Design and implementation of a microrobot system for manipulation of microscopic objects

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***Abstract*—This article presents the proposed approach of a microrobot system for detecting and manipulating microscopic cells. The main functionalities of the system are grouped around 3 modules: the micro-robot itself, the robot control module and the object detection module. This is ongoing research, whereas initial results have been achieved and are also presented in this article.**

***Keywords*—object detection, micro-manipulation, enhancement**

I. Introduction

Nowadays, the need for the manipulation of micro-objects is constantly growing and the detection of living cells is an important issue in automated equipment for living cell manipulation [1]. To perform manipulation tasks, the exact location of the cell should be known. However, the living cells usually are placed in the growth medium, which is non-transparent and makes the visual recognition of cells difficult. Whereas, the image quality can be influenced by the nature of the object material, calibration parameters, ambient light conditions, etc. Existing systems for biological object manipulation are quite often manually controlled and most of these systems are tested not with biological but with polymer or metal micro-objects [1]. User participation is currently required to determine the position of the object and the distance to the object being manipulated. The main aim of this research is to complement the micro-robotic manipulation system with object detection, recognition and positioning using visual recognition and machine learning.

II. System overview

The proposed micro-robotic manipulation system, illustrated in Fig. 1, consists of three main modules, each responsible for different functionality. The object detection module consists of image enhancement and object detector sub-modules and is responsible for the localization of objects of interest. It takes as input a capture of the environment. The capture is first enhanced, to clarify the borders between objects, and then an object detector finds the object's bounding boxes and centre coordinates, which can later be sent to the robot control module.

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The robot control module includes a client, connected to the object detection module, a LabView control application and a LinuxCNC-based robot control sub-module. The control application receives the object coordinates via the client and sends them as control commands to the micro-robot via the robot control sub-module. The micro-robot can then act upon received coordinates to locate the object of interest. Captures of the success of the movement and new environment can be made with the camera mounted upon the micro-robot. The main functionalities are further described in the following subsections.

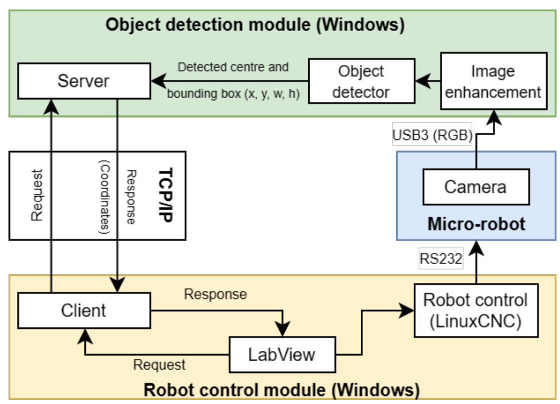

Fig. 1: System architecture

A. Image enhancement

Image enhancement plays a vital role in improving the image quality of living cells acquired from the microscope by emphasizing key features, reducing secondary characteristics, enriching information, and enhancing details. Fuzzy Automatic Contrast Enhancement (FACE) [3] is applied as a contrast enhancement technique for microscopic images of living cells. FACE changes the original pixel distribution to a more uncongested one while maintaining smoothness in the colour distribution to prevent artefacts in living cell images.

B. Visual recognition

Individual living cell image recognition and localization are determined by finding the outline and coordinates of the cell. A state-of-the-art deep learning algorithm YOLOv7 is used, which performs the real-time process of recognition and localization of cell contours and centres. The network detects living cells in two stages using anchor boxes and the predicted objectness score. YOLOv7 learns to predict the bounding boxes and class labels of living cells from ground truth annotations during training, making it highly advanced and efficient for detecting living cells.

