

Enhancing Colour-Coded Poll Sheets Using Computer Vision as a Viable Audience Response System (ARS) in Africa

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DEDICATIONS

DEDICATIONS

I would like to thank the Lord for taking me on this amazing journey.

ACKNOWLEDGEMENTS

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ABSTRACT

Audience Response Systems (ARS) give a facilitator accurate feedback on a question posed to the listeners. The most common form of ARS are clickers; Clickers are handheld response gadgets that act as a medium of communication between the students and facilitator. Clickers are prohibitively expensive creating a need to innovate low-cost alternatives with high accuracy.

This study builds on earlier research by Gain (2013) which aims to show that computer vision and coloured poll sheets can be an alternative to clicker based ARS. This thesis examines a proposal to create an alternative to clickers applicable to the African context, where the main deterrent is cost. This thesis studies the computer vision structures of feature detection, extraction and recognition.

In this research project, an experimental study was conducted using various lecture theatres with students ranging from 50 – 150. Python and OpenCV tools were used to analyze the photographs and document the performance as well as observing the different conditions in which to acquire results.

The research had an average detection rate of 75% this points to a promising alternative audience response system as measured by time, cost and error rate. Further work on the capture of the poll sheet would significantly increase this result. With regards to cost, the computer vision coloured poll sheet alternative is significantly cheaper than clickers.

NOMENCLATURE

ARS – Audience Response system

API – Application Programming Interface

GUI – Graphical User Interface

OpenCV – Computer image library

Python - Computer programming language

ACM - Association for Computing Machinery

RF – Radio frequency

CSC – Computer Science Classroom, University of Cape Town

ZOO – Zoology Building Classroom 1, University of Cape Town

PC – Personal Computer

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CHAPTER 1. INTRODUCTION

Audience response systems (ARS) give a facilitator accurate feedback with regards to a large groups' response to a question posed to the public. ARS have been found to improve the learning and engagement of students ([Caldwell, 2007](#)). Research benefits of audience response systems in education include longer attention spans, enjoyable classroom sessions and the ability to gather feedback on students' understanding. Increased interaction between all the students and the teacher/facilitator was further recognised when using ARS ([Johnson & McLeod 2004](#)). Such interactive lectures resulted in significantly better post-lecture quiz scores over non-interactive lectures as researched by [Schackow, Chavez, Loya and Friedman \(2004\)](#).

1.1 Introduction

In this regard, ARS provide invaluable feedback in educational settings since they facilitate dialogue and engagement, as well as provide a hospitable environment to innovate and cultivate ideas through engaging with the material in an automated way. Additionally, in the case study by Schackow et al. the use of an ARS increased the average post-lecture quiz scores to 93% when compared 61% for non-ARS interactive sessions. Various audience response systems can conduct interactive sessions, common forms of such systems include clickers.

A clicker is a handheld response gadget that acts as a medium of communication between the students and facilitator ([Phatak, 2014](#)), and comes in two types Radiofrequency (RF) or infrared communication. The main advantage to using clickers is that they allow students to directly and anonymously respond to questions posed by the lecturer ([Skiba, 2006](#)). Most clickers allow entry of numerical responses, although more expensive clickers also allow entry of text to enable lecturers to use open-ended questions ([Van Ooijen & Broekema, 2010](#)). Nonetheless, the main deterrent to using clickers for audience response within a classroom is that they are prohibitively expensive for many institutions to adopt. [Knight & Wood, \(2005\)](#) have confirmed that despite the cost, the advantages of using

clickers outweigh the disadvantages. These benefits will be highlighted later in this chapter, with an emphasis on the success rates of clickers in the facilitation of classroom learning.



Figure 1.1: Clicker use in classroom

Many institutions around the world are implementing clickers in their lecture theatres to improve the student learning experience. For example, Nanyang Technological University (NTU) in Singapore rolled out a campus-wide initiative called “Learning that clicks”. This initiative was designed to enable the necessary transformation of pedagogy and promote the learning experience of students ([Laxman, 2011](#)).

1.2 Motivation

“As we gaze out at the sea of slouching bodies and expressionless faces from our podiums, it is hard to resist wondering if students want less education and more entertainment.”

(Guthrie & Carlin, 2004)

According to the quote above by [Guthrie and Carlin \(2004\)](#), there is a global need to make lessons more interactive and captivating. Collaborative lessons are prescribed to promote enthusiasm among students around lectures that they attend on a daily basis. Conversely, the quote further illustrates the need to give facilitators a method of assessing at a glance, whether the ‘expressionless faces’ understand all the concepts mentioned in the lecture.

This research explores the solutions people have come up with to resolve these two issues, and correspondingly proposes an approach to fulfilling this dual requirement.

This research is intended to design a low-cost audience response system as an alternative to the expensive clicker technology. In developing countries, education facilities in many urban and rural areas are not well funded. The cost of tertiary education is very high, and the incremental cost of implementing clickers would increase the associated cost per student in higher education. However, [McDonough and Foote \(2015\)](#) researched that by allowing students to share a clicker this fosters collaborative learning and students were more likely to select the correct answer, in contrast to students having personal clickers. Nevertheless, this would pose further problems inherent with sharing any device, such as responsibility when it comes to keeping the device, using the device or consequence in the event of a lost device. Taking value addition into account, a low-cost method to enhance instructor-led sessions would add considerable value to the students, instructors and the entire education sector.

As mentioned by [Kay and Lesage \(2009\)](#), there are drawbacks to audience response systems. The following two perspectives characterise these disadvantages:

1. From a facilitator's perspective, ARS can take considerable time and effort to assemble. The institutions' IT department conducts this setup, which means, if there is an error in the system, the facilitators will have to get hold of the I.T. department to fix the ARS. Additionally, the facilitator will need to create suitable questions to use ARS effectively ([Heaslip, Donovan and Gullen, 2014](#)). Facilitators will also be required to have the proficiency to be able to respond accordingly to the feedback provided by ARS, which requires practice.
2. From a student perspective, it is a new method of learning, and as a result, it might take them some time to adjust. Students might not be comfortable with the constant monitoring of answers if the ARS is for in-class testing purposes.

There are many alternative methods of Audience Response Systems (ARS) beyond clickers in particular, in the areas of text messaging, smartphone, in conjunction with the

benefits of audience response technology. This research was based mainly on different types of ARS technology available in the developed world.

In India, [Cross, Cutrell and Thies \(2012\)](#) research focused primarily on using Q-cards and video recording. In Japan, the research on computer vision based fiducial markers was conducted by [Miura and Nakada \(2012\)](#). India, Japan and America have carried out a significant amount of research into audience response systems using computer vision. On the contrary, little to no research had been completed with regards to Audience Response Systems in Africa even though [Jones, Marsden and Gruijters \(2005\)](#) conducted case studies in Africa based on text messaging applications in 2005.

According to the observation of the lack of African-centred research with regards to audience response system research, several questions arise regarding the relevance of many of these alternative audience response systems being researched and developed around the globe. [Kiefer, Reyes, Liebman and Juarez-Carrillo, \(2014\)](#) conducted a study on how well these devices perform on audiences with limited English proficiency (i.e. Hispanics) and vulnerable populations giving insight on applying the same devices on different groups of people.

In a globalised world one would propose the approach, people across the world, have similar likes and dislikes, use similar technology, are more similar today than before, hence given the familiarity of different people, the same solution would work for people. The answers would thus be, *“people are still individuals who wish to use digital technology to enhance the way they live their lives, even if those lives are lived in very different contexts. Understanding the different contexts has been the problem, a problem that HCI techniques do not fully address.”* [Marsden, Maunder and Parker \(2008\)](#). Due to these different contexts, the need to create an African centred ARS is what this research tries to accomplish.

In focusing the research on using computer vision to detect and analyse colour poll sheets, the aim was to construct an audience response system that would act as a low-cost alternative to clickers. This ARS system should be robust enough to work in different lighting conditions and produce accurate results with accuracy equivalent to other ARS systems present. Furthermore, it has to be commercially viable for African institutions.

In light of the above, the purpose of this research is to investigate if a low-cost alternative to clicker ARS technology can be created, combined with commercial viability for distribution within Africa. Hence the idea is that this audience response system will place students learning in Africa on the same technological plane as students learning in developed countries.

1.3 Computer Vision/Image Processing Audience Response Systems

Computer Vision based ARS relate to ARS that focus primarily on reading a specific image and then processing this image to produce a certain result from the analysed image. This data can come from a video or a picture taken with a camera.

A computer has to be able to compute pattern recognition to read data from the image of interest and produce a result from the recognition process. [Jain, Duin and Mao \(2000\)](#) state template matching as one of the main techniques of pattern recognition. Other techniques beyond the scope of this research include statistical approaches, syntactic approach and neural networks.

A template-matching pattern recognition algorithm is a computer vision based approach applied to detect and differentiate the different regions of interest from the images of a classroom.

In contrast, clickers do not require any processing of input, but simply record what button on a clicker has been pressed by the student and tabulate this to form a result of the poll.

The arguments supporting such computer vision audience system include:

- The response tool component of the clicker technology is relatively expensive, and a cheaper alternative tool would reduce this cost.
- The low-end PC reception unit with a camera can be used to capture and record responses is cheaper than that of the clicker server system.
- The main driver for a computer vision based system is the ability to create an accurate colour detection algorithm that can detect participant responses. This

algorithm could be written in Python and OpenCV which are open source software, hence reducing the cost of licensing and hence decreasing the cost of the software.

- The nature of the response, which is similar to a person raising their hand in a classroom, should allow for timing measurements that are not much longer than that of the clicker technology.

1.3.2 Metrics for comparing Audience Response systems

Audience response system adoption in Africa faces many significant challenges mainly comprising structural, technical, human resource and financial. In Chapter 2 there will be a deeper elaboration of the structural and technological aspects of the adoption challenges of audience response system within Africa's tertiary education sector.

The current audience response systems in the world are not effective within an African context where the criteria are more skewed towards the cost of implementation than Human-Computer Interaction (HCI). Below we discuss the challenges that current audience response systems face, namely: high costs, low accuracy and high lag times.

High Costs

The first metric is the cost of implementation. Clickers are prohibitively expensive to implement, at the price of about \$200 - \$700 for the clicker server to implement plus an added costs of about \$30 - \$50 per handheld unit [Gain \(2013\)](#). The implementation of the clicker infrastructure is both expensive to acquire, set-up and maintain and the cost of implementation has a sizable weighting when rating an audience response system. [Gain \(2013\)](#) analysed the contrast in total costs needed for implementations of different response technologies, namely: clickers, smartphones, text messaging, fiducial markers and colour poll sheets as can be seen in the figure below.

Method	Max Class	Individ.	Anon.	Accuracy	Cost	Comments
Clickers	1000s	Y	Y	100%	\$200-700+\$30-50 per stud.	
Smartphones	1000s	Y	Y	100%	\$0	must be owned by every student
SMS	1000s	Y	Y	90-100%	\$0.05 per stud. per poll	potential delays
Fiducial Markers	25	Y	N	95-97%	\$0.10 per stud.	
Imaged Poll Sheets	250	N	N	85%	\$0.20 per stud.	not tested above 250

Figure 1.2: Comparison of alternative response systems, Gain (2013)

This high cost of implementation is due to the per-student clicker that ideally needs to be issued out to every student. In addition to every student requiring a clicker, batteries are also mandatory for each clicker. A clicker server depends upon software installed (e.g. TurningPoint software) dedicated to handling clicker response systems. Other audience response systems, such as text messaging response systems become incrementally more expensive with duration and feedback; this is because a text message cost \$0.05 per response, the more responses, the more the participant pays. Computer vision systems do not particularly need a dedicated server and can be hosted on a facilitator's laptop or in the cloud.

Accuracy

Clicker systems have a 100% accuracy rate as audience response systems as tested by [Llena, Forner and Cueva \(2015\)](#) while evaluating clickers in dental tertiary education course. One of the dominant challenges that are faced by computer vision systems is ensuring a high accuracy rate as the sizes of classrooms grow. Classroom environments are usually unpredictable and erratic to formulate appropriate and fully encompassing algorithms for detection of results. Alternative systems, such as smartphones, can closely match clicker accuracy at a lower cost by utilising technology that is readily available to students. However, the cost reduction at times results in lower accuracy attained by the proposed solution.

Lag Time

Response timing relates to the timing of gathering responses, grouping them and presenting them. Clickers have excellent response times [Llena et al. \(2015\)](#) because of the dedicated software records responses as soon as each student enters them. This metric is in part affected by the users, who may spend extra time responding to a certain question. As hard as it is to measure accurately, it is a useful metric to track.

Anonymity

Another challenge faced by current computer vision ARS is the anonymity factor. Clickers, text messaging and smartphone response systems all use anonymity when the users respond with answers. This anonymity is both from other peers' along with the

facilitator. [Raes, Vanderhoven and Schellens \(2015\)](#) study found that peer assessments with anonymity had positive attitudes, reduced feelings of peer pressure and sense of comfort among the participants. The anonymity factor is addressed by placing the camera on the ceiling above the students instead of in front of the class. The students will, therefore, hold their poll-sheets above their heads pointing upwards out of view of all other students, but this might depend on the classroom structure being level.

1.3.3 Proposed Solution building on Gain (2013) research

It was discovered, through the examination of the current Audience Response Systems, that the clicker response system appears to be very accurate with relation to the results acquired, including the time required to gather and analyze results. If clicker infrastructure costs were to decrease considerably, this would lead to high accuracy and fast processing at an affordable amount.

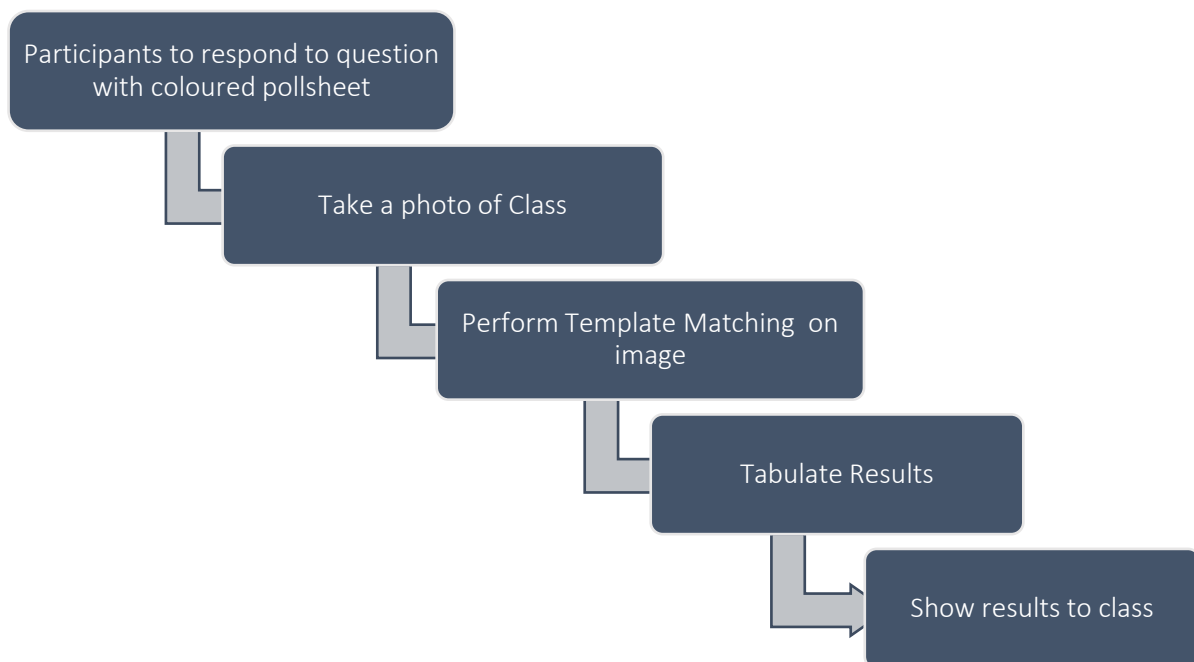


Figure 1.3: Computer vision workflow

The proposed solution is to implement a computer vision coloured poll sheet ARS that uses a template matching python algorithm with Open CV bindings to segment out the sheets and determine the colour. This solution is building on the coloured poll sheet

existing work by [Gain \(2013\)](#). Gain conducted a system test using coloured poll sheets with computer vision as an alternative audience response system to clickers. His study involved colour poll sheets with a white background that students could raise above their heads or in front of them to indicate their response to a question. He conducted his tests on a class size of around 150 students and achieved test results of on average, 85% accuracy, with capture times of around 15 seconds excluding capture and upload time.

By investigating the cost of components of a colour poll sheet ARS compared to the clicker system, one can slowly build a low-cost solution through substituting cheaper components at each level of the system as shown below. For clickers response tools such as the clicker handset cost between \$30 - \$50 and the medium of response cost relatively nothing as this is radio frequency transmission. A reception server and software to tabulate responses cost all in all about \$200 - \$700.

Response tool

To achieve a low-cost response tool, we can evaluate the different response tools of various systems from the cheapest to the most expensive. The cheapest response tool is a sheet of paper that costs a cent, and multiple responses are seen and acquired at once. Mobile phones with no internet capability (– text messaging), as well as the web-capable cell phones (– smartphones), are more expensive response tools.

Smartphones are readily available for most students in developed countries. The most expensive dedicated tool would then be the clicker. One might debate that a mobile phone is more expensive than a clicker device, but at this point, we are looking into a students' additional costs. [Imazeki \(2014\)](#), points to participants bringing their own device, which will reduce the overall implementation cost. For many students in developed countries, mobile phones or smartphones are no extra cost but rather a tool which every student already has readily available for use. However, this is not the case in Africa hence the rationale to structure a different alternative response system.

