THE IMPROVEMENT OF OBJECTIVE MILK FOAM QUALITY ANALYSIS THROUGH IMAGE PROCESSING AND COMPUTER VISION

A Graduation Report

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I ABSTRACT

PCV Group is a product development agency with a specialization in dispensing and dosing systems of coffee machines. Such systems are mainly used in coffee and milk foam treatment. PCV's systems are analysed intensively to ensure their quality. Currently, their milk foam analysing method is operator dependant which is not desirable in this field of work. To improve upon this, we researched the possibilities to improve the objectiveness of milk foam quality analysis through image processing and computer vision. We investigated the current analysing method in collaboration with an operator of PCV Group to determine the operator dependant actions and find design opportunities for a new method. The purpose of this new method is to correctly classify the fineness and distribution of milk foam samples with high reliability and reproducibility. We performed a literature research to acquire a better understanding of computer vision-based techniques that could be implemented in this analysing method. Common techniques recommended by the literature are mainly based on high detail imaging, contrast differences, and measuring bubble sizes through bubble segmentation. To explore which techniques could potentially contribute to this purpose we tested different combinations of imaging techniques, image optimisation techniques and image analysing techniques in an iterative designing process. We found that the segmentation techniques recommended by the literature did not meet our requirements. We investigated other segmentation techniques which led to colour thresholding and machine learning based segmentation being the most promising segmentation techniques in this research. Colour thresholding and machine learning based segmentation are used to exactly measure bubble sizes of milk foam samples, but classification in fineness and distribution is not yet integrated with these methods. The most promising classification technique is machine learning based classification and, in this research, this is used to correctly classify 91% of the fineness scores and 82% of the distribution scores. Some improvements, like increasing training data and creating consistent imaging techniques, are needed before this method can be integrated into the milk foam analysis. However, the findings of this research can be used as a foundation for the design of a new milk foam analysing method.

II ACKNOWLEDGEMENTS

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1 INTRODUCTION

Coffee is one of the most consumed beverages in the world[1]. A lot of people like to add ingredients to their coffee to change and improve the taste and texture. Most of these adjustments are made by adding foamed milk to coffee. This milk foam quality is important for the feeling and experience of the user. For that reason, there are a lot of innovative developments to improve the quality of milk foam.

PCV Group is an innovation-driven product development agency that conducts a lot of research in milk foam dispensing systems for multinationals around the world. It is important that these systems are tested reliably to ensure their quality. These systems are tested through the analysis of their produced milk foam. This milk foam quality analysis is currently conducted by an operator that inspects the foam, compares the visual aspects to images of previously valued foams and measures features like temperature, weight and volume.

Judging with the human eyes makes this a highly operator-dependent process that negatively influences the reliability of the test. Therefore, it is desirable to have an objective analysing method for the quality of milk foam. This makes the qualification of milk foam more reliable and gives the opportunity to better fulfil the client's expectations.

There are a lot of objective analysing techniques that could be implemented in a new analysing method. PCV Group is mostly interested in the opportunities of analysing the optical quality parameters through the use of computer vision-based techniques (CVBT's). There are a lot of different CVBT's, which all have their advantages and disadvantages. Investigating these techniques helps with designing a new milk foam quality analysing method.

There are a few challenges that came up when designing an objective analysing method. First, a high-quality image must be created in order to be processable by a computer. Multiple factors influence the quality of the images and can make it difficult for the computer to get a consistent qualification. Second, the method should optimise the image through image processing techniques. The challenge here is to make the image easier to analyse by the computer but simultaneously preserve the quality of the data as much as possible. Most of the optimizing techniques investigated in this research aim on a better segmentation of the bubbles and the liquid in the foam samples. Lastly, the image needs to be analysed to extract useful data that can be used to determine milk foam quality. This analysis is done with the use of area analysis in segmented images and direct image classification.

From this set of challenges, a few concrete research questions can be formulated to set out a guideline for the research. The main research question is:

- What are the possibilities to improve the reliability of milk foam quality analysis through image processing and computer vision?

To formulate an answer to this question it is necessary to look further into answering the following sub-questions:

- Which quality parameters of the milk foam should be analysed through image processing and computer vision?
- What kind of imaging techniques, image optimisation techniques and image analysing techniques can be used to analyse images of milk foam?
- How reliable are the computer vision-based analysing methods?

The design of the analysing method is divided into multiple sections. First of all, in chapter 2, background knowledge is gathered through literature research and the investigation of previous work. Subsequently, in chapter 3, this background knowledge supports the ideation phase in which new creative ideas are presented and a general analysing workflow is conducted. After the ideation, in chapter 4, the requirements of the chosen concept are set to specify the expectations of the analysing method . Then, in chapter 5, we came to the realisation phase in which we tested different techniques through an iterative designing process. During these tests, we focussed on segmentation of bubbles and the classification of the foam images and found that machine learning could be very useful in milk foam analysis In the last section, chapter 6, the results of the tests are merged into one section to conclude our findings on whether computer vision can improve milk foam analysis. Afterwards, in chapter 7, there is a discussion that evaluates the conclusions. Lastly, in chapter 8, all the additional ideas that could be beneficial in further research are formulated in the recommendations.

2 STATE OF THE ART REVIEW ON MILK FOAM ANALYSIS

2.1 Introduction

This chapter contains background information on a number of topics in the research area. This in-depth knowledge was necessary to start with the ideation of a new analysing method. We divided this state-of-the-art research into four parts. At first, we investigated the characteristics of milk foam through a literature review. This is done in order to determine the visual characteristics that are important during the milk foam analysis. Then, we discussed the current analysing protocol and the reliability issues that come along with this method. After that, the literature review is continued with the aim on image processing and computer vision-based techniques that can help with a more reliable milk foam analysing method. This is done by evaluating previous work related to foam analysis. Lastly, the findings are concluded and from these findings, we computed a workflow of a computer vision-based analysing method that could help with analysing milk foam quality.

2.2 Milk foam quality parameters

For this research it was important to investigate the quality determining milk foam parameters which could be processed through computer vision. To define the visible quality parameters, we started with looking at the general characteristics of foam. A well-accepted research of Campbell and Mougeot [2] identified these foam characteristics by dividing them in three main categories: quality characteristics, foam behaviour and gas phase characteristics. There are multiple features that influence the quality characteristics of milk foam. Researchers agree on the fact that the foam quality is influenced by texture and appearance [2-5]. Campbell and Mougeot [2] included rheology in these features, but the later researchers [3, 4] found that rheology is more connected to the foam behaviour, and therefore rheology is not included the quality characteristics category.