C. *Micro-robot*

An original four-axis micro-robot with scanning electrochemical microscope capabilities is developed and used for experiments. It comprises a mechanical manipulation and optical systems, a motion controller, electrochemical signal reader, and main control unit. The main controller, implemented on a PC, controls the system, runs the user interface, and generates robot movement trajectory and measurement commands. Lower-level controllers and devices handle specific tasks. Driver control is realized using LinuxCNC software enabling compensation of backslashes and synchronized motion of all drives, required for tool manipulation in complex trajectories. The mechanical system of the microscope has four degrees of freedom, based on the kinematic scheme of an orthogonal manipulator with additional z-axis to separate tool movement from optical camera movement. Micromanipulator housing, made of cast iron, provides thermal stability and high stiffness. Precisely controlled drives are installed for high accuracy and resolution. All implemented drives use ball-screw with micrometre pitch, controlled by stepper motors operating in 1/256 micro-step mode. The system has x-y axes for table movement, a z-axis for focal distance control, and another z-axis for electrode, sensor or micromanipulation tool movement.

D. *Traning data acquisition*

The real data consists of so-called raw images taken directly with a micro-robotics system as described in section II-C. Several procedures have already been performed on average acquiring around 150 real images of yeast cells in each run. However, the gathering of real yeast cell images can be a difficult and very time-consuming task as it includes the preparation of yeast solution and manual acquisition of data in a controlled environment [2]. Furthermore, the data needs to be labelled, which again is a tedious process, therefore we have also explored possibilities to synthetically generate yeast cells images. The synthetic dataset consists of computer-generated yeast cell imagery, where replicas of yeast cells were made in the program Blender3D and then automatically implemented into different scenes. Synthetic datasets were generated to the required amount for the performed experiments.

III. Initial tests and results

In the current stage of the ongoing research activities, more emphasis has been put on the testing and verification of different modules of the micro-robot system as described in section II. In regards to the micro-robot itself, its accuracy was tested in different modes. It was experimentally defined that in x and y-axes, positioning accuracy depends on the motion stroke. Avg positioning errors of 0.5 μm, 0.1 μm, and 1.5 μm for the y-axis, and 0.45 μm, 0.2 μm 1.65 μm for the x-axis under the strokes of 1 mm, 10 mm, and 50 mm were defined. Such results show that positioning errors are caused by different phenomena, in the case of a small stroke prevails static friction and the sticking effect, however on a large stroke – cumulative errors.

Regarding visual recognition, several experiments have been performed (example in Fig. 2). 10-fold cross-validation was employed to evaluate the performance of YOLOv7 models trained on original raw and FACE-enhanced images. The FACE training model exhibited a superior average accuracy rate of 95.2% during testing. Notably, the Face training model demonstrated a consistently stable accuracy rate in scenarios of blurred images or unclear cell outlines, which was superior to the original (raw) image training model. Furthermore, several experiments have been performed by diversifying the training data sets for the visual recognition system and adding synthetic object replicas into real images for tackling the problem of imbalanced datasets. Overall the initial results show that using the models trained on diversified training data sets (raw + enhanced + synthetic) outperforms models trained on purely raw data coming from the microscope.

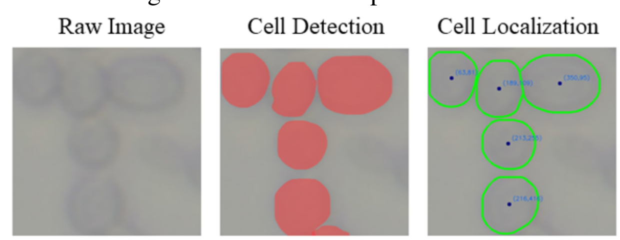

Fig. 2: Cell recognition using YOLOv7

The first tests have also been performed for the verification of the overall functionality of the system, in particular, several sub-modules and the flow of information. Initial tests for capturing an image, detecting an object in it and transferring the object's centre coordinates to the robot control application sub-module have been successful.

IV. Conclusions

In this paper, the architecture of a microrobot system for precise living cell manipulation based on visual recognition and machine learning has been proposed. It can be seen that, by adding a few extra modules to a system, a commonly manually done task can be automated significantly, increasing the productiveness and precision of the whole process.

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