Medium of response

In other ARS, the medium of feedback can either add to the total cost or not add to the expense of the reply system. The proposed solution of a colour poll sheet ARS will not add to the medium of response cost. Clickers, use either radio frequency waves or infrared communication to relay their response to the server [Llena et al. \(2015\)](#), which is free. Mobile phones, use a text message to relay their message across to the server, and this costs an amount per text message. The more text messages sent by participants, the higher the cost. Smartphones can use the Wi-Fi available at the university, and can, therefore, provide a cheaper medium of response in comparison to the mobile phone medium.

1.4 Research Problem Statement and Hypothesis

The coloured poll sheet is an equivalent audience response system to clicker technology. For this to be the case, the computer vision system needs to be able to record the responses of individuals with high accuracy. They also need to be cheaper to implement and produce a result within a suitable time frame.

1.4.1 Hypothesis

Colour poll sheets could provide an alternative ARS to clicker technology. This alternative should be about the cost of implementation and maintenance of the system. This assumption directly determines the following primary research questions:

1.4.2 Research Questions

- (1) *Can coloured poll sheets be used as a viable alternative audience response system to clickers?*

This question above relates to comparing the colour poll sheet ARS to the currently implemented ARS. Emphasis is placed on cost, accuracy and speed to find out if the coloured poll sheet ARS can act as an alternative to current ARS system in Africa.

Moreover, one would assess and determine the different metrics which ARS system would be better to implement.

(2) *Can we use the coloured poll sheets to achieve an accuracy of 85% within the timeframe of 60 seconds?*

One can assess whether or not the poll sheet ARS can reach an accuracy of 85% and detect the right results within a 60-second timeframe. The ideal accuracy target is 100% meaning all coloured poll sheets have been detected, however, because of the stage of the research as well as the consequences of not detecting a specific poll sheet the research will target an accuracy of 85%. Improvements arising from faster processing power, high megapixel cameras or clearer sheets of papers can be made to enhance the accuracy and speed of the colour poll sheet ARS.

The chosen timeframe of 60-second timeframe is the initial research baseline. A 60-second time frame allows for a buffer for the class to settle down and the facilitator to explain any further information before the information is displayed.

1.5 Scope of Study

The research in this thesis primarily focuses on the technical aspects of the solution for creating an alternative audience response system to clickers. The thesis scope is limited to the design, development and implementation of such as system. Two different classroom environments, as well as four different colours for the poll sheets, are used to test the system to produce a robust, accurate and fast system to enhance the teaching experience within the classroom.

This research study does not provide proof on the enhancement of a classrooms experience due to the addition of an audience response system, nor does it go into detail about the inclusion (or lack thereof) in classrooms and the pedagogical approach utilised to achieve the best participation from the students within the class.

For the purpose of this study, we will try and answer the research questions observing some steps within the system. The best measures to observe to respond to the research

questions posed are; *the cost of implementation, the accuracy in recognising responses and calculation time of the system.*

In this study, we will evaluate the use of alternative audience response systems to the clicker-based audience response system. These ARS alternatives include response systems built around text messaging on mobile phones, smartphones, Q-cards, fiducial markers and coloured poll sheets.

An important issue is the ability to determine if an algorithm using Python and OpenCV can detect the coloured poll sheets accurately. A low-end personal computer was used to run the detection algorithm. This implementation will prove whether or not such a product can be made stable, secure and upgradable. Additionally, one can gauge the commercial viability of this alternative ARS. Alternatively, a raspberry π system could also be used to run this implementation providing a low-cost ARS with acceptable performance.

The thesis findings can be used to provide a computer vision equivalent to clickers. The implementations of a computer vision ARS is an alternative where clickers and other ARS are not readily available. Finally, the research concludes, with an examination of the computer vision colour poll-sheet alternative results as well as a breakdown of the possible gaps in future research about computer vision based audience response systems.

1.6 Organization of Thesis / Outline of Chapters

This organisation of the rest of this thesis is as follows:

Chapter 2 looks at the background of ARS, including the various ARS alternatives, with a particular essence on computer vision alternatives to clickers and how they fare against their other alternative counterparts.

Chapter 3 explains the research methodology and design used to produce a system that can achieve accurate results to act as an alternative to clickers using computer vision. In this chapter lies a detailed explanation of the design, development and implementation of the system.

Chapter 4 explores the application of the coloured poll-sheet audience response system and testing the results over some scenarios and conditions including varying parameters in the algorithm. The results are collected and analysed in Chapter 5. The final chapter, Chapter 6 concludes the research thesis, highlighting specific areas both quantitative as well as qualitative.

CHAPTER 2. BACKGROUND ON AUDIENCE RESPONSE SYSTEMS

This chapter explores the history of Audience Response Systems (ARS) and their initial application in education. In this chapter, we look at two groups of Audience Response Systems, namely associated ARS and computer-vision ARS. The related ARS group focuses on clickers, smartphones, web applications and text messaging. The computer-vision ARS looks at Q-cards, Coloured poll sheets and Write-on Cards. This chapter presents background and related literature relevant to ARS and possible alternatives to clickers. The chapter concludes by giving a summary of the various systems and makes recommendations for an appropriate ARS to be investigated given the goals of the thesis.

2.1 History of ARS

In advance to analysing a mechanical audience response systems, it is useful to briefly explore the many historical audience response alternatives and investigate a solution that would apply to the African context. A starting point would be a look at the earliest, most natural Audience Response System known to man. This natural ARS is the use of human vision in detecting the number of raised hands participating in a class to answer a particular question.

Raised hands detected by the human eye can be seen as the origin of audience response and the beginning of the design process. As classes got bigger certain challenges arose, for example, counting hands became time-consuming and prone to human error. These challenges led to the creation of various Audience response systems to solve these problems.

Technology started to create certain tools to improve this audience response system. The first automated Audience Response Systems (ARS) were developed in the 1950's when the United States Air Force used an electronic device to train personnel by employing multiple choice questions integrated into training films ([Judson & Sawada, 2006](#)).

In 1966, two more ARS's were built and installed in lecture halls at Stanford University ([Kay and LaSage, 2009](#)) as well as at Cornell University in 1968 ([Roschelle, Penuel and Abrahamson, 2004](#)), and a prototype called the Classtalk 1 tested for use in 1985. Audience Response Systems (ARS) were then more widely introduced. Nevertheless, it was not until the late 1990s that ARS started being used commercially by many institutions.

As with most technology during earlier times (the 1960's), ARS were prohibitively expensive, cumbersome and took an enormous amount of effort to set-up, use and maintain. This complexity led to the creation of infra-red ARS in 1999 ([Abrahamson, 2006](#)), which made ARS easier to use. In the upcoming years after the first ARS, a common audience response system known as clicker technology was adopted by many institutions in the developed world.

Adoption of this technology subsequently became widespread as of 2010, the use of ubiquitous smartphone technology has led to an upsurge in the number of ARS that are available for use by institutions. These range from smartphone applications, web applications and text applications ([Voelkel and Bennett 2014](#)). Though ARS have become easier to use and have reduced considerably in cost, they remain out of reach for many institutions within the developed and developing the world.

2.1.1 Use of Audience Response Systems in Africa

Firstly, Africa is by far the least computerised region in the world ([Castells, 2000; Jensen, 2006](#)). Except for a few major cities, ([Kamalipour, 2007](#)) found that ICT infrastructure is limited at best and non-existent at worst. ([Bornman, 2012](#)) Observed that Africa lacks the solid infrastructure required for effective computer usage. For example, reliable electricity supply; when electricity supplies are not reliable, efforts to supply the latest technology become futile. Where basic ICT infrastructure does exist, networks are mostly substandard in comparison the rest of the world.

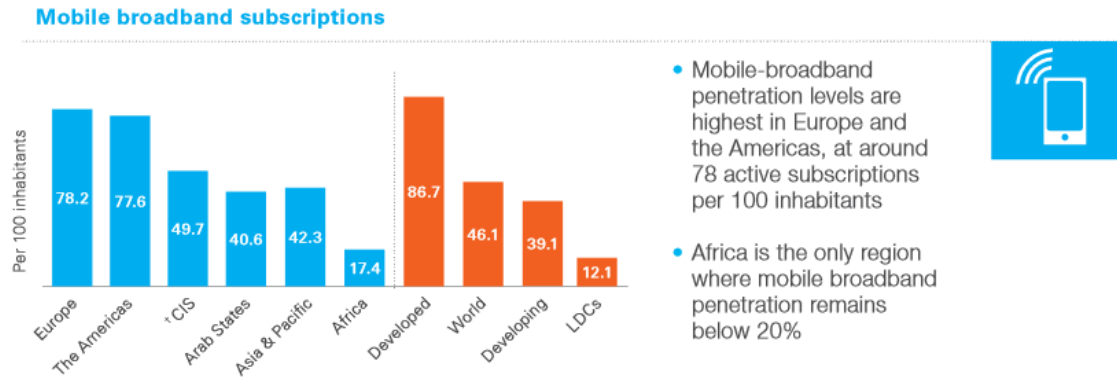


Figure 2.1: Mobile Broadband Comparison Chart

A second major problem brought about by the lack of fibre optic infrastructure is the exorbitant prices of internet connectivity, in particular, broadband connectivity, in Africa (Cherlin, 2009). According to Jensen, (2006) the most important reason for high broadband costs, is the fact that fibre optic links with the developed world have thus far been operated by ineffective state-owned operators. The resulting exorbitant costs lead to relatively low levels of adoption, uptake and use which is the opposite of the intended outcome.

Fixed broadband subscriptions: developing countries lag behind as prices stagnate

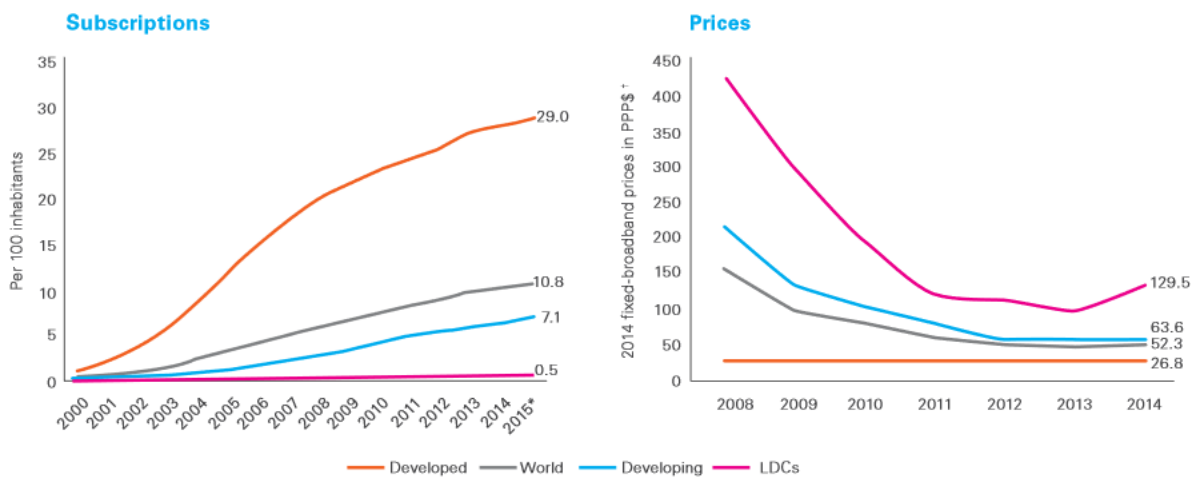


Figure 2.2: Subscription and prices for developed and developing countries

Over the past decade, cell phones have been adopted rapidly in urban African areas. Mobile phones provide a potential avenue for the use of audience response systems in African education systems ([Bormman, 2012](#)). Due to the lack of an all-inclusive adoption by all students, cell phones as the primary audience response system would exclude students without cell phones.

Out of the population of students with mobile phones, a particular percentage of these students would find it hard to constantly send text messages to the response system due to the per-use cost. This per use cost would lead to a further proportion of students being excluded from the polling process and thereby achieving a skewed result for any specific classroom poll.

Owing to the lack of financial, structural and technical resources in many institutions within Africa, the popular ARS alternatives used within the developed world are not applicable to the tertiary education sector within Africa.

2.2 Related Audience Response Systems

2.2.1 Clickers

Clickers are a common form of ARS; these electrical response gadgets act as a medium of communication between the students and facilitator ([Phatak, 2014](#)). Clickers refer to the gadgets whose sole purpose is to respond to a facilitators' questions through the selection of a limited number of buttons. The student clicker device responses are transmitted over a specific radio frequency, linked to the receiver that collects the responses from the other clickers within the vicinity.

Clickers, as depicted in the illustration above, have high accuracy and a quick response rate making them effective as a dedicated audience response system. Typically, a facilitator will post a question on the projector and give the students about 30 seconds to respond. Nevertheless, some clicker users and vendors have realised some limitations present in the current version of clickers. [Bryfczynski, Brown, Hester, Herrmann, Koch, Cooper, and Grove \(2014\)](#) pointed out that most clickers do not facilitate the ability to provide a

comprehensive assessment in certain subjects like chemistry which are graphically intensive.

The major disadvantage of clickers stems from the prohibitively high cost of implementation, maintenance and replacement. This high cost of clickers means that with every class session, clickers have to be given out and collected to minimise the number of clickers that get lost or stolen from the lecture hall. One way to combat this downside is to transfer the cost to the student by having the student purchase a clicker for all their lectures. The implication of this is that it will incentivize students to take care of their clickers and thereby reduce the vandalism that might occur with clickers dedicated to a given classroom.

Consequently, the loss of a clicker will increase the cost of lessons for a student as the student will find it expensive to replace this clicker and might continue lessons without a clicker, resulting in inaccurate findings from the audience in succeeding talks.

The only concern with clickers then becomes who should be responsible for the clicker hardware, the institution or the student. Due to the high cost of audience response clickers, various alternatives have been created to reduce the cost of an audience response system. Examples include Socrative, which uses smartphones and laptops and Poll Everywhere, which uses text messaging. These tools aim to be cheaper than the clicker technology but retain accuracy and the advantages of active participation. This increased competition within the Audience Response Systems (ARS) market, will result in the cheaper manufacture and sale of various versions of clickers.

2.2.2 Smartphones

Due to the high cost of clickers from either the university or student side, a popular alternative has been to leverage smartphone technology, which many students in developed countries currently own. This smartphone technology allows for an inexpensive implementation of response application software. In an age where data costs are constantly decreasing, this alternative has the advantage of being low cost and will use technology that is owned by all students to ensure the data charges do not exclude students without sufficient funds. A free Wi-Fi service dedicated for all students to access during the lecture would make the polling inclusive of all students.



Figure 2.3: Smartphone ARS

This method is advantageous as it drastically reduces the cost of implementation and maintenance. The accuracy achieved by smartphone audience response systems in contrast to different computer vision ARS is comparatively high ([Voelkel and Bennett, 2014](#)). However, this method has the disadvantage of being counterproductive to the main aim for students actively participating in the facilitator's question. If students constantly use their smartphones for participation, there is a decent chance that this will lead to distraction as students could try to view other material. [Stowell \(2015\)](#), the survey found that only 58% of students using mobile ARS never reported or rarely being distracted by other practices of their mobile device. A student may also chat with other people over social media i.e. Facebook during a lecture and zone out of the lesson completely.

Another disadvantage is that not all students have smartphones. A report by the International Data Corporation (IDC) mobile phone Tracker shows that smartphones accounted for 47% of the handsets shipped in Africa during the first quarter of 2015 [Hyde-Clark, N and Van Tonder, T. \(2011\)](#). Excluding students with no smartphone could result in a student having a negative reaction to the ARS since they would be unable to participate.

2.2.3 Text messaging

Text messaging has the same effect of distracting a student as smartphone technology. However, the cost of text messaging technology increases with the number of questions

one needs a response. Furthermore, not all students have sufficient credit for text messaging costs, and this would exclude some students, thus causing a negative reaction to class participation. Accordingly, this would result in an inaccurate reading of data once again.

The benefits of the proliferation of mobile phones in Africa remains a channel for cheap ARSS within the classroom settings and according to [Scornavacca and Marshall, \(2007\)](#) the infrastructure is prevalent in many classroom settings.

