

ESP3903 Major Design Project 2

Designer Drugs: Assembling Custom Dosed Personal Medicines

Gokul Nathan, A0184199M

Phun Zheng Hui, A0167667L

Tan Jin De, A0167372Y

Siah Jing Ze, A0166782R

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Designer Drugs: Assembling Custom Dosed Personal Medicines

Group 3

Gokul,…

Abstract"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum."

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Designer Drugs: Assembling Custom Dosed Personal Medicines

# Introduction

The manufacture of pharmaceutical drugs is a complex multi-stage process that ensures that the correct amount of drug substance is delivered at the appropriate time, rate and at the desired location with its chemical integrity protected to that point (Mohan, 2012).

Pharmacy compounding involves the preparation of customized medications that are not commercially available for individual patients with specialized medical needs. Traditional pharmacy compounding is appropriate when done on a small scale by pharmacists who prepare the medication based on an individual prescription. However, in 2015, the FDA approved for commercial use the world’s first 3d-printed, a form of additive manufacturing, pill (citations required). This opens new opportunities for pharmacy compounding to be done using small scale automated manufacturing. This project seeks to explore the challenges involved in designing a custom desktop automated medicine compounder.

## Objective

The primary objective of this project is to prototype an automated desktop size auto drug assembler.

## Scope

Drug manufacturing and assembly process is large, complicated and multi-step. To achieve the projective objectives in a reasonable time frame, the scope of the project must be narrow.

The prototype designed to pack various counts of multiple sub-millimeter pods into a larger pill. The manufacture, design and suggested dosing of the sub-millimeter pods falls outside the scope of the project. As this project serves as a proof-of-concept validation prototype, the initial pods will be larger and made of more durable steel. Initial testing, calibration and proof of concept will be done utilizing steel ball-bearings of 2.5, 3.0, and 3.5 mm diameter.

# Design

The design considerations are broken down into two areas of focus. A feeder-hopper combo unit that feeds a known calibrated number of pods to packer and sensor package that counts and classifies the pods being packed. (Add overall SW assembly to appendix)

## Feeder-Hopper

Ball-bearings of different sizes will be inserted into the feeder hopper, which consists of a screw conveyor that is encased within a cylindrical tube. This screw conveyor is connected to an external servo motor to create a rotational motion that drives the ball-bearings down a spiral path, leading to the counter-classifier sensor.

## Counter-Classifier Sensor Assembly

The counter classifier utilizes an array of light-dependent resistors (LDRs) and photodiodes to count the number of bearing in the packer and classify them according to size and color. The sensor is based upon the concept of reflection-deflection-scattering pattern forming. A laser of known wavelength fires a narrow 1 mm beam across the polyurethane tubing carrying the pods. As the reflection and refraction co-efficient of the tubing is different when compared to the air surrounding the tube, the incoming laser beam is scattered in a pattern. This pattern changes when another object with different reflectivity and size passes through the tubing. LDRs and photodiodes are used to capture this pattern. These patterns are fed into a neural net to create an automatic classifier algorithm using machine learning (ML) that can classify live pattern data generated when the device is in operation.

# Experiments and Results

## Collecting single sensor calibration data

Testing was done to assess the performance characteristics of the individual sensor assemblies. A 5V potential divide was applied across the assembly. An estimated 1500 lumens illumination source was used as light source. The light was turned on and off using computer control. The rise time was measure using an oscilloscope to characterize the speed and response of the LDR. The performance of a photodiode was measured under identical conditions.

## Analysis of single sensor data

|  |
| --- |
| Project Path: C:\Users\e0310994\Documents\OriginLab\User Files\UNTITLED.opju PE Folder: /UNTITLED/Folder1/ Short Name: Graph3 |
| Figure xyz. Voltage response of LDR between on-off state |

In presence of light

## Capturing Scanned LDR array data

Multiple individual LDR assembly as described in the preceding section are arranged around a 3.5 cm square assembly. They are then wired up as shown in figure xyz. The voltage data across the array is collected using an Arduino Mega 2560 reading analog voltage across the LDR in a serial loop. This data is used to train the ML model using Tensor Flow. Figure XYZ shows the voltage values for 5 key LDR sensors for empty PU tube, 3.5 mm and 3 mm ball bearings are present.

|  |
| --- |
| A screenshot of a video game  Description automatically generated |
| Figure xyz. Counter-Classifier sensor assembly electronic diagram |
|  |
| Figure xyz. Counter-Classifier sensor assembly electronic diagram |

## Analysis of array data

The microcontroller used in the experiment runs at a frequency of 16 MHz. However, as the microcontroller is single-threaded, there exists a large performance penalty in terms the time taken for all the voltage values to be collected. Time taken for complete scan of 9 sensors is 3063 microseconds. However, transmitting this data to the host PC introduces severe performance penalties. The loop time increases to roughly 0.8 s. Code and architecture of the program needs to be revised to reduce this overhead. The microcontroller reads the voltage levels between 0 and 5 volts with a resolution of 9 effective bits. This translates to each step measuring 9.76 mV. Based on collected calibration data, it is calculated that minimum size delta possible to be sensed by the array is 0.4 mm.

It has also been determined that there may not be enough time for the sensors to collect enough data to adequately determine the size and colour of the ball bearings falling through. The time, , that a ball bearing takes to pass through the sensor array can be determined by calculating the velocity, , of the ball bearing as it passes through the array, and using the distance, , that the ball bearing passes through the sensor array divided by to obtain the time, .

Where , ,

After calculations, there is only 65 ms when the ball is detected by the sensor array. Since the current time taken for a complete scan of all the sensors is 0.8 s, it can be deduced that that is not enough time for...

# Conclusions

From the results, it is believed that further improvements are necessary to proceed with the development of the final product. First is to replace the current sensor array with a camera with a built-in microcontroller (Pixy2). Along with machine learning, it is possible to not only identify whether a ball has passed in front of the camera, but also determine its colour, and size (with assistance of a lens) using the Pixy2. The Pixy2 is chosen because the hardware, software, and firmware are open source, software libraries are available for the Arduinos currently possessed, and can perform colour identification at 60fps, allowing for a rapid response time to identify the falling ball bearings. Through machine learning, we will be able to rely on patterns and inference to sort out the various ball bearings based on its colour and size.

# Acknowledgments

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# Distribution of work

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# References

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