

Research Proposal

**Use of automated image analysis to improve
petrographic analysis**

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Research Proposal Executive Summary(non-technical)

Image analysis (also known as computer vision) has been a game changer for many industries across the past 50 years, with everything from barcodes to autonomous cars relying on image analysis-based techniques in order to work. Image analysis is the basis of extracting meaningful data from digital images using a series of pre-processing and processing steps.

Currently geological petrographic samples, that are essentially 30 micron-thick slices of a rock (known as thin sections) are analysed using manual human techniques. An operator will load a slide onto a manual or motorised microscope stepping stage and either count the proportion or measure grains manually (known as grain-sizing or point counting).

Image analysis offers an opportunity for grain-sizing and point counting to be automated using high detail images collected using a photo microscope. This will serve to improve the quality and consistency of data collected from petrographic thin-sections, whilst potentially improving data collection speed.

Research will be conducted on non-proprietary samples provided by Petrostrat LTD, making use of high-resolution stitched images of the thin-section samples for analysis. Existing analytical techniques from other industries such as image watershedding (identification of proportions using binarized RGB images using colour spectrum) and edge detection will be examined to see if currently collected manual data could be automated/semi-automated using image analysis.

The project cost will be approximately £2000 to reflect sampling and licensing of software required. The research project will take approximately 3-4 months to complete, with the conclusion of the research producing a detailed thesis report to answer the following five questions:

1. Can image analysis be used to automate existing scientific data collection techniques? (e.g. point counting, grain size recognition)
2. What new data can be gained that can't be collected quickly or effectively from a manual data?
3. Do existing processes exist within other industries or will bespoke workflows be required to be developed?
4. Can calibration be achieved between datasets for samples of different origin? i.e. can samples from different manufacturers, ages and technicians produce consistent and coherent data.
5. Do geological contents of the samples effect data quality? (e.g. fine grained, cements, etc.)

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1 Introduction

Image analysis (also known as computer vision or image recognition) (Huang, 1996; Sonka et al., 2014) is a multi-disciplinary scientific field that deals with how digital images are processed and analysed by a computer to derive data from digital images or videos. Petrographic analysis is the detailed description of the mineral composition of rocks and textural properties (such as grain size and roundness of mineral grains).

Historically, image analysis has historic beginnings as a military tactic used to record enemy troop movements or forward scouting. This was pioneered during the first world war when the opposing British and German armies would use aircraft mounted cameras to record enemy positions and confirm maps using aerial photography (Beadle & Harrison, 2007). A modern-day example of manual image analysis can be observed in Figure 1, where satellite images are used to record the movements of meandering rivers over time.

Since the development of computing technology in the last 50 years and other artificial intelligence, automated image recognition has been pioneering in the mapping, medical and bioinformatics industries which has successfully used image analysis and processing techniques to aid with the diagnosis of patients (Sonka et al., 2014). Opensource software packages such as NIH and ImageJ provided by MIT University have long been the benchmark for scientific image analysis (Glasbey & Horgan, 1995; Sonka et al., 2014), however, recently, proprietary software have begun to enter the market with the emergence of low-cost high-performance computing, such as Thermofisher's Celleste™ (Bojanowski et al., 2021).

Whilst traditionally confined to the biomedical and mapping industries, image analysis is slowly being trialled in other industries in an attempt to improve data collection efficiency and reliability.



Figure 1 River Ucayali (Peru) captured by satellite at various time increments. Multiple satellite images were used in order to predict the movements of similar rivers worldwide (Parquer, 2018).

1.1 Research Aim and Questions

The aim of this research will be to establish the effectiveness of modern-day image analysis using geological thin-section samples.

