experimental configuration [30].

(Kragic & Christensen, 1999)[31] presented a robust tracking system where a visual cue integration scheme was used to track the end-effector of the robot, namely a PUMA560 robotic arm. The movement of the robot arm was on a straight path and was under external dynamic control. The purpose of the introduced work was to show the ability to design a robust tracking system using simple and fast vision algorithms. Based on the measurements from the images, two colour CCD cameras were used for stereo vision with a resolution of around 0.08 Megapixels, the camera pair was mounted on the pan-tilt unit with 2-DOF and together they make up the "stereo head". A pan–tilt unit was controlled in order to keep the robot end–effector centred in the image. However, no mention was made in the presented work whether the accuracy of the pan-tilt camera has any effect on the tracking performance, although the camera had low resolution and its view to the measurement volume was from a distance of about 2 m. To increase the computational speed, the template matching algorithm is initialized in the region where the area of interest was found in the previous frame. Both the robot manipulator and its workspace were kept within the field of view of the cameras. The reason behind delaying in the processing time when a CCD camera is used refers to its nature as a digital system which is discreetly sampled and therefore causes a delay. Additionally to this disadvantage, digital cameras (digital vision tracking systems) need time for processing images in order to extract the motion and position from the image. Another drawback, digital camera (CCD) consumes a lot of processing power. However, digital cameras (CCD cameras) are still recommended to use for tracking because of the following properties:

1. External active light sources are not required
2. Self-contained system
3. Operates indoors and outdoors
4. Operates in unprepared environment

According to (Welch & Foxlin, 2002)[32] , one camera can be used for tracking multiple objects. The amount of camera rotation is not really important, but the velocity of rotation does. Tracking system should be able to match the speed of camera motion with the speed of moving objects (Mir-Nasiri, 2006)[33].

2.3. Head camera (panoramic setup):

(Gupta & Jarvis, 2010)[34] used a panoramic camera with catadioptric vision for tracking two spherical targets mounted on the top of a robot (see Figure 3), the robot has a wheelchair base and equipped with a UMIRTX arm with 6-DOF for grasping small objects 6-DOF platform, the camera was mounted on the ceiling of the workspace. The reason behind using a panoramic camera rather than other cameras is the ability to provide a wide view in the entire room (i.e., 180 degrees of FOV), making the analysis of the projection much easier compared to that of using a multi camera system. It has been noted that when the camera was used with high resolution (3 Megapixels), a significant reduction in the frame rate occurred (1-2 fps) which caused a low accuracy of the localisation and the tracking system. To cope with this problem the image resolution was reduced from 3 to 0.5 Megapixels. A Kalman filter was used to enhance the tracking accuracy. Although the results showed the effectiveness of the proposed method for tracking and detecting the pose of the robot in indoor environment. Two problems were faced during the tracking experiment; the first is the inability of detecting the position of the markers in the camera image, and the second is the incorrect detection for the markers in the camera image. The first problem can be solved by stopping the robot from the motion. However, the second problem cannot be easily detected and its occurrence is rare according to the author. The tracking process can fail due to the light sources in the room, occlusion of the robot markers or in the case of covered lenses of the camera.

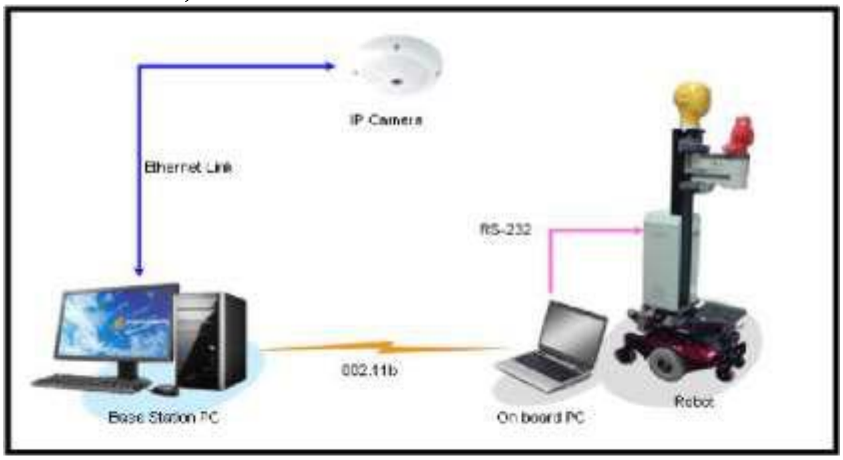


Figure 3. Robot Configuration Setup [34].

