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# TECHNICAL ANALYSIS ON VISUAL TRACKING DEVICES FOR ROBOTIC APPLICATION

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**ABSTRACT -** The most compelling requirements for visual tracking systems are at high detection accuracy and an adequate processing speed. However, the combination between the two requirements in real world applications is very challenging due to the fact that more accurate tracking tasks often require longer processing times, while quicker responses for the tracking system are more prone to errors, therefore a trade-off between accuracy and speed, and vice versa is required. This paper aims to achieve the two requirements together by implementing an accurate and time efficient tracking system. This paper also examines a technique for generating and controlling the observation search window in order to increase the computational speed of the tracking system, the techniques is named Controllable Region of interest based on Circular Hough Transform (CRCHT). Moreover, a new mathematical formula is introduced for updating the depth information of the vision system during the object tracking process. For more reliable and accurate tracking, a simplex optimization technique was employed for the calculation of the parameters for camera to robotic transformation matrix.

## INTRODUCTION

In robotics, the use of vision sensors in industrial tasks such as welding, drilling and pick-and-place tasks has become widespread, as the feedback obtained from these sensors make the handling of unknown and dynamic environments possible. Traditionally, industrial robots have the capability to change their position repeatedly with a small positioning error of 0.1 mm, but their absolute accuracy can be several millimetres because of tolerances, elasticities, temperature, etc. [**1**]. These sources of errors can cause a significant offset to the robot end-effector. Therefore, it is important to measure its end-effector position and orientation in Cartesian space [**2**]. There are two possible solutions for estimating the robot position. The first solution is to use inertial sensors for measuring the position of the articulated robot, for instance by using accelerometers [**3**]. The other solution is to estimate the robot position globally using external sensors such as laser trackers and intelligent global positioning systems (iGPS) [**4**]. The advantage of these measuring systems is in their capability in providing sufficient and reliable way to track the robots. However, these systems are more suited for large dynamic tracking measurements rather than small workpiece volumes, in addition to extra hardware requirements that must be installed in order to cover the desired measurement volume and the number of measurement points which raise the overall hardware cost of the tracking systems. In the aforementioned manufacturing tasks, the vision sensor is required to identify and track moving targets, the tracked target can be the object to be manipulated by the robot for example from the conveyor or it can be the robotic gripper (or the end-effector). There are two main performance requirements for applying vision systems in robotic tasks which are:

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(1) High accuracy of the output results and
(2) A fast response of the tracking system.

In other words, the accuracy and time efficiency are important, particularly in real world applications. However, achieving the two requirements together is very challenging due to the fact that more accurate tracking tasks are often performed at longer processing time, while quicker responses for the tracking system are more prone to errors, therefore the trade-off between the accuracy for speed, and vice versa is required.

**AUTOMATED TRACKING FOR THE ROBOTS**

The proposed tracking system combines two modules: object tracking module and the position estimation module. The object tracking module consists of Circular Hough Transform (CHT) which was using the Phase Coding method [**31**], the key idea of the method is in the use of complex values in the accumulator array with the information of the radius encoded in the phase of the array entries. The votes cast by the edge pixels contain information of the circle radius associated with the possible centre locations. In this work, the CHT algorithm is used for extracting a particular circular feature of the object (a ping-pong ball) obtaining its position along with its motion in pixel coordinates. This information is then passed to the position estimation module in order to calculate the position of the object in world coordinates. The object used is mounted on the end-effector of a six DOF robot (RV-1A, Mitsubishi, Tokyo, Japan) and thus the position of the arm in 3D space can be measured with respect to the target. The details of the two modules are explained in the next sections.

**Object Tracking Module**

In this section, the proposed feature extraction algorithm will be described. An enhanced Circular Hough transform algorithm was used to perform the tracking process in two phases: the initialization and tracking phase. During the initialization phase, the algorithm extracts geometric features of the object from the captured images, the two extracted features are the centre and the radius of a ping-pong ball attached to the robot end-effector. In order to detect the 3D position of the object, the proposed algorithm extracts the location of the ball from one of the two cameras in the XZ plane,

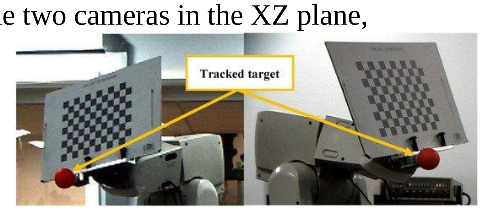


**Figure 1.** Front view (**left**), side view (**right**).

During the tracking phase of the process there is a probability that false circles will appear in the captured images due to the nature of the algorithm (phase coding method) used as an edge detector which detects the objects based on their elliptic shape and brightness compared to the background. The brightness of the object to be tracked depends on its colour, therefore in order to reduce the probability of failure in the object detection, the colour of the object should be carefully selected in order to be easily distinguished from the background and reliably detected and thus tracked by the algorithm.

**Colour Selection**

This part of the experimental work aims to find the appropriate colour for the tracked object, which ideally should meet two requirements: (1) the colour should be easily recognized and distinguished from the scene; and (2) the colour should be robust to the variations of the light illumination. The latter requirement is challenging for our application due to the fact that the proposed visual tracking algorithm will be applied in working environments. A 3D laser scanner (namely a Focus 3D X30, FARO, Lake Mary, FL, USA) was used for full scanning of the laboratory environment by taking hundreds of pictures.