2.2.1 Quality characteristics

The texture and appearance of foam is mostly influenced by the size distribution of the bubbles [2-4, 6-8]. Campbell and Mougeot [2] states that a wide bubble size distribution (nonuniform structure) gives the foam a textual variety and improves the quality. Lau [4] also found the connection between bubble size distribution and foam quality. However, according to Lau, nonuniform microstructures of bubbles results in a reduced foam quality with the elaboration that specific bubble sizes contribute to appearance and other sizes to texture. This deviation makes it important to integrate an objective measurement of the bubble size distribution in the analysing method. This gives the client the possibility to give the foam a quality score that agrees with their preference. The client can decide whether textual variety or uniform microstructure is more important in their milk foam.

2.2.2 Foam behaviour

The second category is the foam behaviour and is widely discussed in the literature. Campbell and Mougeot [2], divided this category in foamability and foam structure. The foamability is the ease of which a foam is formed and can be directly measured by the foam to liquid volume ratio [2, 3]. Even though this is important in the foam behaviour, the stability of a foam is seen as the most important characteristic to analyse foam quality [3, 4, 7]. A lot of researchers investigated this characteristic and found different parameters that influence the stability. One of the parameters that influence the stability is the rate of drainage [2, 4, 9, 10]. This rate of drainage is important and influenced by different features. According to Silva [3] and Campbell [2], rheology is the main feature that influences drainage while Lau [4] found that bubble size distribution is this main feature. This could be explained with the research of David [11] and Germain [12] which connects these discoveries by finding that rheology is attributed to the bubble size distribution. Besides the drainage, the literature found two other stability influencing parameters: Disproportionation (gas diffusion) [4, 9, 10, 12] and coalescence (film rupture) [9, 10, 12]. As seen in *Figure 1* these parameters both have to do with bubble size which means that bubble size is of major importance for in foam stability. This shows again that bubble size measurement is important to integrate in the analysing method.

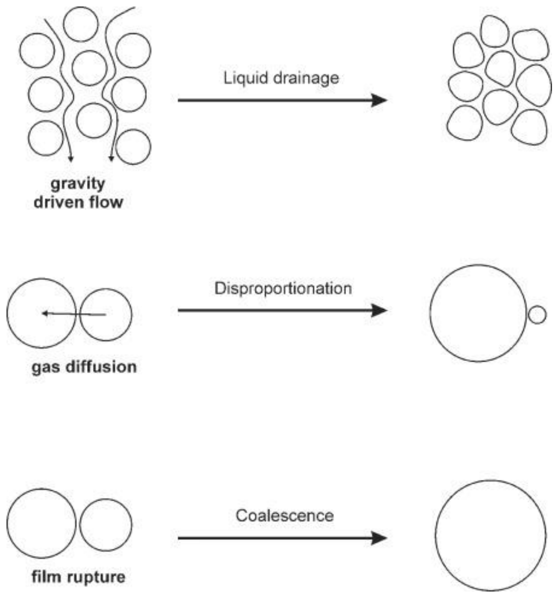


Figure 1 ***Visualisation of stability influencing parameters***

2.2.3 Gas phase characteristics

The last category is gas phase characteristics and includes air content, bubble size distribution and individual bubble behaviour [2]. The air content is difficult to determine so the more accessible parameter overrun is used more frequently [2, 5]. Overrun is the additional air added to the foam and an important characteristic in this category which could be calculated by measuring the foam to liquid volume ratio with the weight [2, 5]. Even though the bubble size distribution and individual bubble behaviour are part of this category according to Campbell and Mougeot's research [2], most other researchers [2-5, 9, 10] discuss these characteristics in combination with drainage which is already previously mentioned . This leaves foam to liquid ratio the most important visible feature of this category.

2.2.3.1 Literature diagram

To provide a systematic overview of the literature, all these quality characteristics could be implemented in a visual diagram. This diagram is shown in *Figure 2*. The connections between characteristics shows their influences or their dependence. It is interesting to see that there is a lot of research is done in the domain of foam characteristics. Some researchers focus more on the overall foam characteristics [2-5] and others focus more on particular characteristics [7, 9, 10]. Nonetheless, all the important characteristics find their roots in three visible features that could be analysed through computer vision: bubble size, bubble size distribution and the foam to liquid ratio.