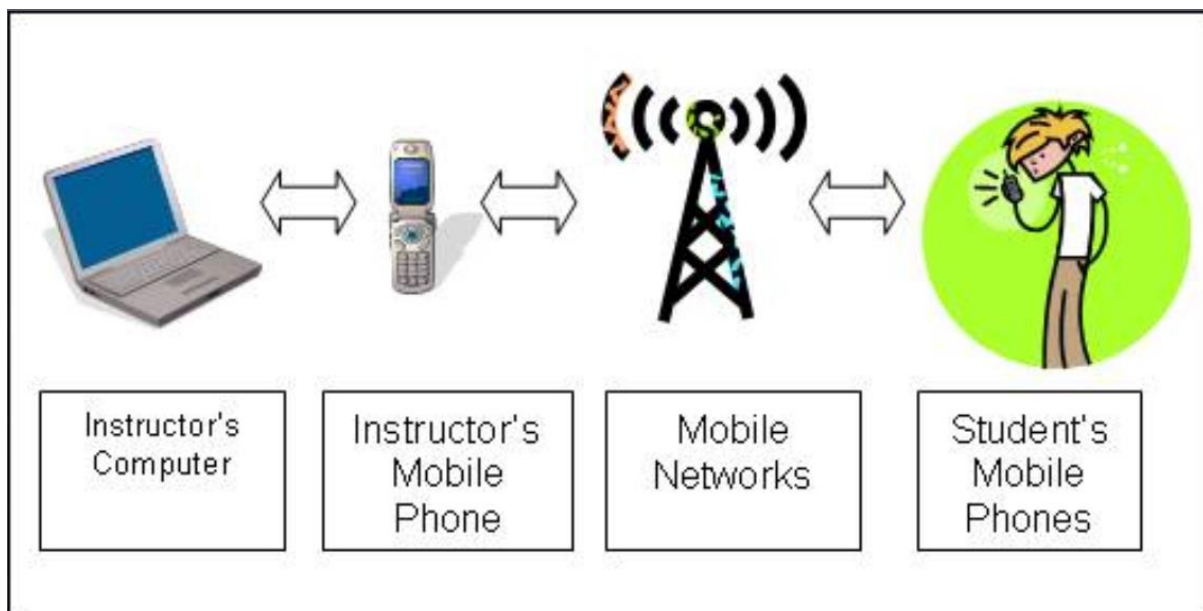
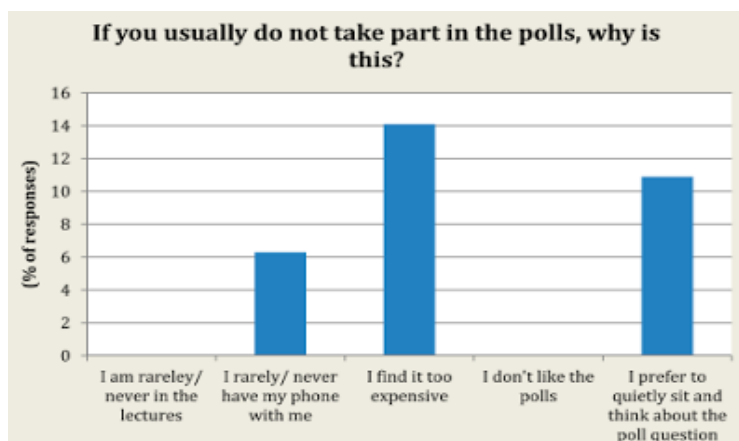


Figure 2.4: SMS Process ARS

[Voelkel and Bennett \(2014\)](#), analysed the percentage of respondents that did not participate in the feedback system and found that many respondents explained that the costs associated with responding to the questions were too high. Although the initial costs seem small, the costs rise with the number of polls completed by each student.



(Voelkel and Bennett, 2014)

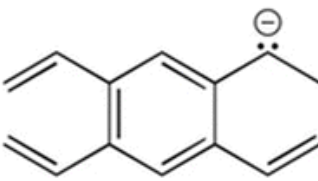
Figure 2.5: Reasons associated with non-participation in text messaging polls, Voelkel and Bennett (2014)

2.2.4 Web Applications via Laptop

Auxiliary low-cost methods used in audience response systems are the use of various web applications. Many vendors in the global community have created web applications that students can use to enter various poll responses for questions asked within the classroom. As researched by [Shea, \(2016\)](#) web-based applications allow for different types of questions such as depicted in the figure below and allow for remote collaboration and feedback. These web applications are commonly free for smaller classrooms with different paid options available as the polling requirements increase. However, there is scepticism due to the potential for distraction when laptops are in a classroom setting.

2. word cloud

71 responses



Which orbital contains the lone pair electrons?

sp

sp³ p 2p

p orbital

orbital sp²
6

Figure 2.6: Example of question, by Shea, (2016)

Another issue with regards to using laptops for audience response within the developing world is that the tool needs to be owned by all the students within a classroom setting. If a student does not own a laptop or if a student cannot connect to the internet this could result in a student not participating in the class. This kind of exclusion would be unfair to students that cannot afford laptops. These problems could all lead to the incorrect polling of student responses within a classroom setting.

2.3 Computer Vision/Related Audience Response Systems

2.3.1 Q-Cards

Q-Cards make use of the Quick Response Code (QR Code), which is a widely used type of 2-dimensional barcode. QR Codes are visual representations of information and can be read by computers. They also contain a significant amount of information in comparison to the one-dimensional barcodes ([DENSO, 2014](#)). The Q-card is a type of QR barcode that students hold up, and information relating to their answers can be captured and aggregated to form an audience response system.

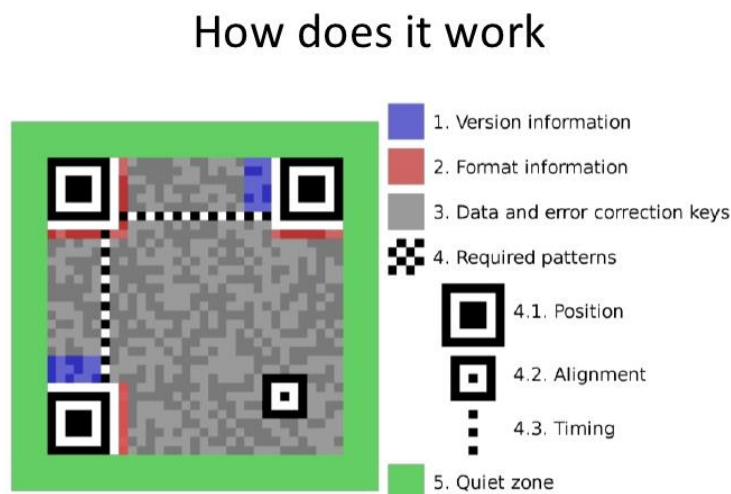


Figure 2.7: Q-card working structure

In this regard, [Cross et al. \(2012\)](#) bring a unique approach when it comes to computer vision based audience response system within a classroom setting. Cross et al. (2012) examined the use of a video camera and Q-cards. They found that their test system records 97% of students' votes in a 25 person classroom (a small class) within the first 10 seconds

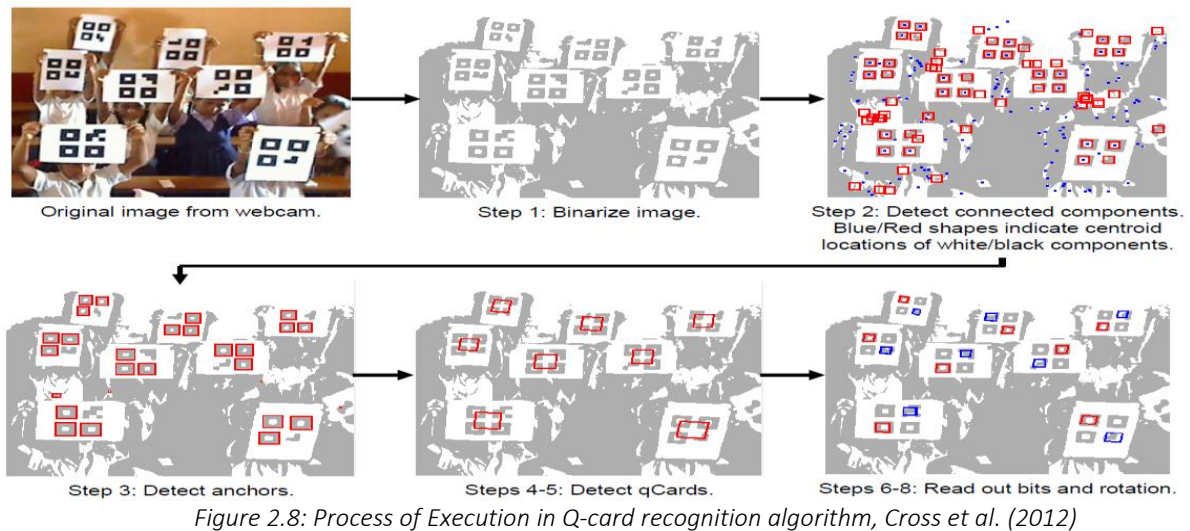
and maintains 99.8% recognition accuracy. Their approach also costs 15 times less than clicker technology.

They created a *simulated* environment for larger class sizes in which they carefully arranged chairs and stuck a Q-card in front of each chair facing the video camera in the front of the class. Within this simulated environment, they could record up to 100 responses within 4 seconds. They also found that by using a higher quality camera to record student responses they could drastically reduce the time of recording. The Q-card system is a response that is highly successful in smaller student groups.

Moreover, the Q-card system is also able to record student ID's associated with each Q-card, through reading the QR code both horizontally and vertically. Students are required to go through a two-step process to respond correctly; firstly they should lift their Q-cards to identify their student number, then turn their card around to answer the question asked. This two-step procedure results in a longer audience response process and may restrict material covered during the lecture period.

The recording of student ID's has advantages and disadvantages. Studies have indicated that one of the features that students enjoy about ARS is its anonymity ([Jackson and Trees 2007](#)). This anonymity can be in the form of peer anonymity or group anonymity. Peer anonymity or peer-to-peer anonymity defined as a student being able to show their answer without other students in the same group knowing what answer they have chosen. Group anonymity defined as the students revealing their answers without any trace back to a specific person.

The software used by Cross et al. is a system built in C#, containing an image library, GUI wrapper and webcam driver to capture live images for processing. The steps followed by the algorithm to detect the correct answers depicted in the figure below.



The technique works efficiently in a well-lit room with fixed lighting conditions but runs a little less smoothly under variable lighting conditions.

2.3.2 Colour Poll sheets

[Gain \(2013\)](#) conducted a system test using colour poll sheets with computer vision as an alternative audience response system to clickers. His study involved coloured poll sheets with a white background that students could raise to indicate their response to a question. He conducted his experiments on a class size of around 250 students and achieve test results of on average 85% accuracy, with processing times of around 15 seconds excluding photograph capture and upload time.



Figure 2.9: Coloured Poll sheet, Gain. (2013)

In a max classroom of 250, colour poll sheets were relatively inexpensive to utilise. However, they had an accuracy level of only 85%. Gain used a system based on Python bindings for the OpenCV image processing library.

The method begins by applying a Canny edge detection algorithm, to extract the binary silhouette image, followed by a blob detection to segment out regions surrounded by edges. Some tests are then run to reject false positives and correctly include blobs within certain test ranges. Finally, a mean colour detection algorithm is executed to categorise a specific colour into a marker classification correctly.

2.3.3 Write – On Cards

[\(Heward, Narayan and Gardner, 1996\)](#), examine the use of both pre-printed response cards and write on cards. The latter adds a different dimension to computer vision ARS with relation to classroom participation. The response cards comprise cards, signs, felt boards, all held up by students to display their responses to problems presented by the teacher.

Write-on response cards would enhance the audience response system (ARS) and cover aspects that some clickers, colour poll sheets and Q-cards do not contain. Which is their ability to capture multiple types of responses; the added benefit achieved at a low cost. However, one should note that this method will take longer for students to respond to, as students will be required to write legibly and in one-word answers. This method is hard to automate, as a tabulation of different responses for aggregation purposes cannot occur.

Pre-printed response cards have some advantages, such as ease of polling and high rates of response. While write-on cards have their advantages as well, such as not being limited to a certain number of replies, they require a more demanding recall-type of response during use in class.

However, write-on cards have a higher error rate in conjunction with a lower response rate compared to pre-printed cards. Write on cards also pose the ambitious problem of recognising student handwriting of different size and legibility. This challenge provides an

excellent area for future research into text recognition and computer vision. Write-on cards would, however, only work in smaller classrooms with less than 25 students and would probably have a higher error rate.

2.4 Research Methods

Quantitative research methods involve the processes of collecting, analyzing and interpreting numerical results. This approach is dependent on the objective of the research as pointed out by [\(Hazzan, Dubinsky, Eidelman, Sakhnini and Teif, 2004\)](#). Quantitative research as described by Creswell [\(Creswell, 2013\)](#), is an approach for testing scientific theories by examining the relationship between variables. Once the resulting data from the examination of variables recorded, the data can be analysed using statistical procedures.

The quantitative research method was selected because it is commonly used in application development when evaluating the benefits of a new approach in comparison to that of an existing method. The term used to describe the existing method is called “the control” because it is the baseline by which we will measure our results in our new method.

There are two types of variables, independent variables and dependent variables. Independent variables defined as the tools that are within our control to change in attaining more accurate results. Dependent variables are variables determined by changes made to the independent variables. In our case, the main dependent variable of interest is the “*error rate*”. Within our research, the error rate can be measured accurately by the performance measures – *Accuracy, Precision and Recall, F-Measure*. Error rate determined by the changes to the independent variables namely;

- Poll sheet colour (Black, Red, Green and Blue)
- Poll sheet size
- Sample size

As the various independent variables changed within the new audience system, the error rate also changes. The error rates of both audience response systems are then compared to analyse which system is quantitatively better, classified as a quantitative method of research.

We have chosen to use the quantitative method of research because a quantitative approach would best illustrate the performance metrics (*count, duration and error rate*) for poll sheets in comparison to clickers as an audience response system within this research. For the purpose of this study, the objective is to conduct a study on the accuracy (*measured by error rate*), cost (*measured in \$*) and duration (*time to compute the result*) of colour poll sheets and concisely compare these to clickers.

2.5 Concluding Remarks

The use of audience response systems provides a positive active learning environment for students of all ages and classroom environments, as discovered by [Wolff, Wanger, Poznanski, Schiller and Santen \(2015\)](#). The more accurate and rapid an audience response system is, the more useful it is as a tool within the classroom setting aiding the teacher in reacting to the class's understanding of specific problems.

[Cross et al.'s \(2012\)](#) methods produced very high accuracy, though the approach applied to a small set of 25 students in a well-lit classroom. The system adopted by Cross et al. (2012) in varying conditions can be extremely slow, hence providing a further hurdle within a live learning environment. The simulated environment of 100 students, does not mimic a typical class of students holding cards at different angles and partially obstructing the cards. This obstruction usually poses a complex problem for the camera to read the Q-cards accurately.

The method applied by [Gain \(2013\)](#) provides a more realistic environment in which responses presented in many ways that are harder to detect. The procedure of a camera to capture a panoramic view involves instructing the entire class to remain still for a few seconds which will not be the case in a live environment. The methods used to handle elevated lecture theatres with a solution for level theatres enhances the robustness of the system providing a system applied in multiple settings. Future research should reduce the total cycle time of the response system and in a similar manner increase the accuracy levels above 85%.

This thesis focuses on providing a robust system that is both accurate in detecting the student responses and can process the responses quickly enough to be available for the teacher to analyse without disrupting or slowing down the class session. The methodology of Gain (2013) et al. was initially tested within a live environment comprising of a higher number of students. This testing methodology indicates a greater level of robustness in comparison to the method tested by Cross et al. (2012) in a smaller sample space and highly controlled environment. Consequently, the research study will seek to improve upon the work of Gain (2013).

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

In chapters 1 and 2, we observed the use of Audience Response Systems in a learning environment. We investigated the problems inherent in the current Audience Response Systems, namely; clickers, smartphone technology, text messaging systems and Q-card computer vision systems and different research methods used.

The major drawback that leads to the need for an alternative ARS is the prohibitive cost of clicker technology. With regards to the African situation, many ARS will not be applicable due to the high costs of infrastructure over and above running costs.

This cost drawback has led to the research design and implementation of a coloured poll sheet ARS using Python and computer vision to present a solution to the high-cost problem of clickers.

In this chapter, we considered a few powerful image recognition algorithms and evaluated some hardware options to assist with the software and hardware integration.

3.1.1 Structure

In this chapter, we describe the design and implementation of the colour poll-sheet audience response system. We briefly look at the experiments/data collection process of the colour poll sheet. A pictorial representation of the coloured poll sheet algorithm is shown below.



Figure 3.1: Pictorial summary of the process

The diagram above depicts the high-level steps that the algorithm follows to detect and recognise the different colour poll sheets.

3.2 Colour Poll Sheets

To conduct the research on colour poll-sheet ARS, Gain created poll sheets out of different colours (Blue, Black, Red and Green). Gain then experimented in two different environments (Class ZOO and Class CSC) by asking first-year computer science students various multiple choice questions and taking a panoramic picture of the polling using a simple iPhone camera. These pictures (12) were later used to create an audience response system algorithm for colour poll sheet recognition.

The Figure 3.0:4 below shows a sample classroom image read into the system with students holding up their various answers for the poll.



Figure 3.2: Example of Image of lecture theatre read into the system

Colour poll sheets were chosen with a wide white border as this background is easiest to distinguish in computer vision and provides strong contrast against a coloured square. The colours red, green, black and blue are also colours that bring about the best contrast against the white background. The square-shaped design of the colour poll-sheet provides a distinguishable shape to detect in image recognition algorithms.

3.2.1 Template Design

A template is a pattern which we will use to find similar patterns in the diagram. In our research, our objective is to find patterns that match the colour poll sheet. In order to find patterns that match our template, our template allows for easier identification within

any environment as well as to be distinct from common features of the classroom background.

The design of the templates are as follows:

1. Rectangular design: This was to make them effortlessly detectable due to the bold straight edges that a rectangle naturally has.
2. Thick white border: this feature allows for easier detection as white is distinguishable from the background. It also provides an extra layer of features as the main colour is on a white background. However, this is not always the case e.g. against white T-shirt.
3. Colour box in the middle – different colours allow for the ability to poll a class and register different responses and makes for a distinct feature within the template.

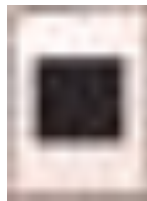


Figure 3.3: Example of Template Diagram

3.3 Hardware Integration

A low-end PC is the hardware platform on which to develop the software for the various reasons outlined below:

1. A low-end PC is affordable with many components already included, reducing the need for heavy integration with other forms of hardware.
2. A low-end PC can be brought to any classroom, regardless of the size, and because of its small dimensions does not obstruct any current infrastructure and requires minimum technical know-how.
3. The ability to program the system with open source software presents a significant advantage of not incurring any license fees. Updating the software can be achieved remotely without any restrictions or extra costs.

3.3.1 Cloud integration

In line with hardware integration, the PC can be connected to the internet or even to the cloud to publish poll results or simply store for future reference by students during revision sessions.