The importance of this part of the experiment is to find a strong colour that can be recognised without any interference with other colours or lighting and background variation. The lab environment was prepared with different coloured objects such as machines, tables, tissues, computers, coloured papers and etc. The algorithm was used for performing simple colour detection via Delta E colour difference. The algorithm converts images from Red, Green, Blue (RGB) colour space to the LAB colour model, then the difference between colours in LAB space was calculated for every pixel in the image between the colour of the pixel and the average LAB colour for the region specified by the user, so the relative perceptual differences between any two colours in L*a*b* can be calculated by dealing each colour as a point in a 3D space (with three components: L*, a*, b*) and then calculating the Euclidean distance between them. This Euclidean distance in L*a*b* space is ΔE (often called "Delta E") [**32**]:

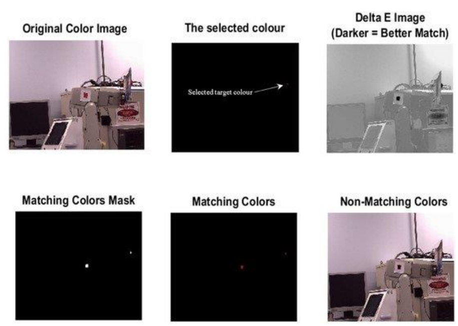


**Figure 2.** Detection of the red coloured objects.

$$\Delta E = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2}$$

The best match for the colour of the specified region is represented by the darker colour in Delta E image as shown in **Figure 2**. **Table 1** which shows a list of colours that the algorithm succeeded or failed to recognise them from the background.The intensity or the force of the colours also should be taken into account, since the intensity of object's colour changes according to the location of the object from the camera. Objects with red colour as an example of how the colour can be successfully recognised at different locations in the scene. As a result of this experiment, the red colour was chosen as the colour of our tracked target. In order to ensure that the selected colour for the object is suitable for the proposed tracking application, different coloured balls (see **Figure 3**) have been positioned at different eight locations in the lab, and the cooperation of a fixed camera system and the CHT algorithm was used to track the object in a video mode. The experiment has been repeated 20 times under different eight lighting conditions and object backgrounds (i.e., each coloured ball was tested 160 times). Also, at different distances for the objects from

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the camera's location (the smallest distance between the camera and the tracked object was around 50 cm and the farthest was approximately 3 m).

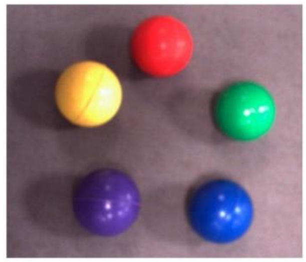
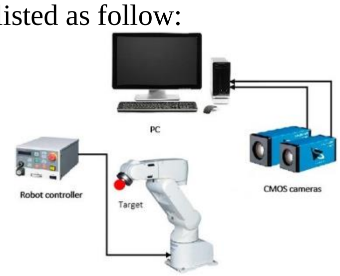


**Figure 3.** Different coloured objects.

## EXPERIMENTAL RESULTS AND DISCUSSION

Before describing the results of the experiment, we must describe the architecture of the tracking system (see **Figure 6**). The system consists of a six DOF robot (Mitsubishi RV-1A, Tokyo, Japan) with a red coloured ball attached to its gripper, a standard PC, and two calibrated CMOS cameras (namely DFK Z12GP031 and DFK Z30GP031) from the Imaging Source (Bremen, Germany) are used for observing and estimating the object motion. The reason behind using colour cameras rather than monochrome sensors is in the capability in using colour filters to control scene contrast, and to keep the other choice applicable which is to convert colour into monochrome. With colour capture, any arbitrary colour filter can be applied in post-production to customize the monochrome conversion, whereas with monochrome capture, the effects of a lens-mounted colour filter are irreversible. The GigE colour cameras are fixed at around 2 m from the object plane and both are connected via Ethernet to the PC, the tracking system was implemented on a Windows environment running on an AMD FX™-9370 Eight-Core Processor 4.4 GHz with 16 GB of system memory. The reason behind the selection of these cameras is due to their distinctive features compared to other manufactured cameras which make them suited for the tracking applications, the main features of the selected cameras can be listed as follow:



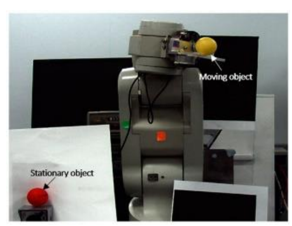




**Figure 4.** Architecture **Figure 5.** Setup

- The cameras have an integrated motorized zoom lens, iris and focus that allow for the user to capture objects of differing sizes or when multiple frames at differing magnifications are required.
- The cameras are implemented with CMOS sensors that are highly sensitive sensors making them uniquely suitable for colour based tasks such as component inspection.
- The cameras are supported with a number of powerful software tools such as IC capture and IC measure, the IC capture provides the ability to control the functions of the camera such as auto white balance, noise reduction, and contrast, saturation, and exposure times. The IC measure provides tools for on-screen

calibration with an ocular microscope, and provides tools for measuring different shaped objects such as polygons, circles and angles, the measurement tools are designed for both macroscopic and microscopic applications. Also, it offers tools for the optical distortion correction which can corrects barrel, pincushion, and vigneting distortions.

Vision-based tracking research, particularly for precision manufacturing tasks, has typically concentrated either on the requirement of the accuracy or the time-efficiency, therefore, this paper aims to bridge the gap between the two important performance requirements by introducing an accurate and time-efficient tracking system that is also robust in industrial environments. This paper presents and validates an Eye-to-Hand visual system for tracking an industrial manipulator performing a pick-and-place task. The cooperation of Circular Hough transform with an averaging filter is used to obtain the visual information of the tracked target. In order to cope with the computational cost of the image processing, a technique named Controllable Region of interest based on Circular Hough Transform (CRCHT) is introduced for speeding up the tracking process by generating dynamic small search windows instead of using full sized images..

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