A Modular Robotic System for Colour-Based Laboratory Sample Sorting

I confirm that any use of Generative AI tools in the preparation of this report complies with Maynooth University's guidelines. Where GenAI tools have been used to support my work, I have acknowledged this appropriately.

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I. Background

Clinical laboratories process large volumes of diagnostic samples, and errors in sorting can lead to misdiagnosis, delays, or wasted resources. Traditional manual sorting of samples is labor-intensive and repetitive, creating opportunities for automation to improve efficiency and reliability. Robotic systems have the potential to undertake such tasks repeatedly with high accuracy while freeing human operators for higher-level clinical tasks [1].

In parallel, modern healthcare is undergoing a paradigm shift driven by the convergence of advanced technologies such as robotics, artificial intelligence (AI), and the Internet of Things (IoT). These developments are part of the broader Industry 4.0 framework, which emphasizes the integration of cyber-physical systems, data analytics, and automation across sectors, including healthcare [2][3]. When applied to healthcare, this approach is often referred to as Healthcare 4.0 or Smart Hospitals, where digital connectivity and intelligent systems improve clinical workflows, patient care, and operational efficiency [2][4][3][1].

This work tackles a specific task within this broader context: developing a modular robotic prototype to sort color-coded laboratory samples. The main problem addressed in this work is the need for a modular, reliable, and scalable robotic system that can:

- Detect and identify samples based on color labels.
- Determine the correct placement for each sample.
- Execute pick-and-place operations with minimal human supervision.

By solving this problem, the system contributes to smart laboratory automation and provides a foundation for broader applications in healthcare robotics.

II. Design Rationale

A. Colour-Based Identification

In clinical laboratory settings colour is frequently an established system used for differentiating various clinical materials. Phlebotomy tubes used for collecting blood samples are a good example of colour coding in clinical settings. Figure 1 shows an example of colour coded phlebotomy tubes from Kindly (KDL) Meditech.

Fig. 1. Phlebotomy Tubes Colour Coding [5]

Although designed to be easily distinguishable, this range of colours clearly shows where human vision may confuse one tube for another, and where computer vision will help reduce errors. The Gold serum-separating tube with a clot activator and gel is visually similar to the yellow tube with ACD/SPS used for DNA testing, blood cultures and immunology. The colour-coded sorting system is also applicable when sorting other categories of medical items in a clinical setting. Medications are also often labelled with colours to differentiate them [6]. As this sorting system is intended to be used alongside staff in a clinical setting, it is a major benefit to align the sorting method along the pre-established human-centred sorting method. Other potential methods of sorting similar items could be QR codes, NFC tags or bar-codes. These methods may be preferable in industrial settings but are not suitable in a clinical setting where aligning with a staff member's method of sorting is more valuable. For these reasons the robotic sorting system has been designed to use a colour based system as the visual identification marker for clinical samples.

B. Modularity

Both the software and the hardware of the robotic system have been designed with modularity as a core feature. This modularity is important as it will allow clinicians to define the colours and sorting order to reflect the pre-established system of the specific clinic. Phlebotomy tube colour coding is not internationally aligned yet despite calls for standardization [7]. Aligning with the established system of a given clinic would help the adoption of the robotic system as it eliminates the need for retraining staff on a new sorting system.

Fig. 2. Photograph of the Interbotix ReactorX-200 Robot Arm with 3d printed camera mount and colour samples

The Interbotix ReactorX-200 Robot Arm (see Fig. 2) was used for development but modularity allows for other models to be used instead where needed. The grippers on Interbotix Arms are made to be fully customizable by utilising 3D printing.[8] The structure and shape of medical sample containers and medications can vary between different settings. The grippers can be customised to fit the precise dimensions of the containers and the requirements of the specific clinic. This software and hardware modularity allows for the robotic arm to be adapted for many different sorting tasks.

C. Cost

The state of the art of medical equipment is unobtainable for many clinics in socio-economically disadvantaged areas. This robotic colour sorting system design is well suited to these clinics. The modularity of the system is a particularly beneficial element as depending on their need, one robotic arm could do much more than one overly specified arm. The footprint and cost of the robotic arm are both significantly less than many current commercially available lab sample sorting systems. The automated sample tube sorting PTL-Machine from Graniten has a large footprint of 1.3x1.6m [9] compared with the small base of 0.25x0.1m RX-200 robot arm, the system demands less space in already crowded laboratory settings. This system aims to reduce costly errors and need for repeated tests, which is also a significant benefit in these communities.

III. System Design and Implementation

A. Overall Architecture

The robotic sorting system consists of two primary modules: perception and control. An overhead camera captures images of the workspace containing one or more colour-coded test containers. The perception system identifies the colour and position of each container and sends this information to a control module that determines the appropriate placement location, computes and executes the motion plan to pick and place the container at its target.

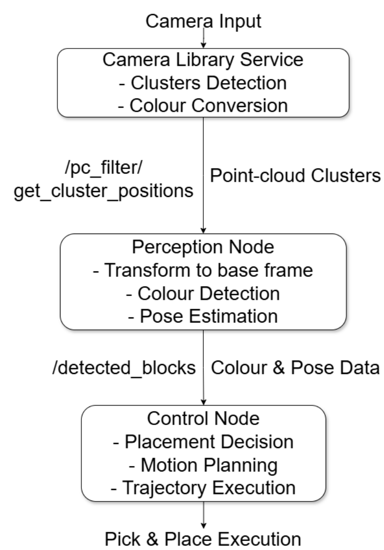

Fig. 3. Modular ROS2 architecture showing **camera input**, **perception processing**, **decision mapping** and **robotic actuation**

B. ROS2 Nodes and Communication

The system leverages ROS2 to structure the software into flexible, reusable components: Perception Node: Uses point-cloud clusters to get the transformed position and colour of the object, and publishing this information as ROS2 messages. Decision Node: Subscribes to perception output and maps colours to target coordinates. Control Node: Subscribes to perception output and maps colours to target coordinates, then uses MoveIt2 to plan and execute paths for the robotic arm. Communication is handled through ROS2 topics and services to support asynchronous, decoupled operation suitable for future scaling.