- 1. Can image analysis be used to automate existing scientific data collection techniques? (e.g. point counting, grain size recognition)**
- 2. What new data can be gained that can't be collected quickly or effectively from a manual data?**
- 3. Do existing processes exist within other industries or will bespoke workflows be required to be developed?**
- 4. Can calibration be achieved between datasets for samples of different origin? i.e. can samples from different manufacturers, ages and technicians produce consistent and coherent data.**
- 5. Do geological contents of the samples effect data quality? (e.g. fine grained, cements, etc.)**

2 Image Analysis Background (literature review)

A literature search was performed using research articles available from Google Scholar. Searches for 'computer vision' and 'image analysis' into Google Scholar yielded over 10,000,000 articles, indicating there is significant saturation within the literature that will justify a more standalone and detailed literature review of different industries. This would serve to identify processes/workflows from other industries that potentially could be applied to geological samples. Despite this, when keyword searches are improved to 'computer vision/image analysis of geological thin-sections', results drop to under 15,000. Nearly all of the 15,000 references returned were not of particular relevance to geological thin-sections and were dated prior to 2005 (where computing power and image analysis techniques were less widely available and understood).

2.1 Image analysis process

As previously mentioned, image analysis (or computer vision) is the use of digital imagery or videos for the purposes of extracting data that would usually be arduous if performed by a human manually (Sonka et al., 2014).

Image analysis usually consists of five distinct stages: image acquisition, image processing, segmentation, data extraction (feature extraction) and classification (Abràmoff et al., 2004; Burger et al., 2009; Sonka et al., 2014).

Image acquisition describes the process of acquiring images (or videos) to analyse (Huang, 1996). These can be from a variety of sources, including traditional photography (now digitally using CMOS digital light sensors), all the way to complex LIDAR (light detection and range) (Perez-Sanz et al., 2017). Image acquisition varies across industries and can vary depending on the use case. For example, a photograph of somebody experiencing abdominal pain would show no defining factor, however, an MRI (magnetic resonance scan) would demonstrate deep medical issues Solomon & Breckon (2011). As shown by Glasbey & Horgan (1995), images can be displayed in a variety of ways, and a traditional pixel map may yield different data to a 3D false-depth image map as shown in Figure 2.2.

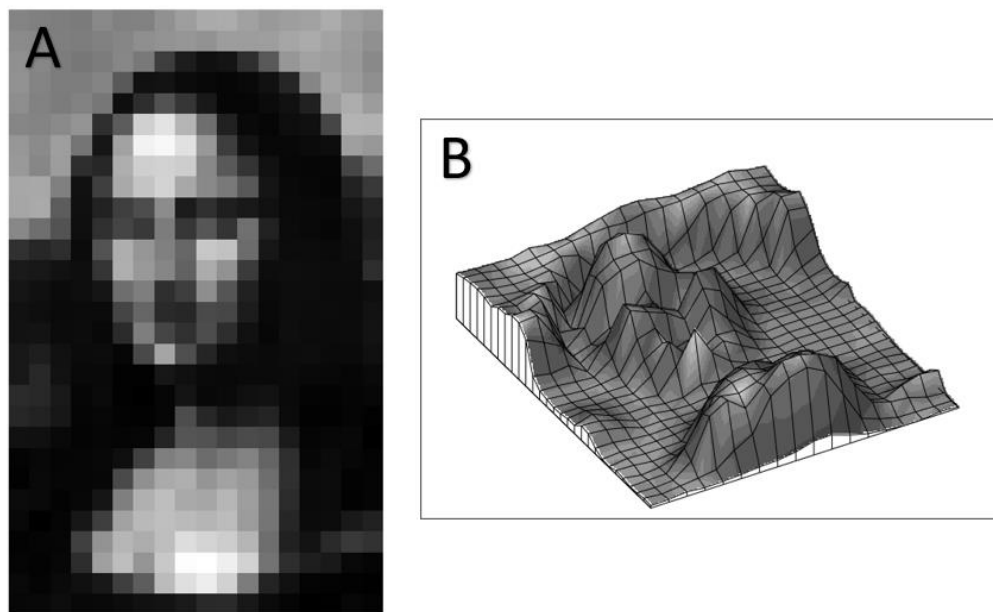


Figure 2 2.A a pixelated Mona Lisa in black and white 8-bit channels. B an alternative of A, where grey levels are replaced by height to produce a 3D topography map (Glasbey & Horgan, 1995).

Image processing is the process of improving an image in order to eliminate noise and improve contrast (Grove & Jerram, 2011; Perez-Sanz et al., 2017; Sonka et al., 2014; Walter et al., 2015). Image processing is the most important step, as a poorly processed image will yield poor results. Further filters (such as Gaussian or bypass

filters) may be implemented to improve the sharpness of an image, whilst images should be cropped to the area of interest (AOI) desired to prevent unwanted analysis (Grove & Jerram, 2011).