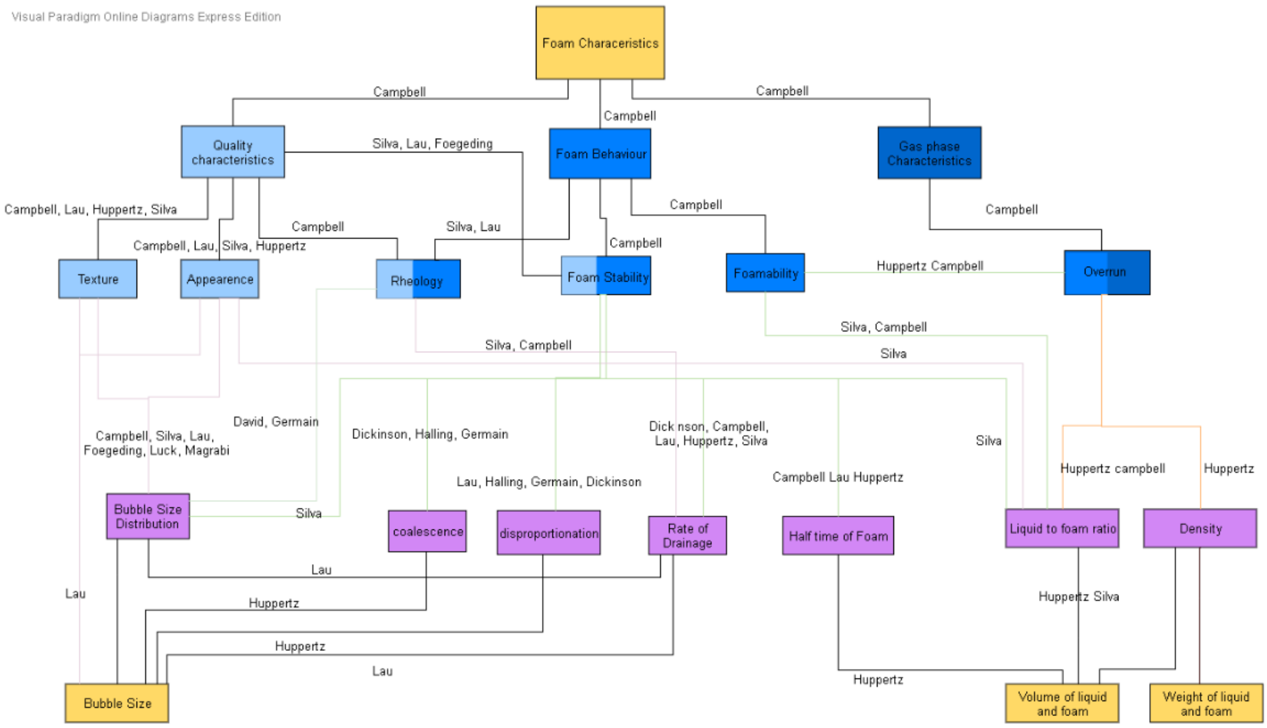


Figure 2 ***Visualisation of foam characteristics according to the literature***

Project FLORIAN

2.3.1 Project description

Project Florian is an internal project of PCV Group which is focussed on building, documenting and sharing coffee related experiences, knowledge and know-how for PCV Group. This is mainly done by supporting students with the supervision of an expert from PCV Group. With this project, PCV Group researches different appliance technologies which are integrated in a coffee machine. One of these technologies is the milk dispensing system. This system is responsible for creating a high-quality milk and milk foam for the consumer. Some functions like milk storage, milk transport, milk heating, air intake and milk foaming are required to achieve this goal. Every function has different ways to achieve the preferred outcome. For this research the milk foaming function is the most important and therefor only this function will be discussed from now on.

In milk threatening there are three different approached to foam creation. The first approach is expansion, this is done by dissolving a gas in a liquid through physical reactions caused by pressure or temperature differences. The second approach is injection, as the name suggests this is done by injecting gas into the fluid with a Jet beam. The last approach is agitation, this is done by the mechanically mixing the gas and fluid with active or inactive foamers. This agitation is mainly used in project Florian and by PCV Group in general.

Agitation with the help of active foamers is the method with highest controllability of the quality features. This makes this method the one that will be used for this research. Analysing these controllable features is very important and needs to be done consistent and reliable to gain more insights and knowledge in new milk foamers and milk foaming methods.

2.3.2 Current analysing method

For the current analysing method there is a protocol created by the Florian team. This protocol is updated if necessary and this research is based on the protocol of 22 January 2020[13]. In this protocol the equipment, the general steps and the optional steps are discussed.

The general steps of this protocol are the preparation of the milk, the dispense of the milk the analysis of the foam and the cleaning of the total installation. Because this research is focussed around the analysis of the milk foam, only this will be discussed in the next section. According to the protocol; bubble fineness, bubble size distribution, milk and foam volume, milk/foam ratio, consistency, temperature, weight and stability are important for the quality analysis of milk foam.

2.3.2.1 Fineness and distribution

According to researchers of PCV Group, a milk foam sample consists of two different types of milk foam bubbles. The first type is the bubble size that is the most common in a particular foam. These bubbles are important to determine the fineness score. The other type represents the bubbles with a deviating bubble size. These outliers determine the bubble size distribution and therefore the distribution score.

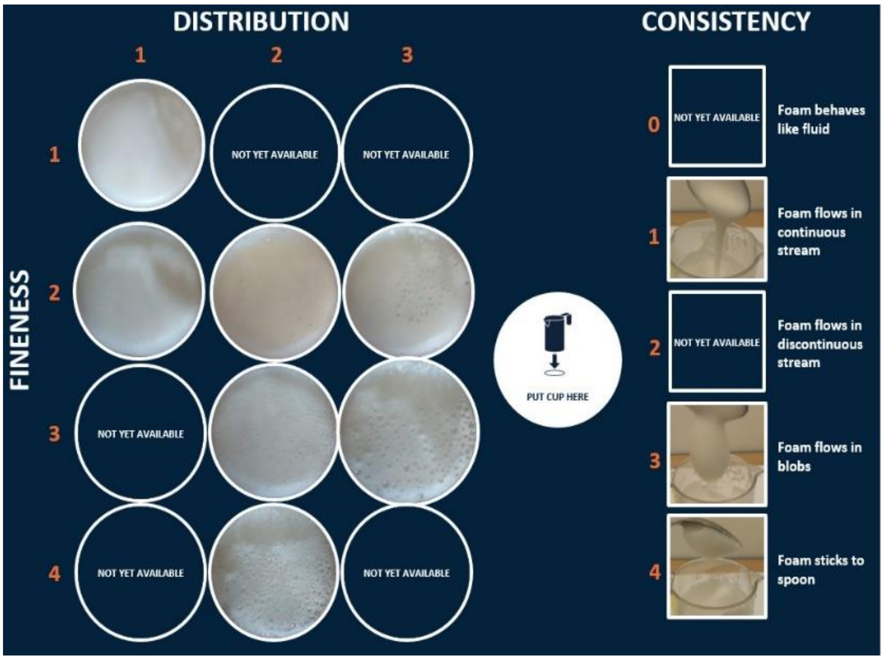


Figure 3 ***Fineness, distribution and consistency chart from scoring protocol***

To analyse the fineness and distribution a comparison chart is used (*Figure 3*). This chart is based on different levels of distribution and fineness. The different bubble size distributions scores are 1 (uniform) to 4 (unevenly distributed). Practise taught us that in some cases it is possible to give scores with a significance of 0.5 to make a clearer distinction. The fineness is divided in three different scores. With a fineness score of 1, the bubble size is very small and with a score of 3 this size is very large. According to the milk foam scoring protocol [13], the target for the optimal foam is an uniform foam with a small bubble size. This means that the fineness score and the distribution score needs to be as low as possible.

To use the F&D chart the cup with the milk foam is physically placed on the "place cup here" circle on a printed version of the chart. After that, the observer choses which image on the chart represents the sample the best. That combination of scores is given to the new sample. After the comparison, a photographic image of the sample is made. To maximize the quality of this image, it is important to have an evenly lighted sample and therefore shadows on the surfaces should be prevented. This is done with two diffused spotlights as seen in *Figure 4* . When this is done, the depth of focus is manually adjusted so that the surface area of the sample is in focus. The sample number is made visible through the use of a note which is visible in the image. This way the image can be associated easily with the information about the sample

According to Jelmer Kuiper (Lead Engineer), comparing the new sample to an earlier scored sample is very operator dependent. The amount of experience of the operator influences the comparison which means that different researchers score the same foam differently. He also stated

Figure 4 ***Current imaging set up***

that there are deviations between comparisons of the same operator. These two problems influence the reliability of this analysing method and makes the current fineness and distribution analyses highly operator dependant.