This ability for remote wireless connection allows for the data to be seamlessly available after the lecture period, to help students quickly, easily, and more efficiently use the data learnt in class to understand further concepts learnt that day.

All this integration is possible through a device and cloud storage facility (i.e. Amazon Drive) to store the information and make it available for the students.

3.3.2 Software Design

Before presenting the algorithm design, one of the most important design features to note is the use of Python with OpenCV as a programming language of choice. The reason outlined below:

1. Python language is relatively easy to learn and write, and the algorithm is only 300 lines of code.
2. Python seamlessly links into OpenCV to attain the image processing ability.
3. The Open Source nature of both Python and OpenCV means there is a large pool of people to help through the design and programming process.
4. The Python language during execution is slow. However, because of the OpenCV bindings to Python are C-based, the image processing execution is fast.
5. It works well with Raspberry π B+, and this can be added in future to reduce the cost of the implementation.

3.4 Challenges in Detection

Computer vision is an area of advancement, and this is primarily due to the complicated nature of the challenges and unpredictability of the live experiments and is evaluated by their accuracy in detecting, and recognising objects [Geman, Geman, Hallonquist and Younes, \(2015\)](#). Most of the mentioned challenges have various techniques for

circumventing them. However, this circumvention comes with certain disadvantages while sometimes providing only slightly better results.

For example, if a photograph is taken with a poll sheet largely obstructed, there is no way to train the program to figure out what the colour of the poll sheet was, hence, recorded as a no vote. Such obstructions are prevalent in image processing in comparison to other forms of Audience Response Systems.

Care must be applied when collecting/capturing of data (photographs) for analysis. Once a picture is captured with hard to interpret data, then the program does not have a middle ground for analysing the data.

Different colour poll sheet sizes

With regards to searching for a specific pattern with the template matching algorithm, there are some alternatives to consider in the design of this algorithm.

The size of the template has to be increased or decreased in size over some iterations to capture all possible changes in poll sheet size, which will execute a loop through the program to make the single template detect multiple colour poll sheets.

This modification in photograph size is done mainly because the students in the classroom are not sitting at the same distance from the camera taking a picture. Some colour poll-sheets at the back of the class appear smaller in the image than the colour poll-sheets at the front of the class due to perspective projection.

The scaling design options are as follows:

- a. The scaling the size of a classroom image through cycles know as a pyramid algorithm.
- b. The scaling the size of a template through cycles referred to as a multi-scale loop.

The options illustrated in detail below (Option A - *Figure. 3.0:6 Resizing classroom image alternative*) or (Option B – *Figure. Resizing the template image alternative*).

Option A.

One of the alternative procedures involves the reduction in the size of the entire picture using a pyramid algorithm. A pyramid algorithm is a scaling algorithm that reduces the picture by a factor each time it loops. In the example below, the first image is about 25% bigger than the second image which is about 25% larger than the picture below it and so on.



Figure 3.4: Option A: Resizing Picture pyramid algorithm

Option B.

One of the approaches in the template matching algorithm used to increase accuracy is a multiple-scaling loop. This scaling begins with the smallest possible template dimensions and then enlarges it through a series of iterations to get a bigger template. This scaling allows the template matching algorithm to detect as many poll sheets as possible.



Figure 3.5: Option B: Resizing Template alternative

The selection chosen was Option B, increasing the template size, as it resulted in faster processing. The picture resizing process took longer the larger the image size as large images are computationally demanding because of the processing required to downsample the picture, particularly, where the difference in size differs between a template of size 20×20 pixels versus the picture of size 1700×1400 pixels.

Overlapping detection Points

One of the challenges faced with regards to detected colour poll sheets was the overlapping of detection points. The picture below highlights how a single detection point is not only matched once but a couple of times as the template matching algorithm runs through the lecture theatre image.



Figure 3.6: multiple poll sheet detection

From the diagram 3.6 above, there are many minuscule red rectangles over one detected colour poll-sheet, representing multiple successful matches. The challenge is in counting these overlapping successful matches in the figure above as one poll sheet detected.

The algorithm, therefore, needs the formula to sort and filter areas where multiple detections occur over one identified poll sheet. Filtering the detections according to the distance between two detection points tackled the multiple successful detection problems.

If the midpoint of a detected rectangle is within 25 pixels in either direction of the next detected rectangles midpoint, then the algorithm considers it as one detection only.

Partially visible poll sheets

Some participants presented half – visible poll sheets, as shown in the figure below which presents a difficult situation for the template-matching algorithm to detect. In this image below, both poll-sheets are partially visible. The green coloured poll sheet is 50% visible, and the red coloured poll sheet is 90% visible, both presenting a similar detection problem, one harder than the other.



Figure 3.7: partial obstruction of a template

How the participant grips the poll sheet provides a further challenge. If the participant holds the poll sheet is obstructing part of it, this impacts the outcome of the program. The algorithm then has to take the partial visibility into consideration when trying to detect the poll sheet.



Figure 3.8: Finger obstructed poll sheet

As can be seen from the illustration above, which is different to the 50% visible image in the representation above.

Overlapping poll sheets

A further challenge arises from overlapping poll sheets. Overlapping poll sheets present a similar problem to partially visible poll sheets. However, these poll sheets overlap each other in the image which can occur frequently. It also depends on the camera height, the elevation/stacking of the classroom seats and the user is holding the poll sheet at certain angles and positions. By placing the camera above the students' heads in the classroom, this camera placement can avoid overlapping poll sheets as each student needs to put the poll sheet on top of their head to show their response.



Figure 3.9: overlapping poll sheets

Extreme lighting conditions

Lighting can drastically change how the program views the poll sheets using computer vision. Some lighting conditions can be reduced or handled within the program. However, some lighting conditions significantly affect colour and hence detection of the poll sheet. In the figure below, the faded colour of the poll sheet becomes undetectable.



Figure 3.10: lighting detection poll sheet

Clothing resembling colour poll sheets

Depending on the type of clothing participants were during the polling process this can result in high false positive results, as shown in the following figure below which presents a difficult situation for the template-matching algorithm to filter out. In this image below, both poll-sheets have a black square within them and a white background. The participant is wearing black square pants detected by the colour poll sheet program. Because the participant is seating in the front of the class, the perspective effect makes it difficult to remove all detection smaller than a certain size.



Figure 3.11: Clothing detected as poll sheet

Limited number of polling captures

The number of photographs captured is limited in our experiment ($n = 12$), nonetheless, per each image captured, there are many single poll sheets collected for our investigation. The colour poll-sheet polling process obtains a relatively large number of results per each student poll; it is, however, limited with regards to the number of polls conducted in a regular lecture or speaking session.

This small number of polls is due to the primary goal of delivering a lesson while aiming to retrieve the secondary goal of useful data in class polls to test the system. This challenge leads to a limited number of photographic images to analyse, achieved in a class of willing participants.

Limited environments used in sample

The use of only two environments limited the variation in the sample of results needed to test the program vigorously. The small number of environments and a repeating set of students from a testing angle will impact the outcome of the results negatively.

Therefore, before the release of the system, a wider test sample will be required to verify the program for its viability fully.

3.5 Template Shape Transformations

Transformations

In this research, template matching is considered as a viable alternative algorithm to detect squares in a classroom where conditions are constantly changing. This constant changing of conditions requires an extra layer of detection incorporated into the template matching algorithm. This additional layer would make the template matching algorithm more robust and allow for a higher detection of poll sheets, by using multiple template transformations such as size, orientations, shearing and colour.

There are many possible transformations we choose to consider rigid transformations.

Rigid transformation can be said to involve every point in the image moving to different coordinates in the picture using the same rules.

In the sections below are some transformations and the movements of general points (x, y) on a Euclidean plane.

Translations

Transformation on x and y-axis:

$$P(x, y) = (x + 2, y - 5)$$

Equation 1. Basic translation transformation

Reflection

Reflection over y-axis:

$$P(x, y) = (-x, y)$$

Equation 2: Point reflection about y-axis

Reflection over y-axis:

$$\begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -x \\ y \end{bmatrix}$$

Equation 3: Matrix reflection about y-axis

Dilation/Scaling

Making entire object bigger or smaller but shape remains the same

$$P(x, y) = (2x, 2y)$$

Equation 4: Scaling of factor 2

Rotation

Rotated around 90 degrees

$$P(x, y) = (x \cos \theta + y \sin \theta, -x \sin \theta + y \cos \theta)$$

Equation 5: Rotation on 90-degree angle

Matrix rotation

$$\begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \cos \theta + y \sin \theta \\ -x \sin \theta + y \cos \theta \end{bmatrix}$$

Equation 6: Matrix Rotation on 90-degree angle

Non-rigid types of transformation are the changing an object shape which we normally call skewing or distorting the image. Typical examples include:

Shearing

Shearing points:

$$P(x, y) = (x + ay, y + bx)$$

Equation 7: Shearing point transformation

Shearing matrix:

$$\begin{bmatrix} 1 & a \\ b & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x + ay \\ y + bx \end{bmatrix}$$

Equation 8: Shearing matrix transformation

3.6 Template Matching Algorithm

The following section looks into the template matching algorithm and explains how various geometric transformations were programmed to detect templates in the image.

Read Image

The first task for the template matching algorithm is to read the images from the system. First, read the image of the entire classroom, and then the image of the template to be matched to the picture is later read into the system.

Grayscale

Template matching first converts the image into a grayscale colour space before trying to detect the various areas of the picture. This modification is done to make the picture easier to read as well as quicker to return a result, mainly because grayscale is a single value.

Pseudo-code for looping through sizes in the python algorithm

```
// Change classroom picture from colour to grayscale after reading it into system
image_rgb = cv2.imread('C:\Python27\Images\p7-CSC-SMALL.jpg')
image_gray = cv2.cvtColor(image_rgb, cv2.COLOR_BGR2GRAY)
```

Figure 3.12: Python algorithm for Grayscale conversion

Iterate through the parameters

To detect the most amount of colour poll sheets using template matching the more templates, the better. However, this would result in a slower system as each template needs to loop through various transformations. In this experiment two templates were used, the first task is to choose a template, then change the size, rotation, affine transformation and then try and find a poll sheet match.

Pseudo-code for looping through sizes in the python algorithm

```
// First create a list of templates to loop through
TEMPLATES = [template3, template4]
for g in TEMPLATES:
    th, tw = g.shape[:2]
// Secondly, resize the template, looping through 20 iterations, from a scale of 1, with an interval of 0.1 cm
    for scale in np.linspace(1, 1, 20)[::-1]:
        r = (int(tw*scale) / g.shape[1])
        dim = (int(tw*scale), int(g.shape[0] * r))
        resized_image = cv2.resize(g, dim, interpolation = cv2.INTER_AREA)
// Thirdly, rotate the resized template, through a set of degrees [0, 15, 30, 45, 60, 75, 90]
        degrees = [0, 15, 30, 45, 60, 75, 90]
        for i in degrees:
            M = cv2.getRotationMatrix2D((rw/2, rh/2), i, 1)
            Rotated_image = cv2.warpAffine(resized_image, M, (rw, rh))
            rh, rw = rotated_image.shape[:2]
// Fourthly, iterate through parameters of the affine transformation
            x = [0.50, 0.60, 0.70, 0.80], y = [0.05, 0.15, 0.25, 0.35]
            for i, j in zip(x, y):
                pts1 = np.float32([[0.25*rw, 0.25*rh], [0.75*rw, 0.25*rh], [0.25*rw, 0.65*rh]])
                pts2 = np.float32([[0.25*rw, j*rh], [0.75*rw, 0.25*rh], [0.25*rw, i*rh]])
                M = cv2.getAffineTransform(pts1, pts2)
                dst = cv2.warpAffine(rotated_image, M, (rw, rh))
// Fifthly, apply a colour reduction to detect faded templates, or lighting conditions
                colour = [0, 40, 80, 120]
                for i in colour:
                    M = np.ones(dst.shape, dtype="uint8")*i
                    Colour_image = cv2.add(dst, M)
```

Figure 3.13: Python algorithm for template transformations

Thresholding

The template can mark a certain part of the picture as detected once it can identify a match with the template. However, the level of matching can be controlled by this thresholding element. Once the template detects a match with 80% accuracy, then we can regard it as matched. The lower this threshold, the more we record false positives. For this experiment, we chose an 80% threshold.

Pseudo-code for detecting points and marking them on the classroom image

```

// Match transformed templates on grayscale image with a confidence threshold of 80%
res = cv2.matchTemplate(image_gray, Colour_image, cv2.TM_CCOEFF_NORMED)
threshold = 0.8
loc = np.where(res >= threshold)
// All detected poll sheets should be marked with a red rectangle, and saved to the colour image
for pt in zip(*loc[:-1]):
    cv2.rectangle(img_rgb, pt, (pt[0]+rw, pt[1]+rh), (0,0,255), 2)
    cv2.imwrite('C:\Python27\Images\Matched.jpg', image_rgb)
// Save the detected points in a list of detected points
detects = []
// Save the Midpoint of detected boxes, calculated as follows
x_point = (float(pt[0]+(0.5*rw))) , y_point = (float(pt[1]+(0.5*rh)))
D = [x_point , y_point]

```

Figure 3.14: Python algorithm for template threshold matching

The threshold is the point of acceptance or rejection when it comes to the core detection of the algorithm, which separates the results into detection or non-detection. The lower the threshold, the longer the number of detected results and the higher the False Positives, a reasonable threshold rate used of 0.80.

Save Detection points

The mid-point of the poll sheets are detected and stored in a .txt file in 2 columns, the first column is the x-point, and the second column is y-point. These points are then sorted according to the algorithm in the following section to filter out multiple detected poll sheets separated by a pixel these are called overlapping detection rectangles.

Overlapping Detection rectangles

A rule was written to find accurately detected centroids that do not overlap the same rectangle and remove all other points that overlap over 25 pixels in the x or y range. In order not to count the same poll sheet twice on detection these other mid-points are removed from the saved and sorted .txt file keeping the first point and removing any other mid-points within the range according to the sorted list.

Pseudo-code for filtering overlap of detection points in python algorithm

```
// Sort out all points in detected list in ascending order of (x, y)
with open("C:\Python27\Images\Detected.txt") as file:
    csv_reader = csv.reader(file)
    Sorted = sorted(csv_reader, key=lambda row:(row[0]), reverse=True)
    np.savetxt("C:\Python27\Images\Sorted.txt", Sorted, fmt="%s")

// Filter sorted points, by removing any points within 25pixels of the point before it, Then run the filter again to check
// until there are no points within 25 pixels of each other
j = 0
for range, x, y in [(25, per_column[0], per_column[1])]:
    j += 1
    pts = [(xx, yy) for xx, yy in zip(x,y)]
    ans_x, ans_y = [list(z) for z in zip(*outrange(pts, rnge))]
```

Figure 3.15: Python algorithm for unique detection templates

Colour Segmentation and Counting

To find which detected results fell in which colour range, a list of boundaries was used to define the different colour segments. For example, because the colour is made up of 3 values (R, G, B) the lower red boundary will be [30, 30, 150], and the upper Red boundary will be [150, 165, 255]. Green would consist of (R, G, B) values [30, 100, 40] for the lower green range and [150, 255, 170] for the upper green range. Each detected midpoint pixel would then match a colour, and this colour would be added up to make a poll result.

Pseudo-code for colour segmentation of detected points

```
// Define list of lower and upper colour boundaries (Remember Format is BGR, not RGB)
l_green, u_green = [30, 100, 40], [150, 255, 170] #Green
l_red, u_red = [30, 30, 150], [150, 165, 255] #Red
l_blue, u_blue = [110, 31, 30], [255, 165, 130] # Blue
l_black, u_black = [0, 0, 0], [100, 100, 110] #Black
```

Figure 3.16 Python pseudocode for colour segmentation

```
// Loop through the colours and select a colour for the point detected
for line in colour:
    column = line.split()
    finale = open("C:\Python27\Images\Finale.txt", "a")
    px = img_rgb[float(column[1]), float(column[0])]
    if ((l_red <= px).all()) and ((px <= u_red).all()):
        finale.write(str(column[0]) + " " + str(column[1]) + " " + str(1) + "\n")
    elif ((l_blue <= px).all()) and ((px <= u_blue).all()):
```

```

        finale.write(str((column[0])) + " " + str((column[1])) + " "+ str(2) + "\n")
    elif((l_black <= px).all() and ((px <= u_black).all()):
        finale.write(str((column[0])) + " " + str((column[1])) + " "+ str(3) + "\n")
    elif((l_yellow <= px).all() and ((px <= u_yellow).all()):
        finale.write(str((column[0])) + " " + str((column[1])) + " "+ str(4) + "\n")
    elif((l_green <= px).all() and ((px <= u_green).all()):
        finale.write(str((column[0])) + " " + str((column[1])) + " "+ str(5) + "\n")
    else:
        print "What colour is this ?", column[0], column[1]
    finale.write(str((column[0])) + " " + str((column[1])) + " "+ str(6) + "\n")

```

Figure 3.17: Python pseudocode for colour segmentation

Combining the three different layers of the algorithm creates a robust but effective colour detection algorithm.

Calculate total detected poll sheets

Run the algorithm to calculate/ add some specific poll sheets in the entire image.

Pseudo-code for calculating detection rates

```

// Formulas to calculate TP, FP, FN, precision, recall and accuracy
TP = len(TP)
FP = (DET - TP)
FN = manual_lines - TP
TN = 0
precision = float (TP / float(TP + FP))
recall = float(TP / float(TP + FN))
accuracy = float (TP + TN)/(TP + FP + FN + TN)

```

Figure 3.28: Pseudocode for calculating TP, FP, Precision and Recall

3.7 Result Display

The result display can either be a bar chart or a pie graph as shown in the Figure 3.19 below. This result display indicates how the class has voted according to both their understanding of the topic and answers to the question.