Image segmentation is where the desired discrete features within an object being analysed are isolated from an image. This step seeks to isolate the desired feature(s) using a preferred segmentation technique (Cheng et al., 2001; Haralick & Shapiro, 1985; Minaee et al., 2021). The most common type of image segmentation is separating objects by RGB colour value ranges (e.g. distinguishing between blue and red objects). These are then binarized and flattened to create a more consistent image.

Feature extraction is where segmented objects are measured (Umbaugh et al., 1997). In the example of RGB water shedding, features would be extracted based on the percentage of an area of an image that displays red vs blue colour intensity (usually on a binarized image).

Classification is where the extracted features measured are automatically assigned. An example for this would be barcodes measured using a barcode reader are automatically assigned to a product in a barcode library of a store.

A simplified workflow can be observed in Figure 3.

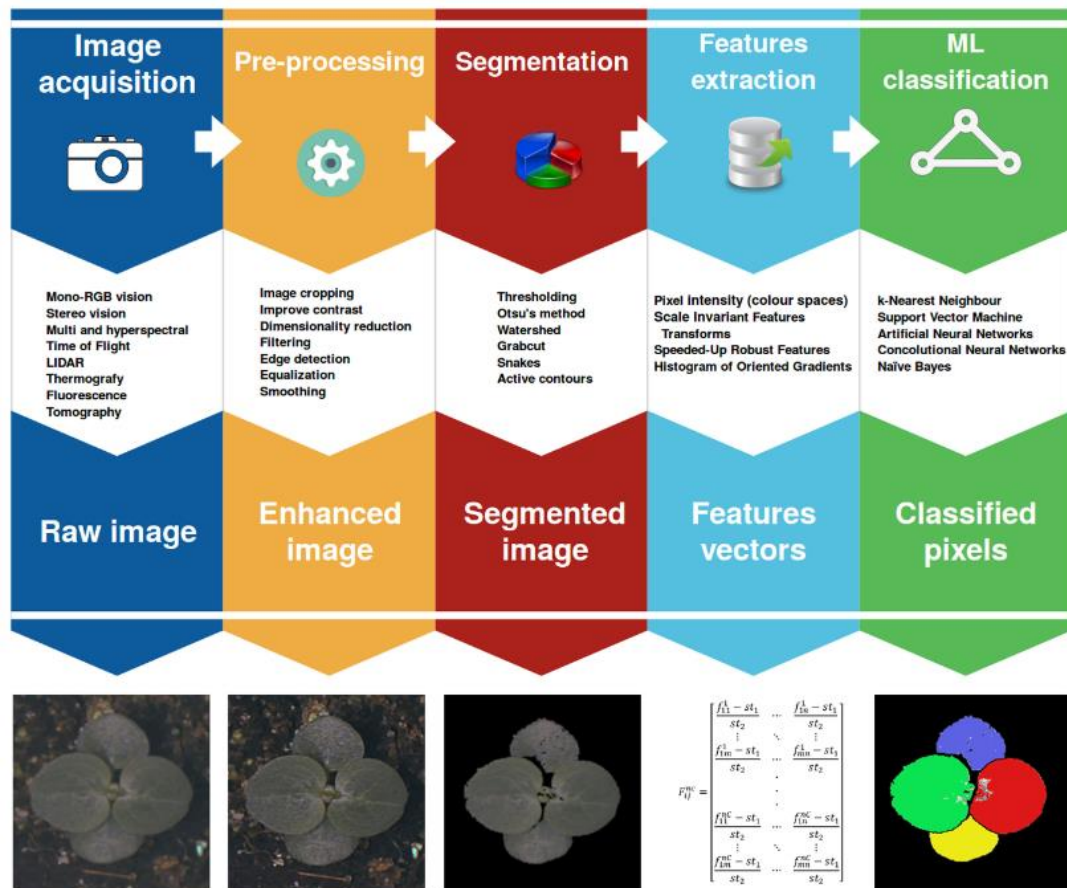


Figure 3. A standard image analysis workflow demonstrated by Perez-Sanz et al. (2017) and examples of each step.

