School of Computing
FACULTY OF ENGINEERING AND
PHYSICAL SCIENCES

Final Report

Chess Vision

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Submitted in accordance with the requirements for the degree of Computer Science

2021/22

<Module code and name>

The candidate confirms that the following have been submitted.

Items	Format	Recipient(s) and Date
Final Report	PDF file	Uploaded to Minerva (DD/MM/YY)
<Example> Scanned participant consent forms	PDF file / file archive	Uploaded to Minerva (DD/MM/YY)
<Example> Link to online code repository	URL	Sent to supervisor and assessor (DD/MM/YY)
<Example> User manuals	PDF file	Sent to client and supervisor (DD/MM/YY)

The candidate confirms that the work submitted is their own and the appropriate credit has been given where reference has been made to the work of others.

I understand that failure to attribute material which is obtained from another source may be considered as plagiarism.

(Signature of Student) _____

Summary

<Concise statement of the problem you intended to solve and main achievements (no more than one A4 page)>

Acknowledgements

<The page should contain any acknowledgements to those who have assisted with your work. Where you have worked as part of a team, you should, where appropriate, reference to any contribution made by other to the project.>

Note that it is not acceptable to solicit assistance on 'proof reading' which is defined as the "the systematic checking and identification of errors in spelling, punctuation, grammar and sentence construction, formatting and layout in the test"; see
`https://www.leeds.ac.uk/secretariat/documents/proof_reading_policy.pdf`

Contents

Chapter 1

Introduction and Background Research

1.1 Introduction

Algorithms such as Deep Blue [1], AlphaZero [] and more recently Player of Games[] have enabled computers to out smart the smartest humans at the game of Chess. But all these algorithms are bound to the digital world, rendered useless when competing against humans on a real board. This project aims to explore a major component of this: vision. We consider the vision problem for chess to be two-fold; what is the current board state and where are all of the pieces? With this information, in combination with the previous algorithms, and a robot arm, the computer is no longer bound to the digital world.

1.2 Literature review

When we ask ourselves: what is the hard part of Chess? One may think it's the strategy, another may say anticipating what the opposition is going to do next and the more statistical among us may formulate it as choosing the most likely action for victory. It is highly unlikely, however, that one would say it is locating where the pieces are in 3D space.
For computers this is among the hardest of the challenges. Make reference to humans huge allocation of resources to vision. [] Why is it so hard for computers then? It's an inverse problem. Compare to solving the decision problem (minimax). The statistal calculation of whether to trade Queen's or block with a pawn has now become trival.

1.2.1 A Short History of Computer Vision

Classical Techniques

How we can use classical techniques to understand images. Neural networks have taken over almost all of the heavy lifting for high level inference. Give an indication of time scale here.

Image Recognition

Le Ye Cunn's work with convolutions [] and MNIST [] and more recently ImageNet [] having become incredibly well known. New methods such as Transformers from the world have NLP have generalised the convolution operation have proved very successful and lots of work here has been applied to vision. [] [] [] (Attention is all you need, ViT, generic model from deepmind)

Object Detection

But in most applications there will be many things we want to recognise in an image. The RCNN [] enters. How Faster-RCNN improves on this []. Why YOLO [] has been so successful (realtime). Transformers are applicable here too.

Instance Segmentation

Why bounding boxes are not enough. What is segmentation? Why instance segmentation is what we actually want. []

Adding More Dimensions

The real world is not percepived in static 2d images. How do we add an understanding of 3 dimensions and time in our computer vision models? [] Important for localisation in the real world. Important for understanding things like object permenance.

1.2.2 Computer Vision for Chess

Finding the chess board is the first challenge, the most common solution as in [] is to use the 'findChessboard' function in openCV for camera calibration. This **how does this work**.

Chapter 2

Methods

<Everything that comes under the 'Methods' criterion in the mark scheme should be described in one, or possibly more than one, chapter(s).>

2.1 Data Collection

At the heart of any machine learning project is the data. It is as important, often more important, than the code and presents many interesting challenges. **Why is this?** Discussed in the following sections are some of the challenges and decisions that were considered.

2.1.1 Sensors

The eminent challenge is acquiring data in the first place. This is highly context dependant, but as vision is primarily focused on spatial awareness the discussion will be limited to the sensors that can measure it.
Sensor choice is an important choice for any robotics application as there are important tradeoffs, as with any engineering challenge, which must be considered.
Outline some of the tradeoffs between spatial sensors
One important distinction to make is the difference between training and inference. Requirements at the time of training my differ significantly to the requirements at inference. Processing power, energy supply and realtime operation are some of the constraints that will have to be met when considering different sensors.
The sensor used throughout this project is the RealSense SR305 which is a RGB-D camera using structured and coded light to determine depth, it functions best indoors or in a controlled lighting situation. For the reasons outlined above the RGB camera stream is mainly relied upon but there will be some discussion and comparision of piece detection with the depth sensor.