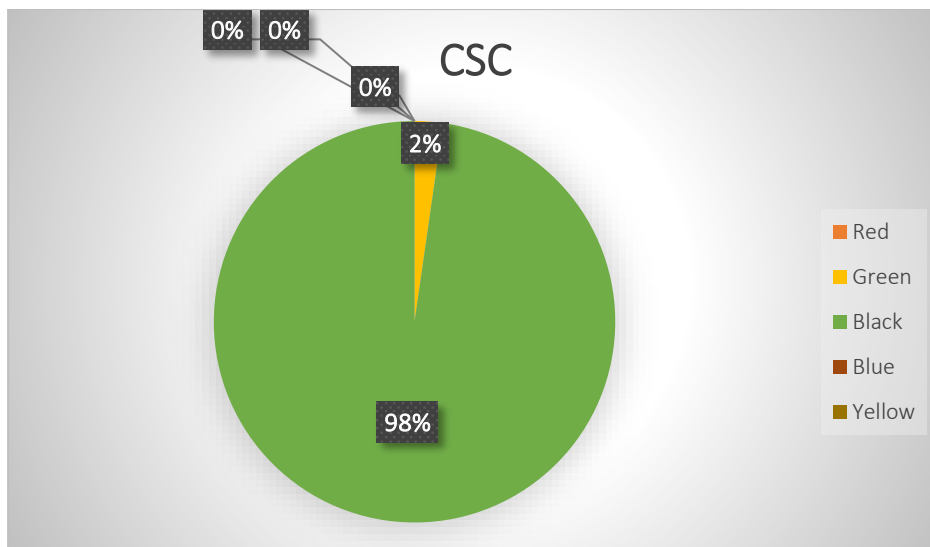


Figure 3.19: Pie chart result display

In this result above 98% voted black and 2% voted Green. No student voted Red or Blue. The figure below depicts the same result as a bar graph.

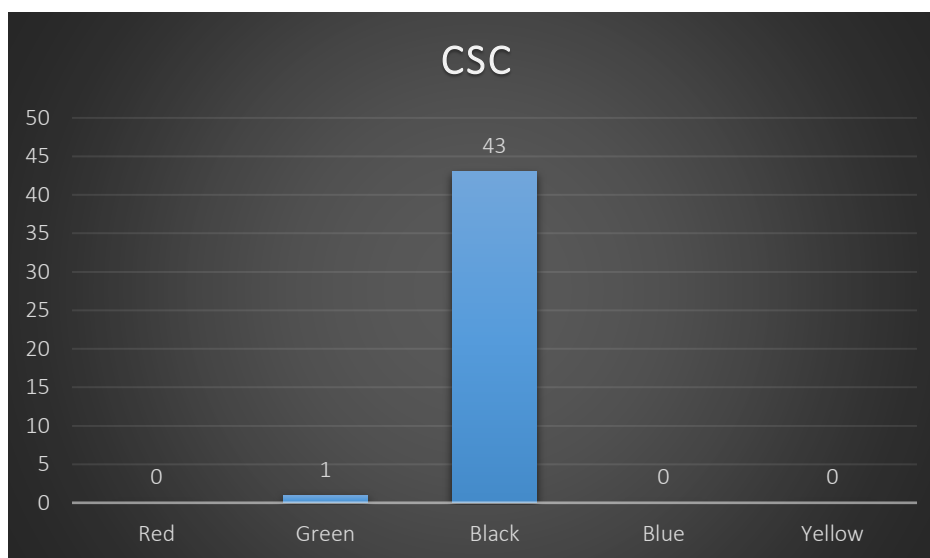


Figure 3.20: Bar Chart result display

For debugging purposes a visual design as illustrated below can be used to indicate which poll sheets were detected and which poll sheets were not detected. This design enables the researcher to figure out how best to improve the detection process or find out what is hindering the program from detecting the poll sheets. The faces are blurred out as well to honour the participants' privacy.

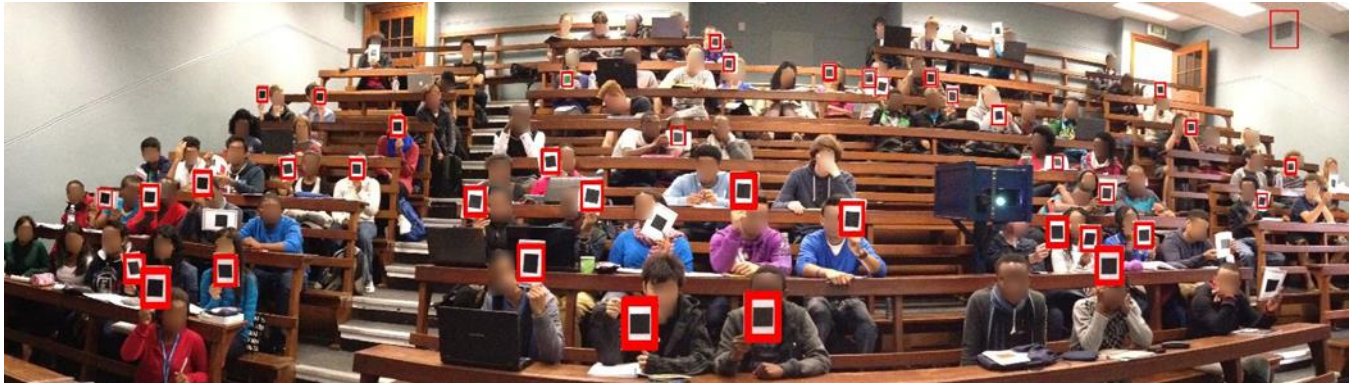


Figure 3.21: Result Display

3.7.1 Results Logging

The system will create log files for diagnostic purposes. For each image received a Picture ID, with a timestamp is created, and the process tracked.

An example of this picture shows the entries as follows from a test run. The logging of results assists with the ethical considerations of privacy. The Log file can be used to tabulate the results of the colour poll sheet instead of showing the picture of the class and the students. This log can then be circulated and compared to universities for research purposes instead of circulating the picture of the class.

```

44 True Positives - Pollsheets have been detected correctly
9 False Positives - Pollsheets have been detected wrongly
3 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.830188679245
The recall of this algorithm is 0.936170212766

0 people voted Red
1 people voted Green
0 people voted Blue
43 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 4481.18604382 seconds
End of program - completed Successfully...

```

Figure 3.22: Example of Results Logging

3.8 Concluding Remarks

From the pseudocode and end of chapter illustration, one can see that the research into creating a coloured poll sheet is a complex task. The algorithm steps are summarised below:

STEP 1. Start time logging

STEP 2. Read Images: Both the template and lecture theatre images

STEP 3. Change size of template and search in images through multiple scales

STEP 4. Filter list to remove overlapping detection points on the same poll sheet

STEP 5. Create Colour ranges for colour definition

STEP 6. Calculation of True Positives and False Positives, False Negatives and True Negatives.

STEP 7. Calculation of Precision and Recall

We can come up with the result displayed as a bar graph of the pie chart in which all participants can view the answer and see their level of understanding of the topic modelled.

In the next chapter, we look at the formulas and the parameters chosen for this research to attain the best results.

CHAPTER 4. STUDY DESIGN

4.1 Study Design

To construct an Audience Response System (ARS) that answers the research question: *Can coloured poll sheets be implemented as an alternative to clickers in audience response systems?*

Our alternative ARS has to be able to function with an audience of over 150 participants, with an accuracy of over 85% and within a time frame of fewer than 60 seconds. The colour poll sheet algorithm described in Chapter 3 was used to identify the number of colour poll sheets in the photographs. The statistics of detected poll sheets were recorded and stored in a table for analysis. The accuracy of the algorithm was calculated by comparing the detected and captured results to the known expected answers. The latter were counted and positioned manually from the photograph by the human eye.

4.2 Performance Calculations – Accuracy, Precision and Recall, F-Measure

To gauge the accuracy of the algorithm, we will look into the results and define the precision and recall associated with the data. We acquired the following samples of results through applying our colour poll sheet algorithm to a classroom sample.

From the sample image below, a few coloured poll sheets are being held up by the participants. The poll sheet algorithm identifies some valid results correctly as (True Positives TP). The algorithm sometimes fails to detect some of these poll sheets at all as (False Negatives FN). There are wrong detections marked as coloured poll sheets, (False Positives FP) and lastly, cases in which a similar but different card is present and not incorrectly detected where not present (True Negatives TN). In this study, there were no bogey poll sheets to calculate the True Negative. However, some participants' clothes had similarities that resembled a colour poll sheets and a very small percentage 2% (Very close to 0) was incorrectly detected as colour poll sheets.

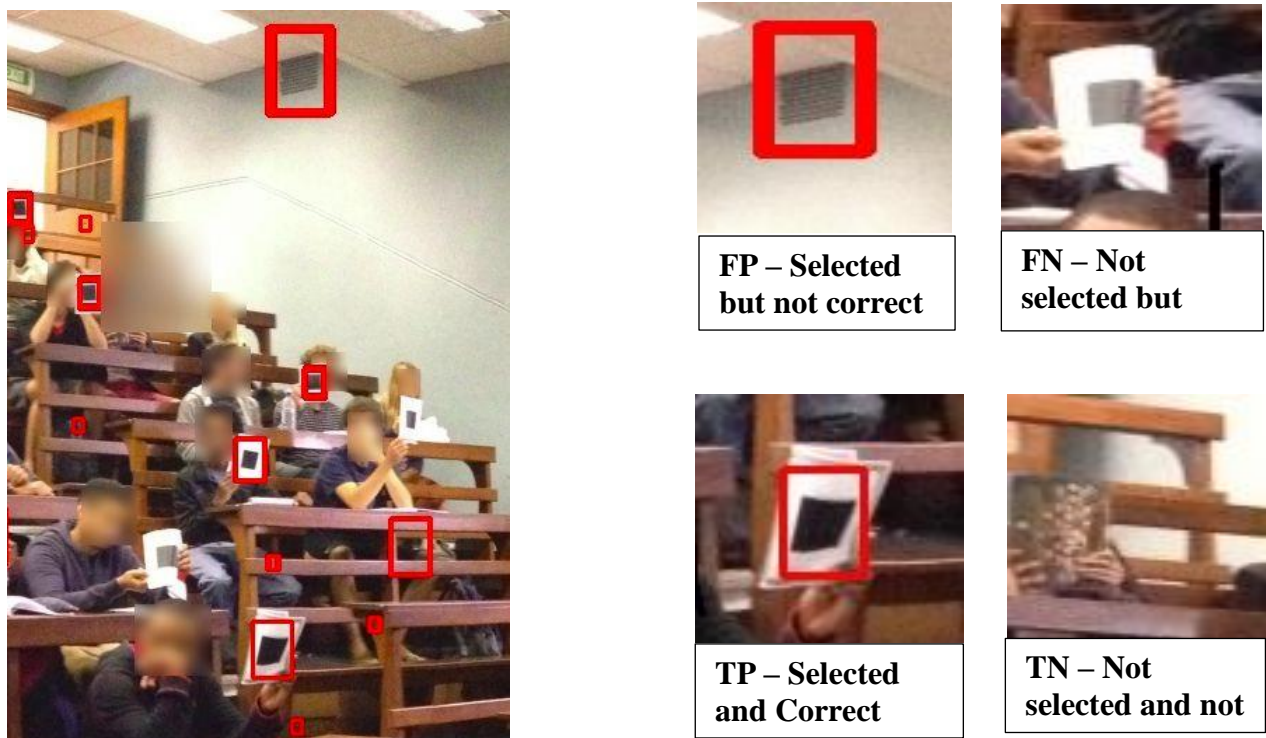


Figure 4.1: True Positive and False Positive example

The Accuracy determined by applying the following formula to the results obtained from the experiment.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

Equation 9 Accuracy formula

However, accuracy is not the best gauge for the computer vision algorithm, as it might not truly give a meaningful statistic. We can manipulate accuracy by reducing the False Positives within the system without particularly increasing the True Positive rate; this would lead to a higher accuracy, however, not a higher detection rate. Hence, analyzing the accuracy rate, it would appear that the system is performing well, but in fact, it would not be detecting more poll sheets than a different system. For this reason, we turn to precision and recall to provide a reliable and relevant statistic to measure the accuracy of our algorithm.

Precision is the proportion of from all detected candidates that are poll sheets (true positives).

$$Precision = \frac{TP}{TP + FP}$$

Equation 10: Precision formula

Recall or Sensitivity is the portion of real positive cases that are correctly positive [Powers, \(2011\)](#).

$$Recall = \frac{TP}{TP + FN}$$

Equation 11: Recall formula

When we are equally interested in both precision and recall, we combine the two and create the F- measure, which is synonymous with the weighted harmonic mean of the Precision and Recall. That is,

$$F = \frac{1}{\alpha \frac{1}{Precision} + (1 - \alpha) \frac{1}{Recall}}$$

Where, the weight, $\alpha \in [0, 1]$

Equation 12: F-measure formula

The Balanced F-measure, commonly denoted as

$$F_1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

Equation 13: F-measure formula

[Patil and Sherakar, \(2013\)](#) expresses a version of the F-measure that combines precision and recall with an equal weight (where alpha = 0.5) hence providing a better measure.

The F- measure is used to determine the True error rate of the colour poll sheet algorithm.

$$F = 2 * \frac{Precision * Recall}{Precision + Recall}$$

$$F_{\beta} = (1 + \beta^2) \cdot \frac{precision \cdot recall}{(\beta^2 \cdot precision) + recall}$$

Equation 14: F-measure formula where alpha=0.5

A balanced F – Measure results in the following:

$$E = 1 - \left(\frac{\alpha}{P} + \frac{1 - \alpha}{R} \right)^{-1}$$

Where the relationship is: $F_{\beta} = 1 - E$

Where: $\alpha = \frac{1}{1 + \beta^2}$

Equation 15: Balanced F-Measure

The F-Measure can, therefore, be used to determine the actual error rate of the colour poll sheet algorithm.

4.3 Parameter Selection

In this sub-section we will explore the effects on the results of changing the following four parameters in our algorithm:

- Template matching threshold (0.75, 0.80 and 0.85)
- Pixel Overlap (15 pixels, 20 pixels and 25 pixels)
- Transformations (Scaling, Rotation, Colour Reduction, Affine transformations)
- Colour Ranges (using Black)
- Templates Sizes and Colours

To find the effects of the results tests on two classroom images for the two different environments.

Template matching threshold (0.75, 0.80 and 0.85)

The template matching threshold looks at the margin of error that the system is will to consider. A threshold of 0.75 means the system has a 75% confidence level that a detection is a True Positive. Hence, 75% detected results are assumed to True Positives leaving a 25% likelihood that any detection is not a true match. By increasing the threshold to 0.80 and detections.

In the example Figure 4.2 below, we start with changing the threshold from 0.75 in the first figure, and then to 0.80 in the second figure and then lastly to 0.85 in the last illustration. The measure analysed is the Detection rate, the precision and the recall.

Threshold of 0.75

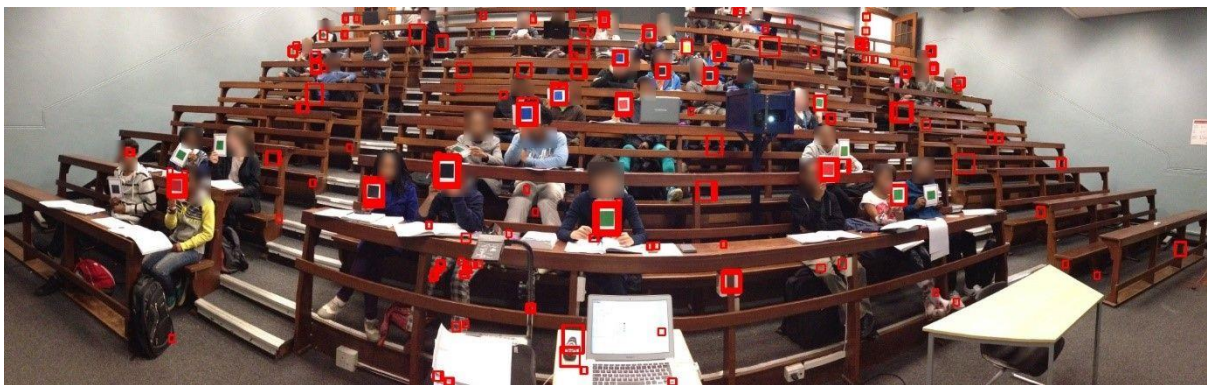


Figure 4.2: Detection Photograph at a threshold of 0.75

The precision result for Figure 4.2 at a threshold of 0.75 is 0.2, whilst the recall result is 0.63888 and accuracy is 0.1811.

Threshold of 0.80

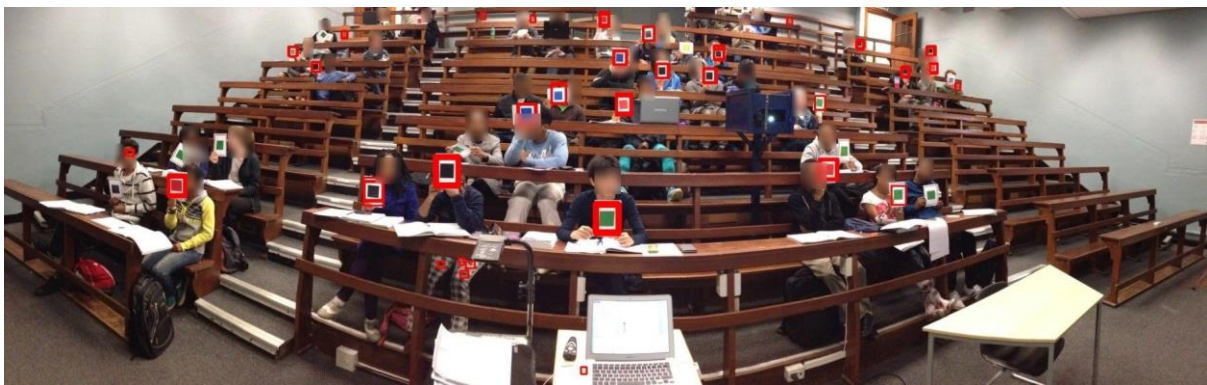


Figure 4.3: Detection Photograph at a threshold of 0.80

The precision for Figure 4.3 at a threshold of 0.80 is 0.7, whilst the recall result is 0.65625 and accuracy is 0.5122.