2.1.1 Current Uses

Image analysis (computer vision) has been used now for well in excess of 50 years. By far most common use of image analysis comes from the use of store barcodes that was developed by George Laurer of IBM in the 1970s (Milne, 2013; Shih, 2009). The simple concept uses differently spaced bars of varying thicknesses to return an intensity of a reflected light to and from a detector. This intensity is then matched to a database of products to return information such as pricing/stock levels instantly. This simple, yet intuitive use is one of the key cornerstones for the beginning of image analysis and was a game changer in the world of retail (Shih, 2009). Prior to the barcode, stock levels could not be accurately maintained across a large store or even multiple stores. The invention of the barcode allowed for this, as well as large scale sales statistics for the first time.

Since then, image analysis (computer vision) has been successfully rolled out in a wide range of industries/uses, and with ever increasing computing power (Schaller, 1997; Thompson & Parthasarathy, 2006) being available in smaller forms and at a lower cost than ever, there is no reason why image analysis can't continue to develop. Modern day image analysis is commonly seen in autonomous cars for recognition of hazards, traffic signals, pedestrians; realtime collection, processing and interpretation of thousands of images allow for vehicles to become autonomous as shown in Figure 4 (Kato et al., 2015, 2018). Further uses include ANPR camera recognition, thermal imaging cameras and missile guidance.

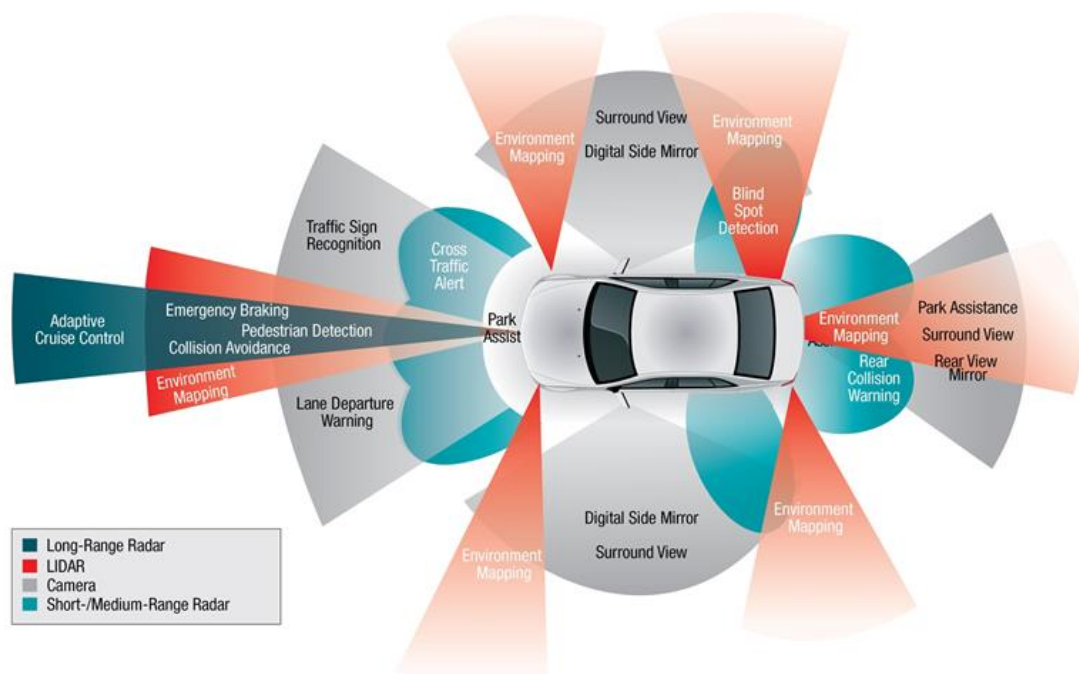


Figure 4 A diagram of the different imaging sensors present in an autonomous car, with multiple different sensors serving different purposes and providing failsafe (Silverio, 2019).