2.3.2.2 Total volume & foam to liquid ratio

The total volume of the milk and foam is read by the operator's eye. The cup that contains the milk foam, has a scale with millilitres and a precision of 5ml. According to Jelmer Kuiper, the separation of the milk and foam is sometimes difficult to read because of the low contrast difference (*Figure 5*). When this is the case, an object like a stick or spoon can be used to help displaying the level of the foam. Another way to solve this problem is to add a contrast fluid like coffee. However, this influences the foam and the total weight which makes the result less reliable.

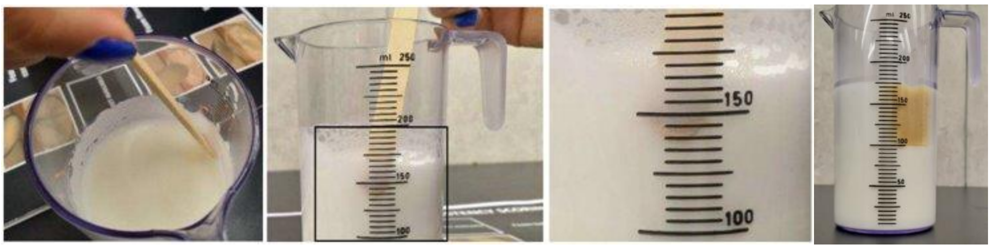


Figure 5 ***Volume measurements according to the milk scoring protocol***

2.3.2.3 Consistency

The level of consistency is a measurement of the viscosity of the foam and is also taken into account in the comparison chart (*Figure 3*). This feature is analysed with the spoon test. The operator scoops foam from the top of the milk foam sample and rotates the spoon 90 degrees in 1-2 seconds and let the foam flow back into the cup. There are 5 different levels of consistency which ranges from level 0 where the foam acts like a fluid to level 4, where the foam is solid and sticks to the spoon and does not fall into the cup. The highest quality foam has a consistency of 1 which means that the foam flows in a continues stream but is not identical to a liquid.

2.3.2.4 Temperature

The temperature is measured with a thermometer with a resolution of 0.1 degree. This thermometer is inserted in the middle of the cup just under the foam layer and stirred around to evenly distribute the temperature. When the temperature does not increase any longer the value is read. This test is very time dependent as the milk and the milk foam temperature decreases over time and measuring right after serving will influence the other characteristics because of the need of stirring.

2.3.2.5 Weight

The weight of the milk foam sample is measured with a scale. This scale can function as surface for the comparison chart to lie on and for the cup to stand on during other measurements. It is important that the cup and the comparison chart are tared on the scale before the milk is dispensed. The weight should be noted in the early stages of the test to prevent other tests to influence this feature.

2.3.2.6 Stability

The stability of the milk foam measured by taking pictures with a time interval of 3 or 5 minutes. The exact amount of time depends on whether a decay of the bubbles can be detected. Or the sound of bubbles popping. Both these measurements are very operator dependant and therefore not reliable. This method is mainly used to test different milk types.

2.3.2.7 Documentation

All the results of these feature analysing method are combined into a datasheet as presented in *Figure 6* The colours in this sheet are based on the desired levels of the features according to the preference of the client *Figure 6*. The green coloured cells have the desired score. The orange coloured scores are further away from the client's desires and the red scores are unacceptable.

							Directly after foaming (30sec to 1minute)						Grote en kleine bubbels	Lepeltest		After 3 minutes					Lepeltest	
Testnr	[illegible]	Milk type	Amount of milk	Temperature	Motor speed	Time	Input temperature at start	Milk temp in machine at end	Total ml	Fluid ml	Foam ratio	Fineness	Distribution	Consistency*	Noise	Total ml	Fluid ml	Foam ratio	Fineness	Distribution	Consistency*	Noise
67	Smallspring - coarse	Almond dream	160	5	6	120	4,5	6,3	215	95	56%	0,5	1,25	0,5	1	215	130	40%	1	1,5	1,5	0
68	Eugster Quirl	Oatly	140	35	7	90	4,2	34,9	210	105	50%	1	1,25	1,25	2	205	120	41%	1,5	1,5	2	2
69	Eugster Quirl	Almond dream	120	65	6	120	3,1		150	105	30%	1,5	1,5	3	0	150	105	30%	1,5	2	3	0
70	Eugster Quirl	Almond dream	160	65	6	120	4	65,3	175	150	14%	1,5	1,5	3	1	170	145	15%	2	2	3	0
71	Eugster Quirl	Almond dream	140	35	7	90	4,3	34,9	215	95	56%	0,5	1,25	1,25	2	190	115	39%	1,5	1,25	2,5	1

Figure 6 ***Scoring chart with parameters according to the protocol***

This table is sometimes summarized into a simpler table were only foam to liquid ratio, fineness, distribution, consistency and stability are taken into account (*Figure 7*).

Whole milk:	Foam ratio	Fineness	Distribution	Consistancy	Stability
Proto 1A	80%	0,5	1	1	1
Proto 1B	85%	0,5	1	2,5	2
Proto 1C	84%	1	1	3	2

Figure 7 ***Simplified scoring chart according to the protocol***

2.3.2.8 Qualitative vs quantitative testing

These features are analysed in sequence for two types of testing. During qualitative testing it is important to test the different milk foam creating components on their performance. Each different component creates a few foam samples with different temperatures, air pressures and foaming techniques. These tests usually have a small sample size. The quantitative test is focussed on the reliability of a component and needs a much bigger sample size. The number of samples in these tests can rise above 100. This high number of samples makes the time it takes to analyse one foam important too.