(Lund, de Ves Cuenca, & Hallam, 1996)[35] built a visual tracking system consisting of one CCD camera mounted under the ceiling of the lab about 2 m above the measurement area (240×40 cm2), and one attached to a mobile robot (namely Khepera miniature). The proposed system can successfully track the motion of the object by obtaining a prominent feature from the object. The tracking process was divided into two tasks, 1) following the trajectory of the robot motion by placing a window of observation around the estimated position of the robot, and 2) predicting the current position of the robot by using a simple dynamic model. In order to decrease the amount of processing data during the process, the size of the window was kept small. The travelling speed of the robot was kept at approximately of 1 m/sec which is suitable during the sampling time (20 *ms*). In the proposed work, the prediction process was based on using the previous position of the robot for estimating its current location. The drawback of the system is the absolute dependency of the tracking system heavily on the LEDs attached to the object. The reason behind putting two LEDs on the robot was not only for the measurement of position of the robot but also its heading.

2.4. ENH setup:

(S. S. Cheng, 2011)[36] used a CCD camera mounted on the end-effector of the robot and a laser stripe sensor (as shown in Figure 4). A laser stripe sensor was added as well in order to combine a light stripe vision system.

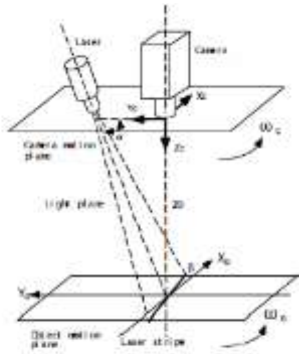


Figure 4. Configuration of the special sensor with a CCD camera and a laser stripe generator [36].

Stereo cameras were also used by (Yoon, DeSouza, & Kak, 2003)[37] for tracking the end-effector of a robot. Two stereo cameras (namely Pulnix TMC-7DSP) were mounted on the end effector of a Kawasaki UX-120 robot. The vision system is used to track three particular circular features of the object (an engine cover) at 60 frames per second (30 *fps* per camera). According to the authors, the proposed tracking algorithm provides very good accuracy compared with other algorithms that are based on CAD models or unconstructed cloud of points (Harris, 1993; Marchand, Bouthemy, Chaumette, & Moreau, 1999)[38, 39]. Due to the difficulty of measuring the error for a moving object, the object was kept static while the camera/end-effector was moving along a random path. The proposed algorithm is only suitable for use in controlled environment such as consistent lighting conditions. Results obtained showed that there is no dependency between the uncertainty in the position of the features and the distance between the camera and the object. These unexpected results were due to some factors which have an effect on the estimation of the pose, these were the condition of the illumination, and the tracking quality for different sizes of the object features as perceived in the image.

(Baek, Park, Cho, & Lee, 1999)[40] introduced a robot end effector tracking system based on the neural networks. A CCD camera with resolution of approximately 0.07 *Megapixels* was used for acquiring Grey level images of the robot. The acquired images were transmitted to the host system for the pre-processing stage. Two artificial neural networks were designed to perform two tasks, 1) detecting the end-effector position of the robot and 2) predicting the next position of end-effector using the current position and the previous estimated value. The authors mentioned the difficulty of estimating the next position of the robot because of its movement which can be varied with different types of motions (i.e., changing the motion pattern with large rotation angles leads to inability of the network to correctly predict the end-effector position. Without having a quick estimation process, the end-effector of the robot can never be placed at the centre of the images. The typical solutions for this problem are by using Kalman filtering techniques. The results showed that the average errors of the neural network recognizer and the neural network predictor are less than 8 pixels in images with the size of 256 x 256. The maximum number of frames could be processed by the proposed tracking system is around 4 *frames/s*.