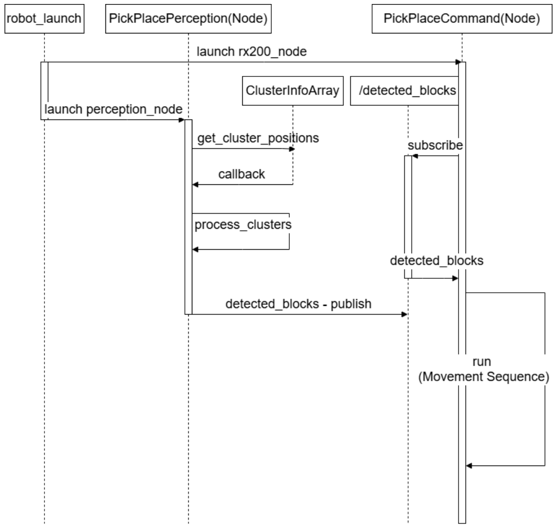

Fig. 4. Ros2 Nodes and Topics Sequence Diagram

C. Hardware and Software Stack

Hardware Components, see Figure 5:

- A 6-DOF robotic manipulator
- Overhead RGB camera
- Standard colour-coded laboratory test containers

Software Stack:

- ROS2 Humble middleware
- Python 3.10
- Interbotix libraries for image processing
- MoveIt2 for motion planning

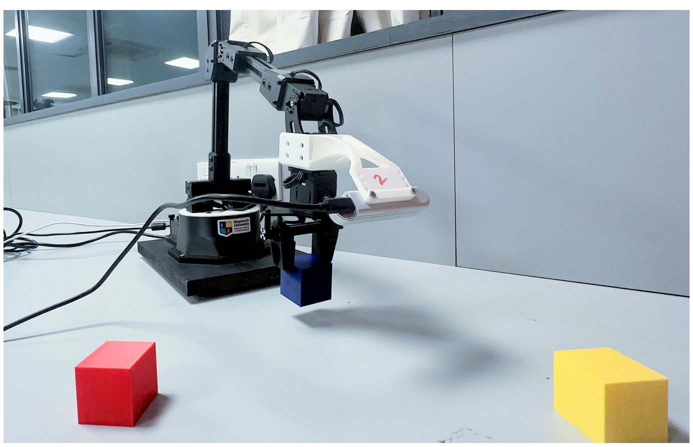

Fig. 5. Photograph of the experimental setup showing the camera, robotic arm, and sample workspace.

D. Perception Pipeline

The perception pipeline starts by detecting point-cloud clusters through a service provided by the Interbotix libraries. Internally, the service processes standard RGB frames and converts them to the HSV colour space, which offers greater robustness to variations in lighting. Colour-based thresholding is then applied to segment red, green, and blue regions within the scene. From these segmented regions, contours are extracted and their centroids computed. The resulting object position and colour information is published by the service and consumed by the perception node, which aggregates the data into a list of coloured objects and packages it into ROS 2 messages for downstream processing.

IV. Method of Assessment

This system was assessed primarily based on its ability to accuracy to detect the example samples colour. The system was tested using an Interbotix ReactorX-200 Robot Arm and a set of three cubes of different colours representing the samples that are to be sorted. The system was tested under various lighting conditions to test the robustness of the colour detection. The locations of the cubes were also varied to test the robot system's ability to detect the sample positions.

V. Findings

The proposed robotic system effectively identified, categorized, and sorted colour-coded laboratory samples through a modular architecture implemented in ROS2. Experimental results showed reliable colour identification and accurate object localization under controlled lighting conditions. The perception pipeline successfully distinguished red, yellow, and blue samples and generated position estimates suitable for downstream motion planning. The robotic manipulator executed pick-and-place actions using collision-free trajectories planned with MoveIt2.

The modular separation of perception, decision-making, and control nodes enabled efficient communication and supported system extensibility. While the system performed reliably under controlled conditions, the experiments highlighted sensitivity to lighting changes, which is characteristic of purely colour-based perception approaches. In addition, small variations in object localization during pick execution revealed opportunities to further refine position estimation and grasp alignment. Overall, the results demonstrate the feasibility of the proposed approach for structured laboratory sorting tasks and provide clear directions for future system enhancements.

VI. Implications and Future Work

A. Implications

This work demonstrates the practical applicability of a modular, ROS2-based robotic system for colour-based sorting of laboratory samples. By automating a repetitive and structured task, the system reduces manual intervention while improving consistency within laboratory workflows. The modular system architecture supports scalability, flexibility, and interoperability, which are key requirements of Healthcare 4.0 and smart laboratory environments. The integration of perception, decision-making, and robotic manipulation illustrates the potential of cyber-physical systems to enhance efficiency and reliability in routine clinical operations.

B. Future Work

Future enhancements include the incorporation of machine learning–based object recognition to support a wider range of sample types beyond simple colour coding. Adaptive grasping strategies using force or tactile sensors could be introduced to improve grasp reliability and reduce handling errors. Integration with hospital or laboratory information systems would enable real-time sample logging, tracking, and traceability. In addition, scaling the system to multi-robot configurations could support higher throughput and automation of larger laboratory workflows typical of modern smart hospital environments.

***Index Terms*—Robotic Arm, Sample Sorting, Computer Vision, ROS2, Healthcare Automation, Industry 4.0, Smart Hospitals**

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