2.3.3 Previous work

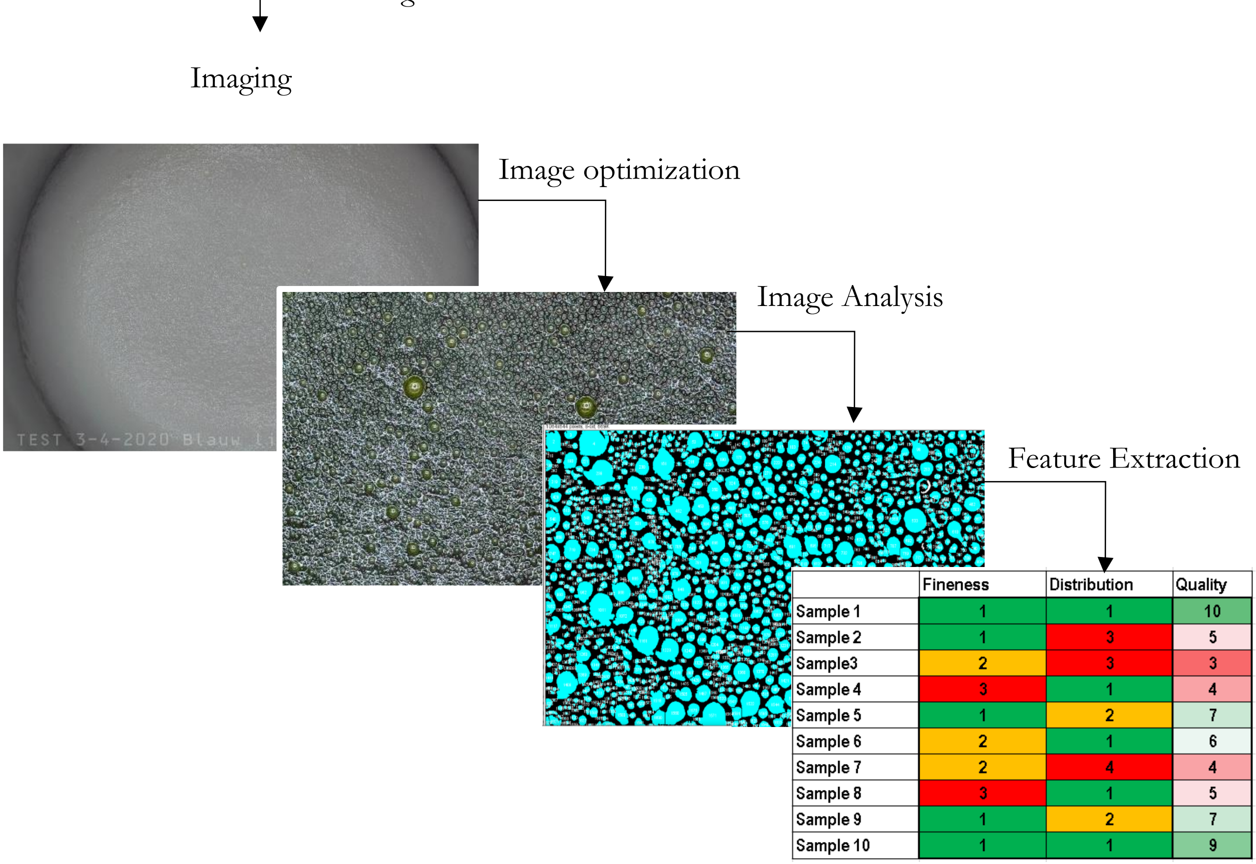
There are other installations that are already capable of analysing the previously named features. The most promising one of these installations is the Dynamic Foam Analyzer – DFA100[14]. This DFA machine uses microscopic imaging and a technique that is comparable to particle analysis to measure exact bubble sizes. However, these machines are very expensive and therefore are not considered feasible for this project at this stage.

2.3.4 Conclusion

The milk foam scoring protocol gives a clear instruction on how to analyse the characteristics of the milk foam. Analysing the temperature and the weight can be easily with objective measuring equipment. However, the methods to analyse fineness, distribution and consistency are very operator dependant and the methods to analyse foam to liquid ratio and stability are not precise enough. The characteristics that could possibly be improved during this research through the use of computer vision techniques are volume, fineness and distribution.

2.4 Computer vision-based techniques (CVBT's)

To analyse these features, there are several CVBT's or methods that combine CVBT's which all have their advantages and disadvantages. The general method workflow starts with image creation, followed by image optimisation and image analysis and finally data extraction [15]. A standard workflow can be seen in *Figure 8*.



	Fineness	Distribution	Quality
Sample 1	1	1	10
Sample 2	1	3	5
Sample3	2	3	3
Sample 4	3	1	4
Sample 5	1	2	7
Sample 6	2	1	6
Sample 7	2	4	4
Sample 8	3	1	5
Sample 9	1	2	7
Sample 10	1	1	9

Figure 8 ***Visualisation of a standard computer vision based analysing method workflow***

Image creation is mainly done with a microscope [4, 16-19] or a (video)camera [5, 6, 12, 15, 19-27]. According to the researchers that uses microscopic analysis, this is more reliable because of the greater detail in the analysed images [16, 17]. Even though the microscopic analysis can be more precise, Cimini [15] and Deotale [27] found that the use of a normal camera is more feasible and improves the efficiency by decreasing the computing time which is important for this research because of the desired testing speed that comes with quantitative testing. In addition, camera analysis creates the possibility to capture a bigger sample with more bubbles which makes the test more reliable [19]. A reason for this disagreement could be that most microscopic methods focus on a particular feature of a small amount of bubbles [16, 17] while the camera methods focusses on a more holistic approach by focussing on the whole surface of the foam[15, 19, 23, 24, 26].

Taking these methods into account, the camera image creation method is preferred in this research because of the importance of total structure, feasibility and computing time.

When the image is captured there are a lot of different techniques that are used for image optimization. Almost all methods use grey scaling to reduce computing time [6, 17-22, 24-26, 28, 29]. Grey scaling is a technique that converts a coloured image to an 8-bit image that consists of pixels with only grey values (*Figure 11*). Only one research[15] did explicitly not use this method. Which is explainable because this was an RGB-colour difference based CVBT. After grey scaling, the researchers which mentioned a lack of contrast, used Image histogram equalisation [19, 25, 29] to be able to increase contrast. Histogram equalisation is an image processing technique that spreads out the most frequent intensity values, i.e. stretching out the intensity range of the image (*Figure 10*)[30]. This step is important in foam analysis because low contrast differences in images hampers the bubble identification [19, 25, 29, 31]. For almost all researchers [6, 17, 18, 21, 22, 25, 26, 29], it was necessary to minimalize the pixel intensity to binary. This technique minimizes the computational costs and this format is necessary to apply other techniques. This technique uses thresholding to change the colour of the pixels to only black or white (*Figure 9*). For the others [20, 24, 28] binary imaging was prevented to minimize leakage of important data. For this research whether computational costs is a determining factor highly depends on the CVBT chosen to analyse this image.