(Jia, Liu, Liu, Loughlin, & Loughlin, 2015)[41] used an ENH system which combines a monocular camera fixed on the tip of a 6-DOF robot (namely axPartner AS-MRobotEII). The target object was represented as a set of points while iterative learning control was used to provide visual trajectory tracking. Only images with resolution of 0.3 megapixels were used for recording the trajectory tracking and the desired velocity trajectory was only used for analysing pose error based on kinematics. The results showed that the convergence of the pose error was minimised to less than 0.5 mm after 5 iterations. However, due to the presence of image noise, the tracking error cannot converge to zero.

(H. Wang, Liu, & Zhou, 2008)[42] used an ENH system which combines a Prosilica camera fixed on the end effector of a 3-DOF robot. The camera captures 100 *fps*, however only 54 frames were used in the adaptive algorithm. The three robot joints are driven by motors and three incremental encoders with a resolution of 2000 *pulses/turn* were used for measuring their angles. The aim of the work was to track a 3-D trajectory of the robot end-effector using point and line features. A Hough transform was used to identify these features. It has been noted that there was a strong effect of nonlinear forces on the motion of the robot, since the robot was light. The effect was caused by the small values for the gear ratios and input motor power.

An ENH system was also addressed by (Hua, Wang, & Guan, 2014)[43] for 3D target tracking. The robotic system was composed of a 6-DOF robot and a camera fixed at the end of the robot. The work aimed to enhance the tracking ability of the robot by using information provided by the camera. The sliding mode control and adaptive technique were employed in the design of the proposed controller in order to remove the nonlinear function of the robot. The effectiveness of the proposed controller had been proved in simulation and on a consideration of using a two link robot manipulator, the results showed that tracking errors between the robot and the moving target in word coordinates approximately converges to zero after around 5 seconds of starting the motion of the target.

2.5. Cooperative E2H and ENH setup:

In order to obtain additional visual information about the tracked targets, the use of multiple cameras is often a more suitable choice compared to single or stereo camera configurations (Hartley & Zisserman, 2003)[44]. However, the drawback 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 (Kragic & Christensen, 2002)[45].

(Gengenbach, Nagel, Tonko, & Schafer, 1996)[46] used a multi-camera system as a part of the workcell of a robot to estimate the pose of a workpiece. The proposed vision system consists of one CCD camera (ENH system) mounted on the hand of a 6-DOF robot. Three stationary cameras (E2H system) used to localise the robot workpiece and were mounted about 2 *m* above the workpiece and cover a measurement volume of 300×300×300 mm^3. After estimating the robot pose, the target is picked up by the arm of the robot. During the grasping period, the ENH system was used to control the robot while the stationary cameras cover the measurement volume. During this process, their common field of view were out of the workspace of the robot in order to avoid collisions. Moreover, lens distortions for the proposed vision system were neglected in order to avoid the computational cost. Extended Kalman filter was introduced as a robust technique which can cope with the problem of occlusion. The work aimed to achieve a positioning accuracy of about 1 *mm*, however, there was not enough information about the actual accuracy achieved.