Threshold of 0.85



Figure 4.4: Detection Photograph at a threshold of 0.80

The precision at a threshold of 0.85 is 1.0, recall is 0.28125, and accuracy is 0.2813

The research decision was to use a threshold 0.80 to include as many detections possible and then filter the detections based on the colour within the middle of the detection. The reason not to reduce the threshold to 0.70 is because there is no addition to the true positives but more false positives are added to the results. If this colour is not within the ranges, then the detection is probably a false positive and not considered as a vote.

This method allows results in a higher success rate than using a lower threshold which includes false positives without a significant increase in detections. The effect is a higher recall rate but a lower precision and longer run time.

Pixel Overlap (15 pixels, 20 pixels and 25 pixels)

Changing the pixel overlap from 15 pixels to 20 pixels and further to 25 pixels resulted in no marked difference in any of the results. This negligible difference is because a pixel is minuscule, the difference from the midpoint of the two poll sheet highlighted in yellow in Figure 4.5 below is 50 pixels even though they are side by side.

Therefore the parameter chosen for pixel overlap is 25 pixels for faster computation given there is no marked difference in recall or precision.



Figure 4.5: 50 Pixel distance between poll sheets marked in yellow box

Transformations (Rotation, Colour Reduction, Affine transformations)

One of the parameters in determining the number of times to transform a template and the intervals between each change. We ran a few tests to determine the scaling factor that would produce the highest detections in the least amount of time.

The more the transformation, the wider the net in which to catch the different template sizes, rotations or colour changes, On the other hand, the longer it takes to run the code as the algorithm has to perform each transform multiple times.

- Rotations, were performed with the following degrees = [0, 15, 30, 45, 60, 75, 90]
- Scaling, was performed with the following intervals = 20 iterations with min 0.2 from 1.0
- Colour reduction was performed with the following intervals = [0, 40, 80, 120]
- Affine Transformations were performed over the following:

$$x = [0.50, 0.60, 0.70, 0.80], y = [0.05, 0.15, 0.25, 0.35]$$

Colour Ranges (using Black)

The colour ranges were changed incrementally with each test to include as many accurate detections as possible. Hence, the higher accuracy would result from performing as many experiments and incrementally adding the range to the colours. Through multiple experiments similar colours i.e. blue and black have a higher chance getting mixed up during the poll sheet computation. Therefore, when applying the poll sheet in

the two different environments, it would be best to go with the following colours, (Black, Red and Green) or (Blue, Red and Green) for the robust accuracy of votes.

Templates Sizes and Colours

The last parameter to test is the templates sizes and colour for the poll sheet algorithm. The template size is increased over 20 scales of 0.5 point each time. Even though this is the case, the template chosen has a big effect on the results obtained. Due to this effect instead of using only one template, the program will use two templates to run the program and search for as many matches as possible. The best possible templates are templates that detect the most different poll sheets.

In the algorithm test, we depict the two templates used below.



Figure 4.6: Templates chosen in the template matching algorithm

Affine Transformation

The affine transformation is applied to handle differential vertical scaling, created by angling the poll sheet away from or towards the camera. This is a very common occurrence in the classroom and distorts the view of the poll sheet. In order to transform the poll sheet the x and y coordinates at all corners of the poll sheet are changed accordingly using the matrix below to produce a template in Figure 4.7 below, and loop through the affine transformations:

$$x = [0.50, 0.60, 0.70, 0.80]$$

$$y = [0.05, 0.15, 0.25, 0.35]$$



Figure 4.7: Affine transformed Template in the template matching algorithm

4.4 Ethics and Approval

Within the discipline of Computer Science research, there are many ethical considerations to take into account from software piracy, user privacy, user data collection and user tracking to data storage after user deletion. In this research, the primary focus has been on the data gathering procedure, the objectivity of data analysis and the protection of subjects' privacy.

Objectivity of data analysis

The program was built to focus on colour poll sheets held up by students and achieve a maximum detection of these colour poll sheets. No discrimination of race, sex, ethnicity or other factors applied within this program.

Protection of participants' privacy

There are ethical considerations to consider when creating the colour poll sheet ARS for the individuals participating in the study. Ethical considerations were accounted for by using a face detection algorithm after concluding the poll and the image results used for debugging purposes. A bar chart or pie graph will be used to depict the outcome of the rest of the class.

We run the face-blurring algorithm on the image before storing it in a database. This blurred image is batch stored with the facilitator's question, bar graph/pie chart and log file. This face-blurring algorithm generates an image as depicted below to aid in privacy for individuals taking the poll.

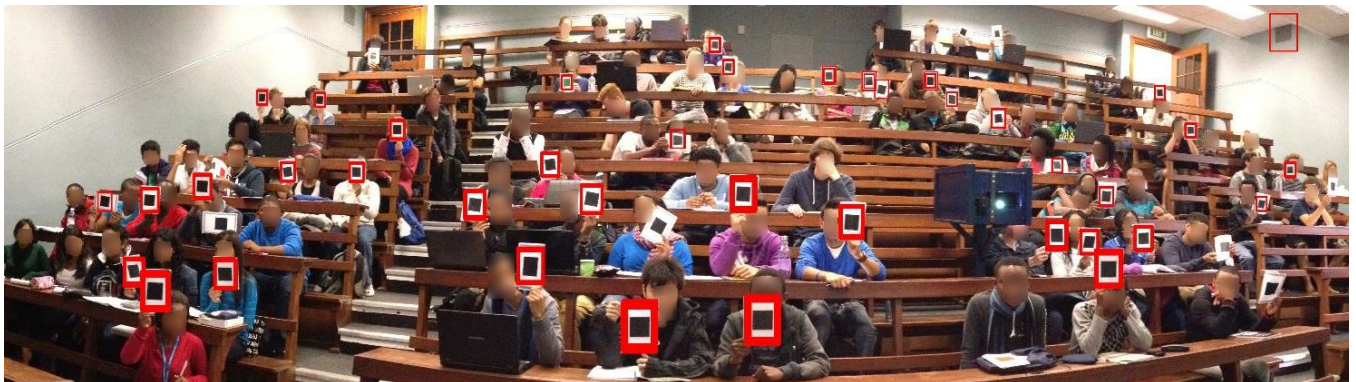


Figure 4.7: Blur Picture to aid with privacy of poll takers

In line with a privacy policy to accompany the system. The ability to blur out faces within the saved image as shown in Figure 4:2 above included in the system. An extension of the system privacy policy can involve the option to delete the images obtained from each detection after a specified number of months. This policy will ensure data gathered is not kept for longer than necessary and in ways not intended by the user during participation.

Data Collection

We use the data set provided by the author of (Gain, 2013). Image-based polling was trialled for five weeks in a first-year university-level Introductory Computer Science course in programming. The data collected in classrooms ranging from 30 – 140 students. Regarding participation, on average, 72% of the class voted during the polls (with a broad range of 51% to 90%).

The data about the accuracy, costs and speed of Clickers and other alternative ARS collected from various resources. This data was analysed statistically to find significant differences between the different systems.

4.5 Participant Attributes

Several attributes were common among the participants. These attributes might have an impact on the uptake of the system within Africa and the success of the audience response system in subsequent use.

The attributes in common are as follows:

Level of education

The participants that contributed to the sample study were all university students. This participant sample means the standard of education the participants had was at least a matriculation certificate. However, due to the nature of simplicity of the poll sheets, the standard of teaching was not viewed as a deciding factor to the results obtained in the research.

Gender

A study performed by the [Kang, Lundeberg, Wolter, Delmas and Herreid \(2012\)](#) found that there was a marked difference between Men and Women in USA and Canada when it comes to science learning between two pedagogical approaches: clickers and traditional classroom structured lessons. Although clickers were found to favour women more than men, this might affect the uptake of this system, however, was not part of the scope of study when implementing the colour poll sheet ARS.

English Language Literacy

The participants within the class had a certain level of English literacy, which might affect the degree of understanding within the training process of the colour poll sheets. That said, in a different environment and or a different country, the primary language communicated to the class by a facilitator, and a similar understanding should be achievable.

Computer literacy

Due to the technological nature of the research, one would be inclined to ask if the users needed to be computer literate to be able to participate in the research. Participants did not need to use a computer or be technologically proficient to any level to participate in the study. Computer literacy is not a requirement in the audience response system involving colour poll sheets.

These highlighted attributes would allow a larger percentage of people in Africa to participate in the audience response system within a classroom setting.

Colour blindness

Colour blindness poses a disadvantage of not allowing the system to be used by blind people or colour blind people. The system will be able to pick up any poll sheet held up, but blind people will not be able to hold the sheet up to the camera. A braille could be placed on each side of the colour poll sheet to communicate which colour is which and a particular sound emitted from the camera as a solution for colour blind people.

Training of Participants

The participants needed a little training to be able to use the colour coded poll sheets. The only instruction is that the colour poll sheet required to be visible to the camera to capture the responses (Gain, 2013).

This minute degree of training was one of the aims of creating a highly acceptable polling system. Due to the slower adoption of technology within Africa in comparison to the rest of the world, a solution for Africa would need to be easy to understand, as well as grasp and explain to students that are not technologically savvy. This simplicity could lead to higher adoption rates and higher participation rates, making the colour poll sheet a commercially viable alternative to clickers within Africa.

4.6 Concluding Remarks

From the chapter, we have gathered that the best measures to determine if the system is successful or not are by looking all the results for Accuracy, Precision and Recall. The better the detection rate, the better the program is performing.

The parameters chosen for the experiment were a threshold = 0.80 meaning an 80% confidence in the detections decided to be true positives. The best colours to use in combination would be Black, Red and Green per question.

We choose the pixel overlap of 25 pixels as it would result in a shorter time to run through the measures reducing the load on the program. However, when it comes to the low likelihood of counting the same poll sheet twice, we could use either pixel overlap measures of 15 pixels, or 20 pixels.

We chose two templates for the detections which resulted in better detections than one template, this added to the program time. However, the primary goal of the system was for a better detection rate. With these parameters, the system would result in the best results at a reasonable speed according to the tests of algorithm parameters.

CHAPTER 5. RESULTS

The objective of this chapter is to explain the analysis of the results from the implementation of the colour poll-sheet Audience Response System (ARS). The chapter begins by recalling the research objectives of the colour poll sheet ARS and then analysing the quantitative elements of the outcomes of the experiment. The qualitative elements of ARS were not the focus of the investigation in this research. The chapter then concludes with a summary and recommendations that can improve results and maximise the success rate of the algorithm. To begin, we first revisit the research questions that motivated this work.

5.1 Research Questions

The study aimed to answer the following:

- *Can coloured poll sheets be implemented as an alternative audience response system to clickers?*
- *Can we use the colour poll sheets to achieve an accuracy of 85% within the timeframe of 60 seconds?*

In evaluating the performance of the colour poll sheet ARS, the research questions above are answered, so as to measure the alignment of the research goals to the results sought. An analysis of the results is investigated below, starting with weighing the detection accuracy with that of an 85% accuracy target and then enhancing the colour poll sheet ARS system. To achieve this, we would need to calculate the strict accuracy measure taking the detected results, the non-detected results and the falsely detected results into account.

5.2 Analysis of Results - Quantitative results of interest

A sample of 12 images of two occupied lecture venues is used to test the audience response system. In this 12 image sample, over 250 volunteers presented over 1100 colour poll sheet readings in only two different environments varying in venue slope, lighting, width and

height. Many of the participants of the experiment came from a computer science background, and the primary colours used for the colour poll sheets experiment were red, black, green, and blue.

A baseline of actual results was manually counted and recorded to make sure the detected results were true positive results and evaluate the accuracy of the detected results of the program. The evaluation expansion of the detection algorithm adds to the algorithm running time and is a useful system option when testing if the algorithm is performing at an acceptable accuracy level.

A top-down analysis of the results was conducted, scrutinising the total results first and then dissecting the results further to determine the major areas affecting the system results. Out of a total of 1103 actual polling results, the template algorithm had a detection rate of 62%.

The reason for this was then to filter out the wrong detections using a colour detection algorithm. If the midpoint of a detected rectangle does not fall within the colour ranges stipulated then we can reject this point and only count the detected rectangles that lie within the specified colour ranges. Of this total detection rate, there was only about 61% True Positive (TP) detected resulting in a total precision of 68% and total F-measure of 0.67 (with alpha at 0.9) and a balance F-Measure of 0.63

Picture	Precision	Recall	F-Measure	Balanced F
Average	0,68	0,62	0,67	0,63

Table 5.1: Average Detection results

In the next section of this chapter we take a further look at the error rates according to different variables, mainly:

- *Class Environment (CSC and ZOO)*
- *Poll sheet colour (Red, Green, Blue and Black)*
- *Class Size / Number of participants*

By inspecting these various independent variables, we can assay which variables will result in better total results and lower error rates. Various adjustments to the algorithm can be introduced to increase the detection rate and reduce the error rates, which will be investigated later in the chapter.

5.2.1 Detection rate analysed on the Environment

Further analysis of the total results uncovers a few details with regards to what makes this detection rate so low. The second thing that comes to mind is a look at the different picture results by the environment. We have only two distinct environments CSC and ZOO.

Picture	Env.	Recall
P3	CSC	0,68
P6	CSC	0,85
P7	CSC	0,66
P8	CSC	0,68
P9	CSC	0,70
P11	CSC	0,87
P1	ZOO	0,73
P2	ZOO	0,40
P4	ZOO	0,69
P5	ZOO	0,42
P10	ZOO	0,43
P12	ZOO	0,32

Table 5.2: Recall results per environment (env.)

The table 5.2 above can show that there is a marked difference between the CSC environment and the ZOO environment signalling that the environment would cause a large enough difference in the recall rate.

The reason the two environments have different results is due to width and elevation of the seating arrangement in environments. The CSC environment is narrower and steeper in comparison to the ZOO environment, this allows the poll sheets to appear bigger and therefore easier to detect mainly because they are relatively close to the camera in comparison to the poll sheets in the ZOO environment. The CSC environment holds fewer individuals in comparison to the ZOO environment. The width of the ZOO environment

and the gentle slope of the seats within this environment makes the colour poll sheets at the back appear smaller in the picture and therefore harder to detect resulting in a lower detection rate in comparison to the CSC environment.

However, the precision and recall rates increase dependent on the environment. For all the CSC environment regardless of the number of people in the classroom, the results are much better than the ZOO environment. The precision rates for all CSC images are above 70% and recall rates above 66%. The ZOO environment precision rates are as low as 32%, and recall rates are as low as 32%.

CSC Environment

Picture	Env.	Precision	Recall	F-Measure	Balance F
P3	CSC	0,76	0,68	0,75	0,71
P6	CSC	0,74	0,85	0,75	0,80
P7	CSC	0,70	0,66	0,70	0,68
P8	CSC	0,77	0,68	0,76	0,72
P9	CSC	0,83	0,70	0,81	0,76
P11	CSC	0,80	0,87	0,80	0,83

Table 5.3: CSC Precision and Recall and F-Measures

Mean and standard deviation on the CSC environment

Picture		Accuracy	Precision	Recall	F-Measure	Balanced F
Total	CSC	3,05	4,59	4,43	4,57	4,49
Mean	CSC	0,51	0,77	0,74	0,76	0,75
Variance	CSC	0,01	0,00	0,01	0,00	0,00
Standard Dev.	CSC	0,08	0,04	0,10	0,04	0,06

Table 5.4: CSC Mean and Standard Deviation

ZOO Environment

Picture	Env.	Precision	Recall	F-Measure	Balance F
P2	ZOO	0,41	0,40	0,41	0,41
P4	ZOO	0,59	0,69	0,60	0,63
P5	ZOO	0,32	0,42	0,33	0,36
P10	ZOO	0,73	0,43	0,68	0,54
P12	ZOO	0,85	0,32	0,73	0,46

Table 5.5: ZOO Precision and Recall and F-Measures

5.2.2 Detection rate analysed on the Poll sheet colour

The results shown by the colour poll sheet program are tabulated in Table 5.6 below as follows:

Picture	Env.	A Col. Red	D Col. Red	Detection %
P1	ZOO	71	55	77%
P2	ZOO	10	6	60%
P3	CSC	13	9	69%
P4	ZOO	33	25	76%
P5	ZOO	16	6	38%
P6	CSC	21	20	95%
P7	CSC	7	5	71%
P8	CSC	79	49	62%
P9	CSC	54	37	69%
P10	ZOO	6	2	33%
P11	CSC	0	0	0%
P12	ZOO	59	21	36%
Total		369	235	64%

Table 5.6: Red Poll Colour Analysis (A Col. Red meaning Actual Colour Red, D Col. Red meaning Detected Colour Red)

As can be seen from the table 5.6 above CSC environment presents a higher detection rate of the two environments. In the row with a detection of 0%, there were no red-poll sheets responses in this poll. The average detection percentage for red colour poll sheets is 64%. The standard deviation associated with the detection of the Red colour is 24.75%.