Figure 12 ***Original image of dog***

Figure 11 ***Image of dog with grey scaling***

Figure 10 ***Image of dog with Histogram equalisation***

Figure 9 ***Image of dog with binary imaging***

The choice of this CVBT depends on the feature that is analysed. For volume measuring this technique is straight forward. Jadhav [32] created a globally accepted volume measuring computer vision method that meets the requirements of this research. In contrast, bubble size analysis is more difficult to accomplish and the literature brings a lot of different methods. According to a review of Aldrich [33] there are two main computer vision based principles to analyse bubble size of forth systems: edge detection and the Watershed method.

Edge detection is used frequently but can cause problems. Edge detection is based on sharp transitions on the value of different neighbouring pixels of the image [33]. There are a lot of different edge detection methods. From these methods, Canny edge detection, [4, 6, 19, 20, 29] , Laplacian edge detection [20], Valley edge detection/tracing [23], ROC edge detection [19] and Declivity edge detection [34] are the most used in bubble recognition. Even though edge detection is used frequently, researchers [23-25] criticize these methods because of three major problems:

1) White spots which are on the interion of bubbles affect edge detection results strongly [24].
2) The grey value changes at the edges between bubbles are not significant when applying the classic edge detection algorithms [23, 24]).
3) As the image quality deteriorates, the performance of these detectors declines significantly [25].

Figure 13 ***Image of dog with Canny edge detection***

The literature found different solutions for these problems. To solve the first problem, Ariff [16] used a polarizing filter which makes it possible to manage reflections. This could be added in front of a camera and could be suitable for this research. The second problem can be fixed with the previously mentioned histogram stretching [19, 25, 29] and illuminating with uniform light with the use of a ring light [26]. The third problem could be solved by preventing the deterioration of the image quality by using a good camera.

The second method mentioned by Aldrich is the Watershed method: a highly available method based on histogram equalization correction and reconstruction of images to construct markers for bubble size and distribution [25]. This is a segmentation technique. Image segmentation refers to partitioning of an image into different regions that are homogeneous or "similar" in some image characteristics[35]. Even though there are no direct signs of unreliability of the Watershed method, this is a very robust method for segmentation but needs a pre-processes image to gain full potential [19]. Therefore, the Watershed method is solitary not enough to identify bubble characteristics. From the researches that used this method [6, 19, 25, 29, 33] articles which were focussed on creating a new method [6, 19, 29] adapted the Watershed in their final method in cooperation with Canny edge detection to achieve best performance. This is certainly promising for the creation of the method in this research.

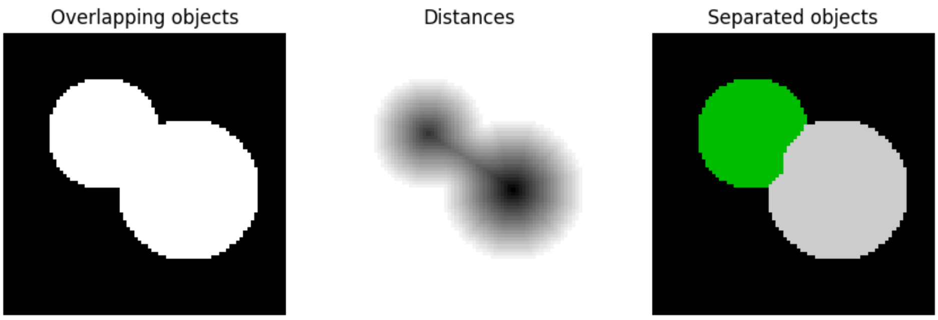


Figure 14 ***Watershed segmentation method***

Besides edge detection and the Watershed method there are some other unconventional methods investigated like: Convolutional neural networks (CNN) [28], local minima [24] and Hough circle detection [18, 20, 22]. However, these methods are not suitable for measuring bubble size in the milk forth domain for several reasons. Despite that CNN is the current most accurate method, it takes to much estimated computing time (1 hour per image) for quantitative quality testing [28] which is preferred. The reason for this long computation time is because this technique uses machine learning to recognize and measure the properties of every individual bubble in an image. The second method, local minima, is only suitable for bigger bubble sizes [24]. The Hough circle detection method on the other hand is an interesting technique which recognizes circular shapes. Even though some researchers [18, 22] are using this method and receive sufficient output data, Zabulis [20] found that Hough circle detection faces significant performance degradation in dens dispersion of particles and that often image's edges do not unambiguously match the assumed geometrical model of the circle. To improve the method Zabulis [20] uses the Hough circle detection in combination with edge detection methods and template matching [36]. Unfortunately, this method cannot be executed in this milk foam research because template matching takes too much manual input [20] which slows down this method and makes it operator dependant. Another technique that could be useful in this method is segmentation. A segmentation process subdivides an image into its constituent regions or objects[35].

2.5 Conclusions of the state-of-the-art review on milk foam

This literature research aimed at answering the following research question: "Which computer vision-based technique(s) could contribute the most to an objective analysing method of the quality parameters of milk foam? ". Research has shown that there are a lot of different characteristics that influence the quality of milk foam. Most of these characteristics can be derived from two visual analysable features: bubble size and volume. These features can be measured through different computer vision-based methods which all have their advantages and disadvantages as can be seen in the table below.

Table 1 ***Computer vision-based techniques***

Techniques	*Dependent feature*	*Pros & cons*
Grey scaling	Pixel intensities	Pro: Less computation time Con: Loss of colour
Histogram equalisation	Pixel intensity histogram	Pro: Increases contrast Con: Unrealistic relative contrast
Binary imaging	Thresholding based on pixel intensity	Pro: Less computation time & necessary for other techniques Con: Discards useful data
Edge detection	Contrast differences	Pro: Extract edges so that shapes can be recognizes Con: Highly influenced by image quality & white spots in bubbles
Watershed	Grey scale pixel intensities	Pro: Robust Con: Solitary not enough to identify bubble characteristics

Bubble classification through CNN	Machine learning program based on individual bubbles	Pro: Current most accurate method Con: High computation time
Hough circle detection	Circular shapes recognition	Pro: Easily accessible & fast Con: Performance degradation in dens dispersion of particles and that often image's edges do not unambiguously match the model of a circle

In these methods, computation time and reliability are of great importance. With the knowledge of the techniques we designed a method that could possibly be able to score the fineness and distribution of a foam sample by assembling techniques used in the literature. The method workflow is shown in *Figure 15*.