(Elena, Cristiano, Damiano, & Bonfé, 2003)[47] used two CCD cameras for estimating the position of the robot end-effector, the robot used was a 6-DOF Staubli Puma 260-b. The first camera (ENH) is a Teli Cs 8530 and was

mounted on the end-effector of the robot arm having the image plane for the camera parallel to the plane where the target is moving. The second camera (E2H), Jai Cv-m10, was used to measure the end-effector position in the 3D space. Both cameras had been calibrated before the start of experiment. The velocity of the target was estimated based on using the estimated position of the end-effector as inputs. The proposed controller has a variable structure which has the capability to change from a PID to a PD and vice versa according to the estimate of the target velocity. The reason behind using a variable controller was that PID controllers can eliminate the steady state error for both stationary and moving targets (moving with a constant speed), but the problem resulted from this kind of controller is the increment in the settling time which can be decreased by using a PD controller. However, the drawback of the latter controller is that the steady state error for moving targets will be non-zero, therefore, the optimal solution would be a variable structure controller which is able to vary its regulation action based on the dynamics of the target.
Table 1 shows the advantages and drawbacks for different camera setups used for detecting and tracking the end-effector of the articulated robots.

Table 1. Typical camera setups with their capabilities and limitations.

Type of camera setup	Advantages	Disadvantages
E2H (Stationary close to the robot)	• E2H camera ensures a panoramic view of the workspace, but typically with a lower accuracy (Lippiello, Siciliano, & Villani, 2005)[48].	• The field of view of the E2H system is obstructed while the robot manipulator is retrieving the object. • Each single E2H will be focused on only a part of the working area, with no possibility to zoom in on that area with increased resolution. (Luo, Mullen, & Wessell, 1988)[49]
E2H (Pan-tilt)	• Adjustable FOV	• They are prone to mechanical faults, e.g., motors.
E2H (Panoramic view)	• a wide FOV of the workspace • suitable for robotic assembly tasks where two parts or more require to tracked during their assembly by the robot. (Mishra et al., 2018)[50]	• low resolution accuracy(Alzarok, Fletcher, Longstaff, & Myers, 2015)[51]
ENH	• The location of the camera is always stationary relative to the hand of the robot. • The target object to be captured and detected cannot be hidden from the camera by interference from the robot manipulator. (Luo, et al., 1988)[49]	• The ENH cameras are so bulky that even the smallest sized camera is too large to allow appropriate physical integration with the manipulator's gripper. (Luo, et al., 1988)[49]
ENH E2H cooperation	Extra visual information about the tracked targets (Hartley & Zisserman, 2003)[44].	• It requires a manual or automatic computation of the relationship between the camera views (Yilmaz, Javed, & Shah, 2006)[52] • high hardware cost

3. Position Sensitive Detector (PSD)

Position Sensitive Detectors (PSD) are one of common types of photo sensors used in many robotic tracking tasks, they can be defined as optoelectronic position sensors that utilises photodiode surface resistance which makes them different from discrete element detectors like CCDs (C. Han, Oh, Shin, & Choi, 2009)[53]. (C. Wang, Chen, & Tomizuka, 2012)[54] used a camera-like position sensitive detector (PSD) for estimating the position and velocity of a moving robot, a commercial measurement system developed by Dynalog (namely CompuGauge) was used for the robot calibration which senses the motion of the robot end-effector by measuring the motion of four cables connected to the end-effector. The reason behind choosing a PSD instead of CCD/CMOS sensors is the ability to sense the position of a light spot which makes it suitable to be used for real time feedback applications and also a faster response time and higher sampling rate can be achieved compared to the other sensors. However, the PSD sensors cannot capture images as vision cameras do and that is the main drawback i.e. its incapability for sensing without markers. The achieved average positioning accuracy was reported to be 0.05-0.1 *mm* over a small measurement area of 450X 450 *mm*.

The velocity of the robot was estimated by fusing information from the PSD with accelerometers and gyroscopes. The sensor fusion technique was introduced as a popular alternative based on estimating velocity from the measurements of the position (Jeon & Tomizuka, 2007)[55]. Most of these techniques are based on dynamic models which require accurate calculations of parameters, and that is difficult due to the complexity of robot dynamics. The proposed work showed the ability to track the position of the robot in a small measurement area, however, in the case of a large measurement area, they suggested using a multiple camera system. The PSD sensor, by itself, was not able to provide good information about the robot because of some drifting phenomena caused by the inaccuracy of the gyroscope calibration. To cope with this problem, the proposed sensor fusion technique needs to be developed.