Picture	Env.	A Col. - Green	D Col. - Green	Detection %
P1	ZOO	27	17	63%
P2	ZOO	105	44	42%
P3	CSC	84	44	52%
P4	ZOO	36	25	69%
P5	ZOO	53	15	28%
P6	CSC	19	19	100%
P7	CSC	11	4	36%
P8	CSC	21	9	43%
P9	CSC	19	10	53%
P10	ZOO	4	0	0%
P11	CSC	1	1	100%
P12	ZOO	8	1	13%
Total		388	189	49%

CHAPTER 5. RESULTS

Table 5.7: Analysis per Green Poll Colour (A Col.-Green meaning Actual Colour Greed, D Col.-Green meaning Detected Colour Green)

When it comes to the green poll sheet, the average detection percentage is only 49%. green was used more in the ZOO environment which the colour poll sheet program had lower detection results. The standard deviation for the detection of the Green colour is 29.16%

Picture	Env.	A Col. - Black	D Col. - Black	Detection %
P1	ZOO	6	2	33%
P2	ZOO	13	3	23%
P3	CSC	17	16	94%
P4	ZOO	15	9	60%
P5	ZOO	13	5	38%
P6	CSC	10	5	50%
P7	CSC	14	9	64%
P8	CSC	4	2	50%
P9	CSC	0	0	0%
P10	ZOO	67	31	46%
P11	CSC	46	38	83%
P12	ZOO	1	0	0%
Total		206	120	58%

Table 5.8: Analysis per Black Poll Colour (A Col.-Black meaning Actual Colour Black, D Col.-Black meaning Detected Colour Black)

The average detection rate for the black poll sheet colour was 58%. The standard deviation for the detection of the Black colour is 27.70%

Picture	Env.	A Col. - Blue	D Col. - Blue	Detection %
P1	ZOO	12	11	92%
P2	ZOO	4	0	0%
P3	CSC	6	2	33%
P4	ZOO	32	21	66%
P5	ZOO	21	19	90%
P6	CSC	26	20	77%
P7	CSC	3	3	100%
P8	CSC	22	17	77%
P9	CSC	1	1	100%
P10	ZOO	0	0	0%
P11	CSC	0	0	0%
P12	ZOO	1	0	0%
Total		128	94	73%

Table 5.9: Analysis per Blue Poll Colour (A Col.-Blue meaning Actual Colour Blue, D Col.-Blue meaning Detected Colour Blue)

The average detection rate for the blue poll sheet was 73% which is the highest detection rate of all four colours. From the Table 5.9 above we can see that blue colour has a relatively high detection rate in any environment. The standard deviation for the detection of the blue colour is 36.80%

5.2.3 Detection rate analysed on the Number of participants/Class size

To ascertain whether some participants affect the accuracy attained by the program, we could try and prove whether the error rates increase the more participants are present. Most of the experiments have about 70 - 120 students in the participation.

The Table 5.10 below shows precision and recall results.

Env.	# of Participants	Precision	Recall
ZOO	116	0,68	0,73
ZOO	132	0,41	0,40
CSC	105	0,76	0,68
ZOO	116	0,59	0,69
ZOO	75	0,32	0,42
CSC	75	0,74	0,85
CSC	32	0,70	0,66
CSC	113	0,77	0,68
CSC	69	0,83	0,70
ZOO	77	0,73	0,43
CSC	45	0,80	0,87
ZOO	69	0,85	0,32

Table 5.10: Precision and Recall per Class

The number of participants does not seem to affect the results drastically, with higher numbers not correlated with the higher results. As the graph in figure 5.1 shows, there is no correlation between the class size and the precision or recall rate of the table arranged according to class size.

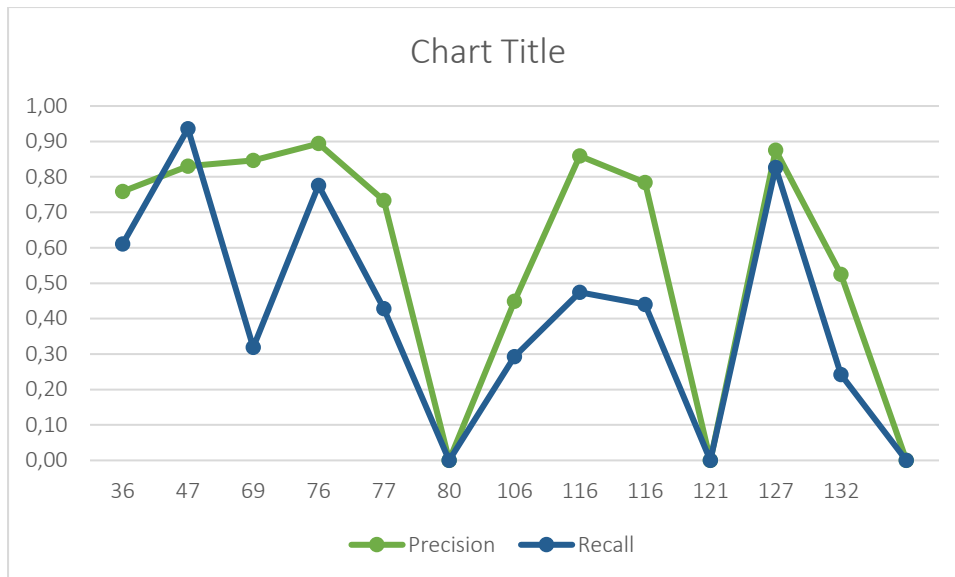


Figure 5.1: Precision vs. Recall participant graph

According to the chart above in figure 5:1 the blue line shows the actual results sorted in ascending order. However, the detected results do not indicate any pattern similar to that of the real results. Therefore we can conclude the number of participants does not affect results of the program. There is also no correlation between, a higher number of students and greater or lower error rates.

Ideally, a situation in which one detects more results and then filters these to obtain a greater number of actual results leads to a better algorithm.

To answer one of the research questions, *Can we use the coloured poll sheets to achieve an accuracy of 85% within the timeframe of 60 seconds?*

We can analyse any variables changed to reduce the error rates within the system. Once we have identified the main variables to change and improve on, an enhancement will result in higher accuracy and lower error rates. This improvement will help answer the question as to whether an enhancement can produce as accurate a response system as clickers.

5.2.4 Detection analysis on research question

A few samples of the program detections depicted as follows.

Figure 5.2 below depicts a samples size of a medium-sized classroom with not that many people.



Figure 5.2: Example of Small classroom illustration

Figure 5.3 below depicts a samples size of a medium-sized classroom with more participants in the same environment as the smaller classroom.



Figure 5.3: Example of a Medium-sized classroom detection

Figure 5.4 depicts a samples size of a large-sized classroom with more participants in a different environment.



Figure 5.4: Example of an extensive classroom detection

5.3 Answers to Research Questions

5.3.1 Comparison with 85% Goal

Our research goal was an 85% target; the implementation recorded a mean recall rate of 73% and a mean precision of 76% in the CSC environment with some participants ranging from 32 – 113. When we include the ZOO environment, the average recall rate drops to 62% and the mean precision drops to 68%. Computer vision ARS have the limitation of requiring a direct line of sight hence the error rates will be higher in computer vision based ARS.

This result shows that in an environment, such as an in-class poll, where the aim is to induce interaction and get a general idea of whether the class understands the topic. Colour poll sheets can be a promising alternative to clickers. However, the error rate is too high for grading assessments of participants. Nonetheless, in conclusion, the experiment did not achieve the 85% goal stated in the research question.

5.3.2 Comparison with Gain (2013) slower and less accurate

The results of this research are lower than the results attained by Gain due to the calculation of Detections by Gain and the research below. Gain, calculated detections based on whether the algorithm detected or did not detect a square. Whereas, the research below calculates a detection as a True Positive.

Gain (2013) algorithm detects blobs to detect the result and hence is much quicker in comparison to the template matching algorithm conducted in this thesis. The template matching algorithm runs through the images multiple times with each template transformation hence taking much longer in comparison to Gain (2013).

5.3.3 Comparison with 60-second Target

Picture	Env.	Time (Seconds)
P3	CSC	321, 23
P6	CSC	178,54
P7	CSC	132,7
P8	CSC	307
P9	CSC	183.71
P11	CSC	308, 61

Table 5.11: Time (Seconds)

The class size affects the amount of time it took the colour poll sheet algorithm to complete a cycle. The time took between 132 seconds - 321 seconds within the CSC environment. This result is above the 60-second target set in the original proposal. The ways to reduce this time would be to remove some of the transformations that are in the system. Instead of cycling through 6 rotations. The program can cycle through only three rotations transformations. This reduction in transformation will reduce the run time taken by the program.

5.3.4 Can the implementation of coloured poll sheets be an alternative audience response system to clickers?

The Computer Vision alternative had an average of about 62% accuracy rate which is a lot lower than the accuracy achieved by clickers 99% Gain (2013). According to the accuracy rate, the computer vision alternative cannot be used as an alternative audience response system to clickers. The time ranging from 132 – 321 for the colour poll sheet alternative is once again considerably higher than a timeframe of < 10 seconds for clickers Gain (2013). However, when looking at the cost of colour poll sheet alternative, which is considerably lower than clickers. Therefore colour poll sheet is a promising alternative however currently cannot be implemented as an alternative audience system to clickers.

5.4 Recommendations

According to the analysis of the results, a few recommendations can be made to eliminate the factors that led to higher error rates, and this should produce higher accuracy rates. These recommendations are as follows:

5.4.1 Colour of poll sheet used in polling

The colour of poll sheets can positively affect the success factor of the algorithm. The time of the day will affect the lighting emanating from the different colours of the colour poll sheet resulting in less detectability when the lighting conditions changed significantly.

5.4.2 Size of poll sheet used in polling

The Size of the poll sheet was viewed to have significantly affected the results when presented in a class of 200 people. The standard poll sheet was of the sizes 10cm and 10cm. Therefore one would recommend using a poll sheet of the sizes 20cm and 20cm as this would allow for easier detection especially in classes which are big.

5.4.3 Holding the poll sheet correctly

Given the various factors mentioned in this chapter, different factors on how participants held the cards affected the result of the study. When participants held the card facing the camera and did not obstruct any part of the card this led to the high success rate of the colour polling system. Most of the errors rates came from partially obstructed cards. Hence a new border would be beneficial as this new border would be the extra space where a participant can hold the poll sheet, without affecting the template section for matching.

5.5 Concluding remarks

As initially discussed in the first chapter, the problem faced by institutions was the high relative costs of using clickers in classrooms in Africa. Which motivated the exploration of a cheaper alternative, settling on the creation of a computer vision ARS to detect colour poll sheets. Extensive investigation into current literature on computer vision programs in Africa as alternatives to clickers was not readily available hence motivating the research of this thesis in Chapter 2.

Chapter 3 looks into the implementation of the program as well as the data collection process and challenges of data gathering and participation. Chapter 4 explains the algorithm used; Chapter 5 examines the results obtained from the colour vision ARS and an analysis of these results.

The most notable issue in the interpretation of results is the importance of holding the colour poll sheet correctly, as well as not obstructing it in any way to allow for accurate template matching.

If students do not have a particular issue with answering the questions while being recorded, and there is no psychological hindrance to accurate results, then colour poll sheets can be used as an alternative to clickers. If students are shown a detection photograph of the participants at the beginning of the polling process, it will allow the students the ability to see which results were detected and which results were not detected. The picture would enable the students, who held up their poll sheets incorrectly to adjust their poll sheets accordingly to the next question.

This research also shows that in an environment, such as a class poll, where the aim is to induce interaction and get a general idea of whether the class understands the topic. Colour poll sheets can act as an alternative to clickers if this polling is not for assessments of participants for grading purposes. Audience response systems for grading might result in cheating, non-participation or passive participation especially if participation is rewarded for attendance only as discovered by an experiment by [White, Delaney, Syncox, Akerberg](#)

[and Alters \(2011\)](#). Coloured poll sheet ARS will not induce adverse effects of the audience response system as studied by [White, Syncox and Alters, \(2011\)](#).

CHAPTER 6. CONCLUSION AND FUTURE WORK

6.1 Introduction

In this research, we intended to investigate cheaper alternatives to audience response systems (ARS) by building a computer vision ARS using colour poll sheets. The challenge we faced was designing an algorithm to achieve an accuracy of 85% using a computer vision approach in which there are infinite variations to a single poll as well as handling differences in the environment polled.

This chapter concludes the examination of the implementation and results gathered by the experiments conducted. Furthermore, this chapter gives a summary of the algorithm with regards to the comparison to clickers. Over and above the summary, the chapter finalises the implementation by recommending future work that could be investigated to improve the computer vision algorithm to make it more flexible and accurate as an alternative to clickers.

6.2 Conclusion

In conclusion of the colour poll sheet alternative research, we found that there are some limitations of a computer vision ARS. The level of precise instructions has to be given and followed to attain the results required. In a classroom, this is not precisely possible hence computer vision requires layers of alternative detection methods to cover these possibilities.

To cover as many possibilities we used different templates, which we transformed as much as possible to detect as many poll sheet as possible without drastically increasing the time taken to collect these poll sheets.

These findings significantly assist in laying down the groundwork for future work to be done to enhance the accuracy of a colour poll sheet algorithm. We find that the colour poll

sheet ARS is promising as an alternative ARS. In the next section, we discuss some elements that can be added to the algorithm and research to increase both the accuracy and the speed of the program.

6.3 Future Work

One of the main motivations to research a computer vision based audience response system stems from the potential future work that one can follow up to advance computer vision.

6.3.1 Algorithm

At present, the template algorithm performs changes to the template, according to the following differences:

- Size
- Rotation
- Lighting
- Skewness

Extra changes can be added to the poll sheet algorithm to make it robust for the various conditions such as:

- Cutting section of the template
- Fingers obstructing the template
- Other poll sheets are creating a partial obstruction.

The speed with which it detects the colour poll sheets is another element of the algorithm that can be improved. The smaller the image, the faster it computes, however by shrinking the image this also affects the accuracy of the algorithm. There is an iterative improvement of the poll sheet algorithm through the integration of the cloud for accessibility to all the institutions to use and achieve additional updates to the algorithm as well as include improvements to algorithms. This continuous improvement will allow the results to be scrutinised to forge better improvements to the poll sheet algorithm.

6.3.2 Raspberry π

A raspberry pi can be used to hold the software as well as take pictures, therefore would act as an ideal tool for this implementation. The resolution of pictures taken by the raspberry pi is high enough to capture large classrooms accurately, and all the software is in one single unit. The raspberry pi has inbuilt Wi-Fi to allow connection onto the network and a facilitators laptop without any manual connections.

The raspberry π is a mini-computer which can be enabled with a camera to detect and capture the results. We install the raspberry π with software to decode the pictures and tabulate the results.

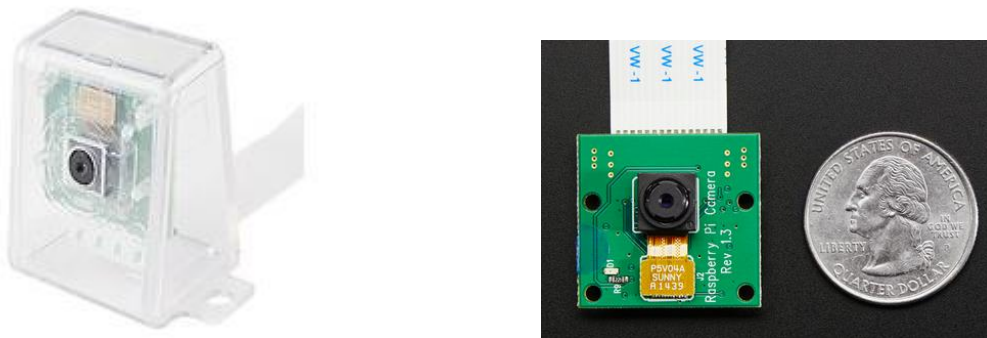


Figure 6.1: Raspberry π Camera case and lens

The main purpose of the colour poll sheet alternative is to achieve an accuracy high enough to be able to provide relevant feedback to the lecturer and class. This feedback will then be used to make a decision on whether to explain further or reiterate a specific point. Once over 80% of students understand the topic the lecturer can move on to the topic.

6.3.3 Contour Approximation

To increase the accuracy of results the algorithm would need some contour approximation algorithm such as the Douglas-Peucker algorithm [Fernández-García, Martínez, Carmona-Poyato, Madrid-Cuevas and Medina-Carnicer, \(2016\)](#). As best described in the OpenCV documents. If we were trying to detect a square but didn't get a perfect square in our image as shown in the picture below, we could use the Douglas Peucker algorithm to approximate the shape. How it does this is by formulating a

threshold called an epsilon, which is the maximum distance from the contour to the approximated contour.



Figure 6.2: Approximate contour illustration

In the education system, future work could involve research into facial expression recognition; this is a point whereby a computer can try and read students faces and find out if the students are confused or understand particular topics.

Additional areas of future research can come about through an audience response system that recognises not only specific answers but can recognise written boards to present these to the lecturer for answering during or after the lecture. As well as picking out answers that are words, sentences and hence expanding the range of questions to ask. In mathematics, for example, computer vision should be able to pick out numbers as an answer to questions.

6.3.4 Multi-threading

The speed can be amplified by multi-threading the algorithm, which could easily provide 2-3 times speed, and a 50% reduction in time spent. This increase in speed would allow the algorithm to attain a suitable speed for in-class assessments and providing feedback for the students to quickly react to the answers they have given.

APPENDIX A.