2.1.2 Challenges

Whilst humans recognise images visually using stored images in the brain, computers work differently. A great example is dogs. A human will be able to identify a dog based on a couple of simple features (e.g. four legs, snout, wagging tail, *etc.*), whilst a computer may not be able to distinguish further than the first level (Level 1: dog, Level 2: breed) – they will definitely know it is a type of dog! Whereas a computer can be shown what a dog is, it will not necessarily recognise a dog as a dog again. This is due to all images being seen mathematically as a number of pixels as opposed to a qualitative image. The commonly cited “chihuahua vs muffin” (Togotokh & Amartuvshin, 2018) images are a common example of where a computer cannot distinguish between two mathematically similar images where a human could.

Additionally, challenges are related to sample quality and consistency. It is often noted that no two geological samples are the same. This could mean that a process/method for one rock in one region of the world may work perfectly fine and produce statistically valid results, however, another rock may not. This could be down to changes in composition, grain size or sample quality. Even differences in colour between different geological samples may have an effect. In order to test this, samples of varying geological compositions, sample quality and type should be tested. However, existing challenges to data quality exist from the human differences in data collection (Grove & Jerram, 2011), therefore it could be presumed that

2.1.3 Alternatives to image analysis of 2D images

SEM-EDS (scanning electron microscopy electron dispersive scanning) is a type of image analysis where a scanning electron microscope scans over a sample in a set grid. The resulting spectra is compared to a library of mineral spectra which is then used to create a vectorised false-colour image map of recognised minerals (Wooldridge et al., 2018). Using proprietary software, further statistics can be gained such as mineral percentages, porosity and in some cases grain size (where minerals are not closely touching).

Whilst this does represent an alternative to image analysis of petrographic thin-sections, the technique is expensive and slow (with some samples taking up to 3 days to be analysed). Meanwhile, an image stitch of the same sample could be collected in under 30 minutes which could be used for various image analysis techniques.

3 Research

3.1 Materials

Materials for the project will be sourced from internal (Petrostrat owned) thin-section samples (thin slices of rocks) or publicly available research libraries (such as British Geological Society or Norwegian Petroleum Directorate) sample images.

Where physical samples are present, 'manual' petrographic analysis will be performed from thin-sections prepared from the sub-samples of rock taken from the core (30 microns thick); using a Leica DFC 2900 polarising microscope to analyse samples initially using optical microscopy and identify key minerals. Point counting will be conducted using a Leica DFC 2900 microscope and a Petrog point counting stepping stage that will be mounted to the microscope in order to deliver a manual dataset for calibration to image analysis derived data. Additional images in the form of SEM-EDS image maps (Scanning Electron Microscopy with Energy Dispersive Spectroscopy), BSEM and MRI scans of thin sections may be used for additional materials where available.

Preferred samples that could be used for the purposes of this project includes 20 thin sections from the Formby MFA-1 oil well, which has been extensively analysed and has publicly available point count data for calibration to image analysis methods (Scorgie et al., 2021).

3.2 Software

Preferred software to be used for the purposes of the research project will be IPSDK by Reactiv'IP (<https://www.reactivip.com/image-processing/>) (Cazaurang et al., 2021). IPSDK is proprietary image analysis software specialising in geological and

biomedical image analysis, integrated with Python for custom image analysis scripting.

If IPSDK not available, open-source image analysis software is available. ImageJ (Fiji) is provided by MIT (Abràmoff et al., 2004; Grove & Jerram, 2011) and is an industry standard for image analysis, allowing for custom Python scripts.

Adobe Photoshop/Corel PhotoPaint will be used to process 2D RGB images and creative custom colour palettes (Grove & Jerram, 2011).

3.3 Methods

Research will be conducted by first collecting 20 full size image stiches of thin sections from the Formby MFA-1 sample set, following Petrostrat's internal image stitching protocol. A 'stitch' is a full representation of a thin-section sample, consisting of 200-700 individual photographs to give the impression of one large photograph of the whole sample.

Collected images will then be pre-processed to crop to a region of interest, images will have filters applied (e.g. gaussian/bypass filters). This step is performed in order to improve image quality & remove any noise that may have a potential effect on the performance of image analysis techniques.