(Lin, Wang, & Tomizuka, 2014)[56] also used a position sensitive detector (PSD) for estimating the position and orientation of a moving robot (FANUC M-16iB) in two different motion patterns; a straight line without rotation and a curve with rotation. The desired position of the target was generated by using an infrared LED marker mounted on the end-effector of the robot while a proposed vision sensing dynamics VSD compensator was used to estimate all the target poses. However, the performance of the compensator might be affected by the tracking errors of the robot, such as, the marker trajectory is not exactly as planned.

Advantages:

- PSD sensors require less time for image processing compared to CCD sensors. It is preferred in a certain environment when the intensity of the target is lighter than its environment due to their ability to quickly and directly transduce the projected position of the light into an analogue current. Can track at high robot speed (1m/s)

Disadvantages:

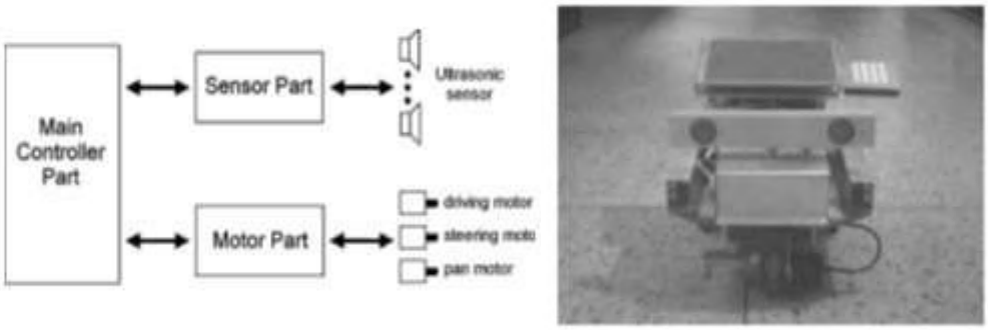
- incapability for sensing without markers

4. ULTRASONICS:

Ultrasonic sensors have been also used for robotic tasks, especially for obstacle avoidance with autonomous robots, they can have the capability to detect presence of an object located close to the robot. The working principle of the ultrasonic sensor is based on the use of the ultrasonic wave. If the wave collides with an obstacle near the robot, the wave then will bounce back to the sensor. If the receiver receives this reflected wave this means that there is an obstacle existent in front of the robot (Shahdib, Bhuiyan, Hasan, & Mahmud, 2013)[57]. (Y. Han, Han, Cha, Hong, & Hahn, 2001)[58] used two solar sensors (as shown in Figure 5) mounted in the front of mobile robot in order to detect the objects in its patch or trajectory, with additional sensors two of them mounted on the right, and the other two mounted on the left, used to detect the wall.

The advantages of using ultrasonic sensors rather than vision systems:

1. The simplicity to implement.
2. A quicker detection of moving objects with good accuracy and they can be lower cost as well.



(a) **(b)**

Figure 5. The structure of the mobile robot and its picture: (a) block diagram of the mobile robot system; (b) picture of the mobile robot [58].

The disadvantage of using ultrasonic sensors is time of flight dependent on air temperature.

5. LASER RANGE FINDER:

Laser range finders have been widely applied in many robotic applications, such as for object tracking (Brscic & Hashimoto, 2006; Sasaki & Hashimoto, 2009)[59, 60], obstacle avoidance (Negishi, Miura, & Shirai, 2004)[61], geometric feature recognition (Premebida & Nunes, 2005; Ueda)[62, 63] and self- localization (Bahari, Becker, & Firouzi, 2008)[64]. (Duchon, Dekan, Jurisica, & Vitko, 2012)[65] reviewed the uses of range finders within some applications of mobile robots, particularly in localization and navigation tasks. Ranging sensors have the advantage of being a reliable and high speed sensor. However, their hardware cost is too high due the necessity to implement additional equipment to perform tasks such as for 3D modeling and surface scanning (Duchon, et al., 2012)[65]. Moreover, the range sensors can also be used for tracking moving objects such as moving vehicles and have the capability to estimate their position and motion, they can process 75 scans per second when working on 600*MHz*, and also have the ability to fuse data from various scanners (360̊ sensing around) (MacLachlan & Mertz, 2006)[66].