All Results for the 12 Classroom Photos

P1-ZOO

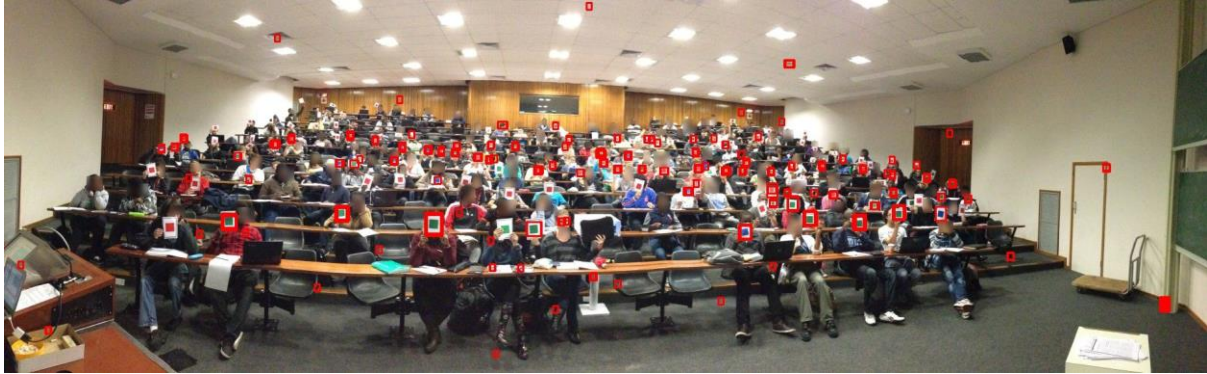


Figure A: P1-ZOO Class Detection Photograph

57 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
43 False Positives - Pollsheets have been detected wrongly
59 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.57
The recall of this algorithm is 0.491379310345
The accuracy of this algorithm is 0.358490566038

36 people voted Red
13 people voted Green
8 people voted Blue
0 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 114.77272005 seconds
End of program - completed successfully....

Figure A:5 P1-ZOO Class Detection Log Result

P2-ZOO



Figure A: P2-ZOO Class Detection Photograph

24 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
53 False Positives - Pollsheets have been detected wrongly
108 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.311688311688
The recall of this algorithm is 0.181818181818
The accuracy of this algorithm is 0.12972972973

5 people voted Red
19 people voted Green
0 people voted Blue
0 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 104.247527206 seconds
End of program - completed successfully....

Figure A:5 P2-ZOO Class Detection Log Result

P3-CSC- Participants



Figure A:3 P3-CSC Class Detection Photograph

```
71 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
23 False Positives - Pollsheets have been detected wrongly
34 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.755319148936
The recall of this algorithm is 0.67619047619
The accuracy of this algorithm is 0.5546875
```

```
9 people voted Red
44 people voted Green
2 people voted Blue
16 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 321.231117874 seconds
End of program - completed successfully....
```

Figure A:5 P3-CSC Class Detection Log Result

P4-ZOO



Figure A: P4-ZOO Class Detection Photograph

35 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
52 False Positives - Pollsheets have been detected wrongly
81 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.402298850575
The recall of this algorithm is 0.301724137931
The accuracy of this algorithm is 0.208333333333

9 people voted Red
9 people voted Green
11 people voted Blue
6 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 107.927126146 seconds
End of program - completed successfully....

Figure A:6 P4-ZOO Class Detection Log Result

P5-ZOO



Figure A: P5-ZOO Class Detection Photograph

29 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
76 False Positives - Pollsheets have been detected wrongly
77 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.27619047619
The recall of this algorithm is 0.27358490566
The accuracy of this algorithm is 0.159340659341

6 people voted Red
9 people voted Green
11 people voted Blue
3 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 141.489277465 seconds
End of program - completed successfully....

Figure A:6 P5-ZOO Class Detection Log Result

P6-CSC-32 Participants



Figure A:6 P3-CSC Class Detection Photograph

```
64 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
22 False Positives - Pollsheets have been detected wrongly
11 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.744186046512
The recall of this algorithm is 0.853333333333
The accuracy of this algorithm is 0.659793814433
```

```
20 people voted Red
18 people voted Green
20 people voted Blue
5 people voted Black
1 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 178.543690955 seconds
End of program - completed successfully....
```

Figure A:6 P6-CSC Class Detection Log Result

P7-CSC-32 Participants



Figure A:6 P7-CSC Class Detection Photograph

```
21 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
9 False Positives - Pollsheets have been detected wrongly
11 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.7
The recall of this algorithm is 0.65625
The accuracy of this algorithm is 0.512195121951
```

```
5 people voted Red
4 people voted Green
3 people voted Blue
9 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 132.700427957 seconds
End of program - completed successfully....
```

Figure A:6 P7-CSC Class Detection Log Result

P8-CSC- Participants



Figure A:6 P7-CSC Class Detection Photograph

```
77 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
23 False Positives - Pollsheets have been detected wrongly
36 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.77
The recall of this algorithm is 0.681415929204
The accuracy of this algorithm is 0.566176470588
```

```
49 people voted Red
9 people voted Green
17 people voted Blue
2 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 307.850088344 seconds
End of program - completed successfully....
```

Figure A:6 P8-CSC Class Detection Log Result

P9-CSC- Participants



Figure A: P9-CSC Class Detection Photograph

```
48 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
10 False Positives - Pollsheets have been detected wrongly
21 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.827586206897
The recall of this algorithm is 0.695652173913
The accuracy of this algorithm is 0.607594936709
```

```
37 people voted Red
10 people voted Green
1 people voted Blue
0 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 183.715350584 seconds
End of program - completed successfully....
```

Figure A:6 P9-CSC Class Detection Log Result

P10-ZOO



Figure A:6 P10-ZOO Class Detection Photograph

34 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
48 False Positives - Pollsheets have been detected wrongly
43 False Negatives - Pollsheets not detected, yet should have been detected

The precision of this algorithm is 0.414634146341
The recall of this algorithm is 0.441558441558
The accuracy of this algorithm is 0.272

3 people voted Red
0 people voted Green
0 people voted Blue
31 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized

Program completed in 121.251043477 seconds
End of program - completed successfully....

Figure A:6 P10-ZOO Class Detection Log Result

P11-CSC



Figure A:6 P11-CSC Class Detection Photograph

```
39 True Positives - Pollsheets have been detected correctly
0 True Negatives - Pollsheets that have been correctly identified as negative
10 False Positives - Pollsheets have been detected wrongly
6 False Negatives - Pollsheets not detected, yet should have been detected
```

```
The precision of this algorithm is 0.795918367347
```

```
The recall of this algorithm is 0.866666666667
```

```
The accuracy of this algorithm is 0.709090909091
```

```
0 people voted Red
1 people voted Green
0 people voted Blue
38 people voted Black
0 people voted Yellow
0 vote counted but colour not recognized
```

```
Program completed in 308.618645073 seconds
```

```
End of program - completed successfully....
```

Figure A:6 P11-CSC Class Detection Log Result

BIBLIOGRAPHY

Abrahamson, L. (2006), *A brief history of networked classrooms: Effects, cases, pedagogy, and implications* D.A. Banks (Ed.), *Audience response systems in higher education*, Applications and Cases, Hershey, Pennsylvania: Information Science Publishing, p. 1–25.

Bornman, E. (2012), *The mobile phone in Africa: Has it become a highway to the information society or not*, *Contemp. Edu. Tech*, Vol. 3(4).

Bryfczynski, S.P., Brown, R., Hester, J., Herrmann, A., Koch, D.L., Cooper, M.M. and Grove, N.P. (2014), *uRespond: iPad as Interactive, Personal Response System*, *Journal of Chemical Education*, Vol. 91(3), p.357-363. URL <http://dx.doi.org/10.1021/ed4006453>

Caldwell, J.E. (2007), *Clickers in the large classroom: Current research and best practices tips*, *CBE - Life Sciences Education*, Vol. 6(1), p. 9-20.

Castells, M. (2000), *End of Millennium: the information age: economy, society and culture*, Vol. III (2nd ed.) Oxford: Blackwell, URL <http://www.cedtech.net/articles/34/343.pdf>

Cherlin, E. (2009), *An Internet bandwidth bonanza is coming to Africa*, Retrieved September 29, 2016, URL http://www.olpcnews.com/internet/access/internet_bandwidth_bonanza_africa.html

Creswell, J. (2013), *Research design: Qualitative, Quantitative, and Mixed Methods Approaches*, SAGE Publications Inc, 4th edition.

Cross, A; Cutrell, E and Thies, W. (2012), *Low-cost audience polling using computer vision*. *In Proceedings of the 25th annual ACM symposium on User interface software and technology*, ACM New York, NY, USA 2012, p. 45 – 54.

Denso, ADC. (2014), *QR Code Essentials*, Retrieved June 31, 2016, URL, <http://www.nacs.org/LinkClick.aspx?fileticket=D1FpVAvvJuo%3D&tabid=1426&mid=4802>

Fernández-García, N.L., Martínez, L.D.M., Carmona-Poyato, A., Madrid-Cuevas, F.J. and Medina-Carnicer, R., (2016), *A new thresholding approach for automatic generation of polygonal approximations*, *Journal of Visual Communication and Image Representation*, Vol. 35, pp.155-168.

Gain, J. (2013), *Using poll sheets and computer vision as an inexpensive alternative to clickers*, *Proceedings of the South African Institute for Computer Scientists and Information Technologists Conference*, ACM New York, NY, USA, p. 60- 63.

Geman, D., Geman, S., Hallonquist, N. and Younes, L., (2015), *Visual Turing test for computer vision systems*, *Proceedings of the National Academy of Sciences*, Vol. 112(12), pp.3618-3623.

Guthrie, R and Carlin, A. (2004), *Waking the Dead: Using interactive technology to engage passive listeners in the classroom*, AMCIS 2004 Proceedings, 358, URL <http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1934&context=amcis2004>

Hazzan, O., Dubinsky, Y., Eidelman, L., Sakhnini, V. and Teif, M. (2006), *Qualitative research in Computer Science Education*, Proceedings of SIGCSE 2006 – The 37th Technical Symposium on Computer Science Education, Houston, Texas, USA, p. 408-412

Heaslip, G., Donovan, P. and Gullen, J G, (2014), *Student response systems and learner engagement in large classes*, Active Learning in Higher Education, SAGE Publications, Vol. 15(1), p. 11-24.

Heward, W.L; Narayan, J.S; Gardner III, R; Courson, F. H and Omness, C.K. (1996), *Everyone participates in this class: Using response cards to increase active student response*, Teaching exceptional children, Vol.28(2), p.4-10.

Hyde-Clark, N and Van Tonder, T. (2011), *Revisiting the “leapfrog” debate in light of current trends of mobile phone Internet usage in the greater Johannesburg area, South Africa*, Journal of African Media Studies, Vol.3(2), p. 263-276.

Imazeki, J. (2014), *Bring-Your-Own-Device: Turning Cell Phones into Forces for Good*, The Journal of Economic Education, Vol. 45(3), p.240-250. URL <http://dx.doi.org/10.1080/00220485.2014.917898>

Kang, H., Lundeberg, M., Wolter, B., DelMas, R., and Herreid, C. F. (2012), *Gender differences in student performance in large lecture classrooms using personal response systems “Clickers” with narrative case studies*, Learning, Media and Technology, Vol. 37(1), p. 53-76. URL <http://dx.doi.org/10.1080/17439884.2011.556123>

Kiefer, M., Reyes, I., Liebman, A. and Juarez-Carrillo, P. (2014), *The Use of Audience Response System Technology With Limited-English-Proficiency, Low-Literacy, and Vulnerable Populations*, Journal of Agromedicine, Vol. 19(1), p. 44-52. URL <http://dx.doi.org/10.1080/1059924X.2013.827998>

Jackson, M.H and Trees, A.R. (2007), *The learning environment in clicker classrooms: Student processes of learning and involvement in large university-level courses using student response systems*, Learning, Media and Technology, Vol.32 (1), p. 21-40. Taylor & Francis.

Jain, A.K, Duin, R.P.W and Mao, J.C. (2000), *Statistical pattern recognition: a review*. *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 22(1), p. 4-37.

- Jensen, M. (2006), *Lowering the costs of international bandwidth in Africa*, APC Issue of Papers Series 2006, Retrieved September 23, 2010, URL http://rights.apc.org/documents/fibre_bandwidth_EN.pdf.
- Johnson, D and McLeod, S. (2005), *Get Answers: Using student response systems to see students thinking. Learning & Leading with Technology*, Vol. 32(4), p. 18 – 23.
- Jones, M, Marsden, G and Gruijters, D. (2005), “*Using mobile phones and PDA’s in AD-hoc audience response systems*” in “*Audience Response Systems*”, Idea Group Publishing.
- Judson, E & Sawada, D. (2006), *Audience response systems: Insipid contrivances or inspiring tools. In D. Banks (Ed.), Audience response systems in higher Education: Application in cases*, Hershey Pennsylvania: Information Science Publishing, p. 26 – 39.
- Kay, R and LeSage, A. (2009), *Examining the benefits and challenges of using audience response systems: A review of the literature*, *Computers & Education*, Elsevier, Vol. 53(3), p. 819-827.
- Knight, J.K and Wood, W.B. (2005), *Teaching more by lecturing less*, *Cell Biology Education*, Vol. 4(4), p. 298 – 310.
- Laxman, K. (2011), *A study on the adoption of clickers in higher education*, *Australasian Journal of Educational Technology*, Vol. 27(Special issue, 8), p.1291 – 1303.
- Llena, C., Forner, L., & Cueva, R. (2015), *Student Evaluation of clickers in a dental pathology course*, *Journal of Clinical and Experimental Dentistry*, Vol.7(3), p.369–373. URL <http://doi.org/10.4317/jced.52299>
- Marsden, G, Maunder, A and Parker, M. (2008), *People are people, but technology is not technology*, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, Vol.366 (1881), p. 3795 – 3804.
- McDonough, K., Foote, J.A. (2015), *The impact of individual and shared clicker use on students' collaborative learning*, *Computers & Education*, Elsevier, Vol. 86, p. 236-249. URL <http://dx.doi.org/10.1016/j.compedu.2015.08.009>
- Miura, M and Nakada, T. (2012), *Device-free personal response system based on fiducial markers. In wireless, mobile and ubiquitous technology in Education (WMUTE)*, 2012 IEEE, Seventh International Conference, p. 87 – 91.
- Patil, T.R. and Sherekar, S.S., (2013), *Performance analysis of Naive Bayes and J48 classification algorithm for data classification*, *International Journal of Computer Science and Applications*, Vol.6(2), pp.256-261.
- Phatak, D. (2014), *Clicker System Optimization*, *Indian Institute of Technology Bombay Mumbai*, URL http://www.it.itb.ac.in/frg/wiki/images/b/bc/Final_stage1_report_123050062_Anoop.pdf

- Powers, D.M., (2011), *Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation*, Bioinfo Publications, URL <http://hdl.handle.net/2328/27165>
- Raes, A., Vanderhoven, E. and Schellens, T. (2015), *Increasing anonymity in peer assessment by using classroom response technology within face-to-face higher education*, *Studies in Higher Education*, Vol. 40(1), P. 178-193. URL <http://dx.doi.org/10.1080/03075079.2013.823930>
- Roschelle, J, Penuel, W.R and Abrahamson, L. (2004), *The networked classroom*, *Educational Leadership*, Vol. 61(5), p. 50 – 53.
- Scornavacca, E and Marshall, S. (2007), *Txt-2-Lrn: Improving students learning experience in the classroom through interactive SMS*, In *system sciences, 2007*, In HICSS 2007, 40th Annual Hawaii International Conference, IEEE, p. 1-8.
- Schackow, T.E., Chavez, M., Loya, L and Friedman, M. (2004), *Audience response system: Effect on learning in family medicine residents*, *Family Medicine* Vol. 36(7), p. 496-504.
- Shea, K.M. (2016), *Beyond Clickers, Next Generation Classroom Response Systems for Organic Chemistry*, *Journal of Chemical Education*, Vol. 93(5), p. 971-974. URL <http://dx.doi.org/10.1021/acs.jchemed.5b00799>
- Skiba, D.J. (2006), *Got large lecture hall classes? Use clickers*, *Nursing Education Perspectives*, Vol. 27(5), p. 278 – 280.
- Stowell, J. R. (2015), *Use of Clickers vs. mobile devices for classroom polling*, *Journal of Computers & Education*, Elsevier, Vol. 82, p. 329-334. URL <http://dx.doi.org/10.1016/j.compedu.2014.12.008>
- Van Ooijen, P and Broekema, A. (2010), *A Novel, Image based Voting tool based on Handheld Devices*, *Journal of the Research Centre for Educational Technology (RCETJ)* Vol. 6(1), p.122-128.
- Voelkel, S and Bennett, D. (2014), *New uses for a familiar technology: introducing mobile phone polling in large classes*. Taylor & Francis. *Innovations in Education and Teaching International*, Vol. 51(1), p. 46-58.
- White, P.J., Delaney, D.G., Syncox, D., Akerberg, O.A and Alters, B. (2011), *Clicker Implementation Models*, *EDUCAUSE Quarterly*, Vol. 34 (4), p. 1 –4.
- White, P.J., Syncox, D and Alters, B. (2011), *Clicking for grades? Really? Investigating the use of clickers for awarding grade-points in post-secondary education*, *Interactive Learning Environments*, Vol. 19(5), p. 551-561. URL <http://dx.doi.org/10.1080/10494821003612638>.

BIBLIOGRAPHY

Wolff, M., Wanger, M., Poznanski, S., Schiller, J. and Santen, S. (2015), *Not Another Boring Lecture: Engaging Learners with Active Learning Techniques*, Journal of Emergency Medicine, Elsevier, Vol. 48 (1), p. 85-93. URL <http://dx.doi.org/10.1016/j.jemermed.2014.09.010>

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