Images will then be loaded into a photo processing software IPSDK (or ImageJ). Images will be binarized using the method outlined previously by Grove & Jerram (2011).

A series of mathematical processes will be applied in order to obtain grain size data and pore-throat size. Edge detect algorithms defined by Shrivakshan & Chandrasekar (2012) and Ziou & Tabbone (1998), will be used to isolate different grain boundaries. Results of the edge detection will be manually evaluated and compared to the original images for accuracy. As there has been little research interest in image analysis of geoscience samples up until now, there is very little in the literature on what may be the best edge-detection method for geological samples.

3.4 Budget

The proposed budget required for the completion of the research project is outline in Table 1. The total cost of the project will be ~£2000, funding is to be confirmed.

Resource Required	Cost	Amount Required	Total Costs
Polished thin-section stitches	£59 /unit	20 thin-sections	£1,180
IPSDK License	£200 /month	3 months	£600
Code academy subscription	£15.92 /month	3 months	£48
		Gross Total Cost	£1,828

Table 1. Proposed budget required for completion of research project.

3.5 Timeframe

The timeframe for the completion of the research project is approximately 3 months from the starting date. A Complete project timeline can be seen in Table 2.

Project Timeline:'Use of automated image analysis to improve petrographic analysis	April				May					June				July				August					September		
	04-Apr	11-Apr	18-Apr	25-Apr	02-May	09-May	16-May	23-May	30-May	06-Jun	13-Jun	20-Jun	27-Jun	04-Jul	11-Jul	18-Jul	25-Jul	01-Aug	08-Aug	15-Aug	22-Aug	29-Aug	05-Sep	12-Sep	19-Sep
Pre-project Planning			Personal Holiday					Work Trip (~3-4 weeks)		Work Trip (~3-4 weeks)															
Concept Idea with tutor																									
Meet with colleagues to discuss areas of interest																									
Preparation																									
Project proposal (draft version).																									
Literature review - Gather papers and confirm review title.																									
Literature review, first draft.																									
Literature review, final draft.																									
Project proposal final submission.																									
Oral defense of project proposal.																									
Acquisition of software for project use																									
Data Collection/Analysis			Personal Holiday					Work Trip (~3-4 weeks)		Work Trip (~3-4 weeks)															
Collection of stitched thin section images																									
Collection of manual point count data																									
Image analysis using IPSDK																									
Image analysis using ImageJ (if IPSDK unavailable)																									
Comparison of manual point count data to image analysis																									
Inclusive of alternative automated methods																									
Project Write Up																									
Pre-write up plan.																									
Write up- Introduction, background and methods.																									
Write up- Results.																									
Write up- Interpretations.																									
Write up- Discussion, evaluation and conclusions.																									
Talk prep- Prepare talk outline.																									
Write up- Full first draft.																									
Talk prep- Finalise talk.																									
Write up- Final Draft																									
Talk prep- Practice talk.																									

Table 2. Image analysis project timeline.

4 Results

Results obtained from the project will include: grain size statistics, indices of roundness, mineral percentages (based off RGB water shedding of mineral colours), porosity measurements and pore-throat area.

Where possible, results obtained from image analysis will be compared to that of manually captured data from point counting (where minerals are manually measured for grain size or compositionally distinguished from 200-point counts across a set sample area). Whilst results may not be directly comparable, they will be indicative of how close image analysis-gained results are to a manual data collection.

5 Study Impact Evaluation

The impact of this study will assist the geological community and Petrostrat LTD to the effectiveness and commerciality of analysing geological samples using image analysis techniques.

It is hoped that new techniques and workflows could result from this research, potentially enabling quicker and more accurate analysis in the future at a lower cost. However, time constraints for the project and lack of unlimited computing power could prove a barrier for the project, as well as inconsistent samples meaning that results obtained cannot be compared on a project by project basis.

The addition of image analysis would help to remove some of the associated 'human-bias' that exists during manual counts from person to person. This will improve business resilience and allow for more consistent data results where it would be unrealistic to expect the same individual to collect the data manually. Processes can be outlined and documented in SOPs (standard operating procedures) so that they can be performed in the same way each time.

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7 Notification of competing interests

The author notes that there is no funding from competing interests for the purposes of this research.