6. Microsoft Kinect sensors :

Kinect sensors or depth cameras have been also preferred by many researchers for robotic motion tracking tasks, due to the advantage of being cost effective compared with other tracking sensors (Fraś, 2017)[67]. They have been applied in many robotic applications such as for monitoring and detecting obstacles around robots and provide safe interactions between the robot and human operators (Frese, Fetzner, & Frey, 2014)[68], and for tracking the pose of industrial manipulators, assisting them to grasp moving targets (H. Cheng, Chen, & Liu, 2013; Hossain, Capi, Jindai, & Kaneko, 2017; Husain, Colomé, Dellen, Alenya, & Torras, 2014)[69-71]. (Nakamura, 2011)[72] used a Microsoft Kinect sensor (as shown in Figure 6) for real-time tracking of moving 3D objects (robot), the Kinect sensor consists of two cameras to measure depth and color, the tracking method was based on getting color information and depth pixels in order to identify the target which is the end of the robot arm called i-ARM5 (as shown in Figure 7).

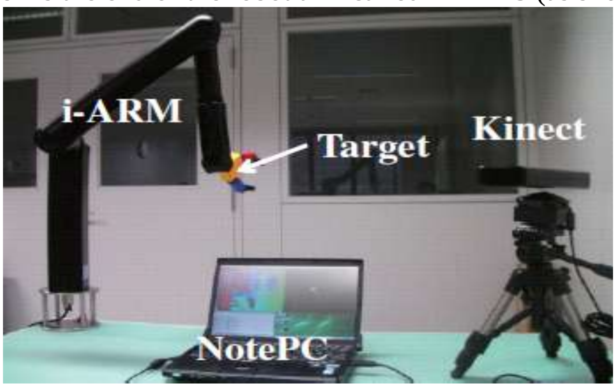


Figure 6. Overview of Experimental Environment [72].

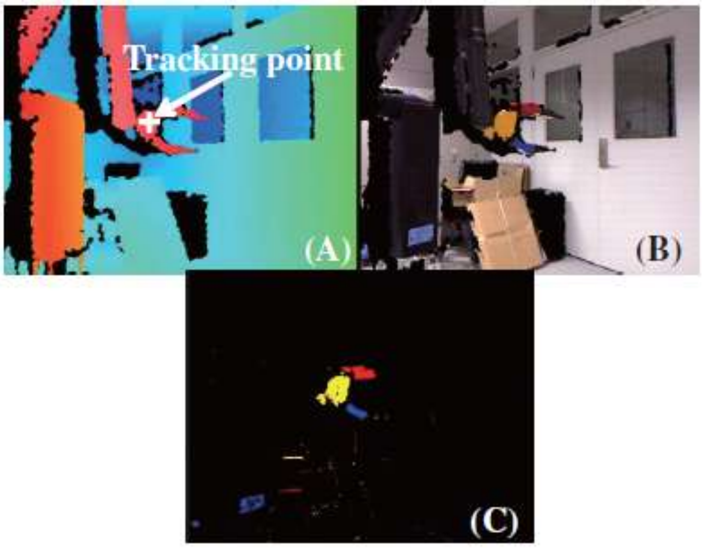


Figure 7. Experimental result of Image Processing [72].