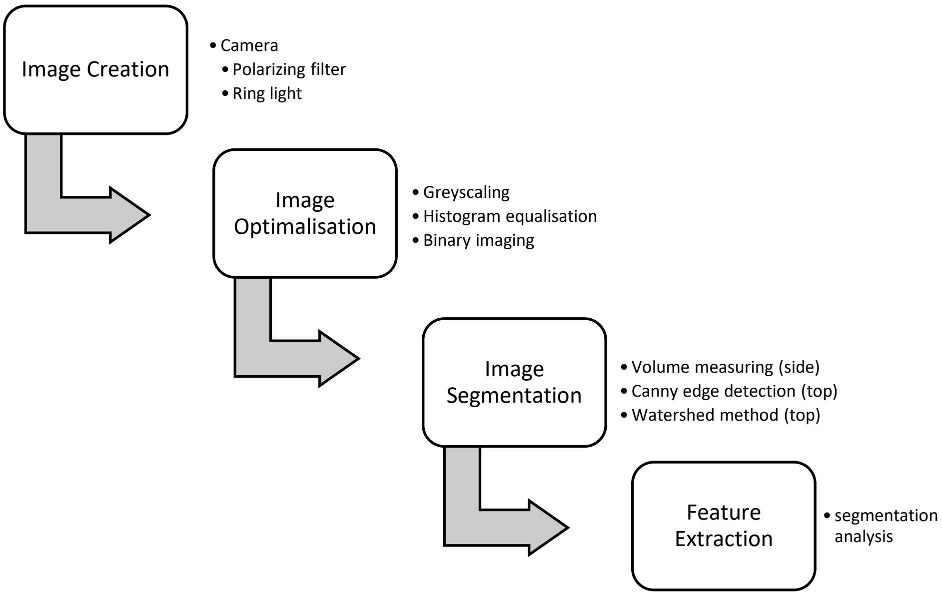


Figure 15 ***Workflow of optimized computer vision-based method to analyse bubble size and volume of milk foam based on the literature***

2.6 Discussion

Although the method constructed in this state-of-the-art research (*Figure 15*) could be the current best method, the combination of these techniques is not yet researched in a milk foam analysing method. Some techniques could unexpectedly influence each other and deteriorate the results. Besides this major uncertainty, future technological improvements could also influence the view on this method optimisation. When computer processors improve and the computational times decrease, other methods like CNN based individual bubble recognition and microscopic analysis could be implemented together with other more complicated image segmentation and classification techniques.

3 IDEATION

3.1 Introduction

This chapter uses the knowledge obtained from the state-of-the-art research to focus on finding creative techniques that could assist in different stages of the milk foam analysis. The final part of this chapter will consist of a method choice which will be specified more in the next chapter.

3.2 Imaging techniques

The technique that is used to create the data is the root of the analysing method. The choice of the creation technique influences the way the data can be optimised and the techniques that could be used to analyse this. This makes the data creation technique of great importance and thinking of new imaging techniques interesting.

3.2.1 Macro photography

Macro photography makes it possible to render small objects with more detail than can be detected by the naked eye or a standard lens. A macro lens has the ability to focus from infinity to 1:1 magnification. A macro lens is expected to work better than a standard camera lens because it is specialized in creating images with of small objects with high detail. This lens is expected to provide a higher quality image which contributes to a more reliable analysing method.

3.2.2 Video graphic analyses

The current analysing method uses a spoon test to measure the consistency as described in chapter 2. The movement of the spoon and the rotation speed of this action is really operator dependant. It is interesting to look at a robotic arm that does this movement consistently for us. It is possible to film this action and analyse the video with video processing software. The form of the foam and the velocity of the falling blob is a determining factor of the consistency of the foam. Being able to correctly analyse these features contributes to the reliability of the analysing method.

3.2.3 Milk foam colouring

The addition of coffee to the milk foam sample is used previously to create more contrast in the foam and to make the bubbles more visible[13]. As described in the state of the art this negatively influences the reliability of the data analysis due to volume differences and colour differences in the foam. Adding a drip of food colouring on the other hand has less influence on the volume of the sample. This could be used to create a bigger difference in colour between the bubbles and the liquid and make it easier to analyse features like fineness, bubble size distribution and the foam to liquid ratio. As shown in *Figure 16*, coloured milk foam makes the difference between liquid and foam decently noticeable for the human operator and that makes this an interesting method to implement in the analysing method. A downside of this technique is that this food colouring needs to be added in every sample. This requires an extra operators' action and the exact colour of the foam is reliable on the exact amount of food colouring that is added. Adding one drop too much to the sample could change the colour and the contrast differences and give an unreliable analysis.

Figure 16 ***Milk foam with blue food colouring***

3.2.4 Thermal imaging

Thermal imaging is an infrared imaging technique. Thermal cameras detect radiation on the long infrared range of the electromagnetic spectrum. All objects emit infrared radiation and that radiation increases with temperature[37]. This makes it interesting for this method because a thermogram (the image created through thermal imaging) gives a visualization of the temperature in an image. This could give a clear visualization of the difference between bubbles and liquid if there are temperature differences. The air in the bubbles could influence the temperature of the surrounding liquid to an extend that could possibly be segmented through computer vision techniques. This technique also immediately provides the temperature of the milk foam. Which makes the thermometer test not necessary and reduces the amount of operator actions during the

Figure 17 ***Thermal imaging of liquids in cups***

analysing method.

3.2.5 Micro-CT: 3D Internal Imaging

A key benefit of micro-CT[38] is that it is non-destructive. This technique can image the internal structure of the material in 3D without damaging or affecting the sample. The volume is reconstructed virtually on the computer where it is possible to take virtual planes of specific layers of the foam. The result can be processed by software. From this result, multiple features could be calculated like the thickness of the liquid in between the bubbles and the void size distribution. These features could be important in milk foam analysis and the qualification.