2.1.2 Auto-Labelling

A closely related challenge of acquiring the data is that of labelling it too. It is widely known that neural networks scale with the number of examples []. This will be explicitly explored for Chess Vision in section 3.1. This however poses the question about how do we get access to a lot of labelled data for chess. **Some examples of other auto labelling techniques** The overall approach I took...

2.1.3 Dataset Versioning

With all this data the next challenge becomes self evident. It is concerned with the question: How do we manage all of this? Some of the problems... and why you need versioning... Transitioning from git lfs to aws s3. Perhaps a quick mention of other solutions. How the Game class solves some of these challenges for us.

2.2 Model Training

Due to how we are autolabelling and the process of finding the corners we can stick with simple image recognition and find a network that gets us the best result.

2.2.1 Architectures

We start with a baseline.
Start with a super simple network and overfit. Remove bug until training works. Add a feature... more layers, convolutional layers ect. and repeat process.
With just a 3 layer fully connected neural network with no optimisations an accuracy of over 60% can be achieved.
All the way back in 1980 [] convolutions showed promise in simple computer vision tasks, convolutions since have showed extreme promise [], so this was the first improvement made to the architecture. An immediate problem presented itself: overfitting. Now 50% accuracy is the best we are seeing, with overfitting beginning just 50 epochs in.
Attempt using a ViT.

2.2.2 Experiment Tracking

Express importance of experiment tracking. Some of the solutions [] and their tradeoffs. Why guild was chosen and how it was used.

2.3 Realtime Inference

2.3.1 The Realiable Approach

As in [] the most reliable way to implement infrence during play is for a user to input when a move has been complete. This is not ideal because...

2.3.2 The Not-So-Reliable Approach

What if the system constantly updates with each new frame? Why this is what we want, but is not as important for finding board state. Some of the challenges involved and how we overcame them.

Chapter 3

Results

<Results, evaluation (including user evaluation) *etc.* should be described in one or more chapters. See the 'Results and Discussion' criterion in the mark scheme for the sorts of material that may be included here.>

3.1 Model Evaluation

3.1.1 Board Identification

Aruco vs Chessboard vs heatmap.
Compare results of 5 examples. Why chessboard [] will struggle with peices on the board. Breif intro to Aruco. For capturing data Aruco is very reliable, but won't always be possible to add onto the board. Why heatmap solution looks like the best appraoch in the realword with unknown environments. []
Time comparision for the 3. And compare accuracy of heatmap against aruco.

3.1.2 Piece Recognition

Will include basic evaluation. What happens what you increase layers, use more data, data augmentation. Include Recall / Specificity / Sensitivity

3.1.3 Piece Detection

A benefit of having the depth sensor is an easier way to detech piece presence. Fixed threshold vs clustering. Adding a margin. How we actually did it. Using paried T-test to evaulate.
Using a neural network instead as an additional class with our piece recognition network. Compare that two having a two stage network, the first for piece detection and the second for recognition.

3.1.4 Deep Dive into CNNs

Visualising convolutional layers to analyse effectiveness.

3.2 Realtime Analysis

Frames per second. Problems.

3.3 Comparison to Existing Solutions

Summaries how my solution compares to others. Need a table?

Chapter 4

Discussion

<Everything that comes under the 'Results and Discussion' criterion in the mark scheme that has not been addressed in an earlier chapter should be included in this final chapter. The following section headings are suggestions only.>

4.1 Conclusions

Aliquam lectus. Vivamus leo. Quisque ornare tellus ullamcorper nulla. Mauris porttitor pharetra tortor. Sed fringilla justo sed mauris. Mauris tellus. Sed non leo. Nullam elementum, magna in cursus sodales, augue est scelerisque sapien, venenatis congue nulla arcu et pede. Ut suscipit enim vel sapien. Donec congue. Maecenas urna mi, suscipit in, placerat ut, vestibulum ut, massa. Fusce ultrices nulla et nisl.

4.2 Ideas for future work

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References

[1] D. Parikh, N. Ahmed, and S. Stearns. An adaptive lattice algorithm for recursive filters. *Acoustics, Speech and Signal Processing, IEEE Transactions on*, 28(1):110–111, 1980.

Appendix A

Self-appraisal

<This appendix should contain everything covered by the 'self-appraisal' criterion in the mark scheme. Although there is no length limit for this section, 2—4 pages will normally be sufficient. The format of this section is not prescribed, but you may like to organise your discussion into the following sections and subsections.>

A.1 Critical self-evaluation

A.2 Personal reflection and lessons learned

A.3 Legal, social, ethical and professional issues

<Refer to each of these issues in turn. If one or more is not relevant to your project, you should still explain *why* you think it was not relevant.>

A.3.1 Legal issues

A.3.2 Social issues

A.3.3 Ethical issues

A.3.4 Professional issues

Appendix B

External Material

<This appendix should provide a brief record of materials used in the solution that are not the student's own work. Such materials might be pieces of codes made available from a research group/company or from the internet, datasets prepared by external users or any preliminary materials/drafts/notes provided by a supervisor. It should be clear what was used as ready-made components and what was developed as part of the project. This appendix should be included even if no external materials were used, in which case a statement to that effect is all that is required.>