Although that (Nakamura, 2011) considered the results obtained by using the Kinect sensor are accurate, but there is no evidence supports his view. However, it would be interesting to see enough information about the ability of the proposed tracker to track slow motion for the object, the resolution of the used cameras, and the time for processing images. The extended work proposed by the researcher is estimating variations in rotation by tracking multi-parts of the tracked object. (Lenz, Lee, & Saxena, 2015)[73] used RGB-D depth image of Kinect sensor and a two-step cascade structure of deep networks for robot grasping. They placed only one object at a time to be recognized. (Pinto & Gupta, 2016)[74] trained a convolutional neural network for predicting the grasp locations using trial-and-error experiments. The grasping model is improved by collecting additional data from Kinect and high-resolution camera during the real-time experiments. (Wei, Liu, Yan, & Sun, 2017)[75] proposed a multi-modal deep extreme learning machine structure for feature extraction and object recognition.

7. 3D SCANNER:

The 3D scanner is often used in 3D metrology, particularly in Quality Control and Reverse Engineering applications. Distortion patterns are viewed from two different stereo cameras and a special software was used for processing pertinent images in order to extract part surface geometry in terms of a point cloud. The setup of cameras depends on the scanning volume and the accuracy needed. The 3D scanner was used whilst the robot was incrementally moved along the desired trajectory. (Angelidis & Vosniakos, 2014)[76] used a 3D white-light scanner (namely IScan M300 by Imetrics) to measure the position of a robot end effector Stäubli RX90. The images were taken for the robot end effector at designated points within the measurement volume area of the scanner. In order to track a large number of points in the trajectory, there was a requirement of dividing the measurement area into smaller areas and keeping the robot stationary during the relocation of the equipment from one area to the next. At each new area, both the projector and cameras are required to be moved in parallel to the linear trajectory. The optical calibration process was suggested by the manufacturer and was followed in order to ensure the accuracy of the measurements. The use of 3D scanner for tracking the target at large number of points is time consuming. Moreover, using better cameras was suggested for improving the measurement results and also to increase the scanning volume and focal length. Generally speaking, despite the drawback of a 3D scanner in terms of time consumption and the accuracy of measurements, white light metrology has the advantage that it does not require alignment devices, and also provides measurements in 3D because of the combined translation and rotation. (Angelidis & Vosniakos, 2014)[76]

8. Encoders:

The encoder is a type of sensors that converts the angular displacement into electrical pulses. It can be classified into four categories based on the detection principles: photoelectric, magnetic, inductive and capacitive (Janisch, 2006)[77]. (Jeong, Kim, Kwak, & Smith, 1998)[78] introduced a parallel wire mechanism for measuring the position and orientation of the end-effector of a robot by using encoders. A CMM (with an accuracy of ±0.5 μm and a measurement volume of 800×300×350 mm^3) was used for the calibration and for evaluating the accuracy of the proposed technique. The Newton Raphson method was used for solving high order nonlinear equations of the forward kinematics. The effect of longitudinal deformation and gravitational deflection was considered and complemented analytically. The developed mechanism had a positioning accuracy of ±0.05 *mm* and an angular accuracy of ±0.1° which can be easily used for measuring a robot pose. However, it can be seen from the presented work that the proposed mechanism may only be useful for the pose detection if there are no requirements for the robot to continuously change its location, and thus may not be practically valid for pose detection in trajectory tracking applications. (Visioli & Legnani, 2002)[79] investigated the influence of decentralized and centralized controllers on the tracking performance for a 3-DOF robot manipulator (Fanuc M–710i). Only the first two links have been utilized in their experiments. Incremental encoders were used for the position measurements and tachometers were used for the velocity measurements. The tracking performance has been evaluated by imposing the condition on the end-effector of the robot to follow a circular trajectory. (Zhou, Meng, Ai, Liu, & Wu, 2013)[80] used photoelectric encoders for measuring the position and velocity during tracking a circular trajectory by a 6-DOF parallel platform robot. The tracking errors increase gradually when the velocity of the target grows, especially at the beginning during maximum acceleration of the robot. The velocity control errors are apparent at the beginning due to the weight of the motors, and because of the static and kinetic friction force which has to be overcome. A practical velocity closed-loop controller based on the fuzzy PID adaptive method was developed and the experimental data was recorded by using photoelectric encoders. The results showed that the average tracking velocity error of the platform was minimised from 0.154 *mm/s* to 0.057 *mm/s* in the circular movement, and also the ability of the proposed adaptive method to adapt its self in order to improve the tracking accuracy of parallel robots at the beginning of the their motion due to the adjustment of PID parameters in real-time based on fuzzy rules.

9. Other sensors:

(Hasan, Hamouda, Ismail, Aris, & Marhaban, 2009)[81] used a sensor system fixed on each joint of a 6-DOF serial robot (Fanuc M–710i). The proposed sensor systems can detect the angular position and velocity as well as the Cartesian position, orientation, and the linear velocity of the robot end-effector which are recorded to acquire data for the training of neural network. The ANN technique has been used to predict the trajectory of the robot, through their results, the highest tracking error percentage (the difference between the desired and predicted trajectory) for Cartesian positions was in the X coordinate and for the orientations was when the robot's joints rotated with a pitch angle.(García-Rodríguez & Parra-Vega, 2011)[82] used two joint position sensors fixed on the links of a planar manipulator and a force sensor attached at its end-effector. The aim of their work was to make the end effector of the robot follow a circular trajectory. A Cartesian sliding PID controller was proposed which does not need knowledge of the robot dynamics. The simulation results showed that the Cartesian tracking error exponentially converged to around zero, and the desired trajectory was closely followed by the robot end-effector. The trajectory tracking accuracy was not available in numbers in their presented work. Force sensors have been suggested and used by many researchers in the contact assembly tasks to compensate for the shortcomings of the vision sensor, since they have the capability to work in the stage of contacting the object. Therefore, force sensor based methods, such as introduced by (Payeur, Pasca, Cretu, & Petriu, 2005; Skubic & Volz, 2000)[83, 84], sensory techniques such as hybrid sensor-based methods which are based on a combination of force sensors with other sensors have been suggested by many researchers, in order to combine the advantages of these types of sensors, vision-force sensor is one of popular examples for these techniques (Wen-Chung Chang & Shao, 2010)[85].

10. SUMMARY:

In summary of this section, the use of sensory techniques for enhancing the performance of mobile robots have been reviewed, it can be said that these techniques succeeded in obtaining information about the robot end-effector along its motion trajectory, also assisting to avoid obstacles. The researchers aimed whether to introduce fast, cheap or accurate sensory techniques. It can be notified from the reviewed works that there is a difficulty in achieving a high measurement/ tracking accuracy with low processing time and hardware cost. Vision sensors as non-contact sensors have been preferred by researchers for different robotic applications that require real time tracking tasks, due to their distinctive features such as high detection accuracy and enough fast response for feedback control. Also, they are cost effective compared with large metrology systems such as laser trackers and iGPS. However, sensors such as Ultrasonics and range finders are more suitable than vision systems for obstacle avoidance tasks, particularly use with wheeled robots rather than industrial robots that have a number of degree of freedom. Moreover, sensors such as encoders and joint sensors also have also been applied by many researchers for monitoring the robots during machining processes, they are often used with other sensors like vision systems in order to obtain high quality information. The reason behind their use within sensor fusion techniques because they are individually less likely to obtain reliable and accurate measurements in the industrial environment. Also they don’t give a sufficiently good indication of the tool condition throughout their monitoring process.

11. CONCLUSION:

During the last two decades sensory techniques have been developed into a very useful technology within industrial robotic applications. This paper has reviewed the contribution of popular sensors for improving the performance of industrial robots in machining applications such as the pose estimation, object tracking and obstacle avoidance tasks for the industrial robots. This paper also highlights the advantages and drawbacks for these sensors during their practical use in the field of robotics. It is envisaged that progress in the sensory technology will further improve the precision of information extracted from or collected by sensors and minimise the computational and hardware cost. This development will further extend the potential of sensing technology and allow sensors to be used with robots more widely, probably in high-speed machining tasks.

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