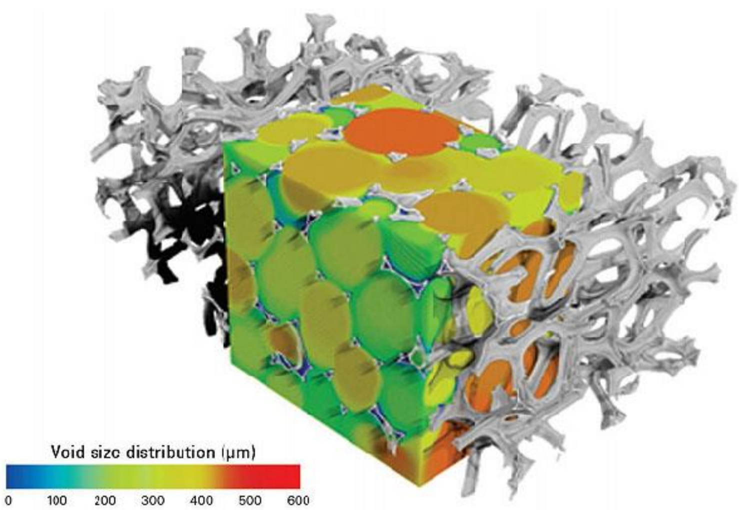


Figure 18 ***Micro-CT scan of a foam sample***

3.3 Image optimisation techniques

In almost all analysing methods it is useful to optimise the created data. This is done to simplify the analysis of the data in a later stage of the method. Because the visual characteristics of liquid and the foam are very similar, it is important to increase the minor differences to make it easier to distinguish them.

3.3.1 Thresholding

There are a lot of different thresholding techniques that could help with the segmentation of milk foam images. These techniques are explained by a survey[39]. The combination of the earlier named technique of food colouring could help with increasing the visual differences that could be analysed by thresholding. A relatively new colour thresholding technique is based on the differences in pixel colour between parts of objects [35]. This is an open source technique with the possibility to automatically select the threshold. If the lighting on all samples is the same, the reflection and the colour of the bubbles should be equal as well. Which means that after determining the colour of the bubbles once, this threshold can be used for all future samples.

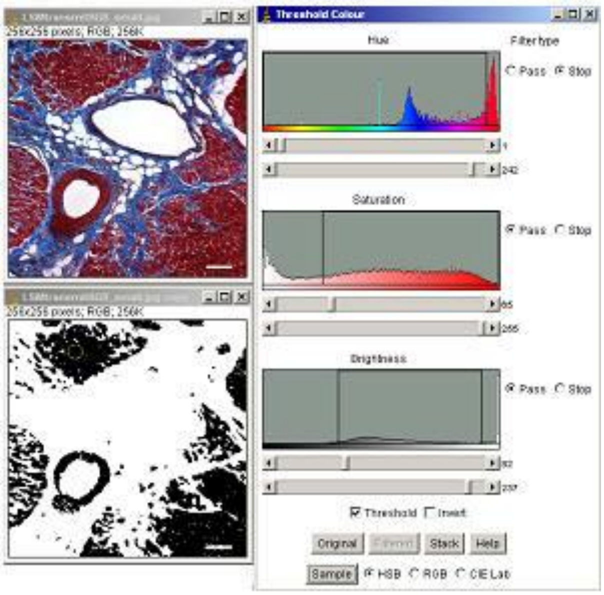


Figure 19 ***Colour thresholding technique in Fiji***

3.3.2 Uneven background correction

As previously explained, evenly lighting of the sample is important for visual data analysis especially when the segmentation is based on colour differences. These colour difference should not be influences by uneven environmental light. Uneven lighted data could be restored through background correction as described on the Fiji Website[40]. This uses a Fast Fourier transform bandpass filter to remove noise created by the background liquid.

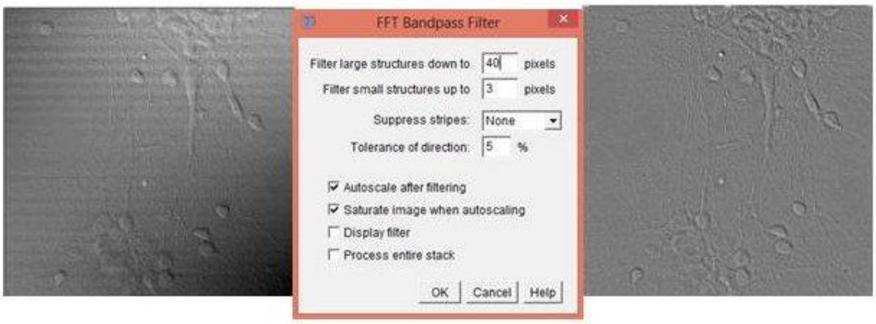


Figure 20 ***Uneven background correction***

3.3.3 Trainable Weka segmentation tool

Machine learning is a broadly discussed topic with a lot of different uses[41]. One of these uses is the segmentation of images. The Weka segmentation tool is an easily accessible tool that can be trained to learn from segmented data and perform the same segmentation later in unknown data.

The Trainable Weka Segmentation[42] is a Fiji plugin that combines a collection of machine learning algorithms with a set of selected image features to produce pixel-based segmentations. The tool can be trained in recognizing the difference between liquid and foam. By labelling multiple

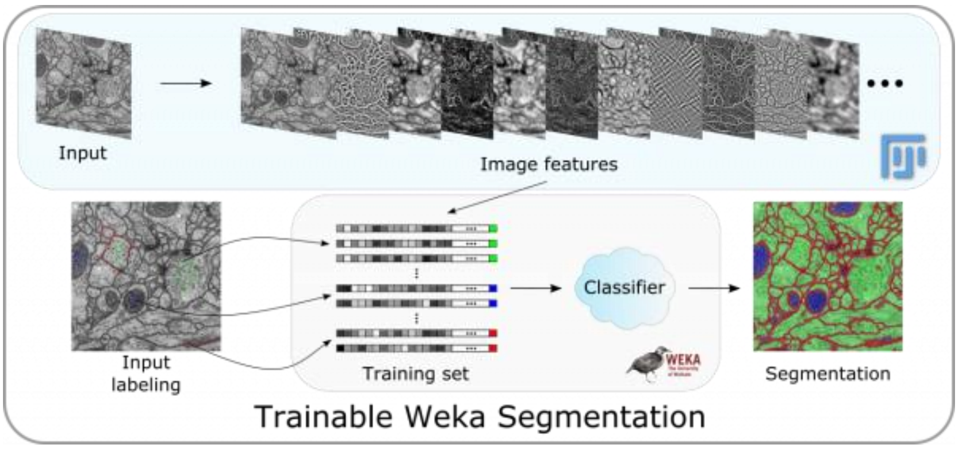


Figure 21 ***Trainable Weka Segmentation workflow***

areas of the image the tool can extract pixel features of these areas. These features are used to classify the remaining pixels and segment the individual bubbles and the foam. A pipeline of this technique is shown in *Figure 21*. There are multiple analysing methods that are able to analyse a segmented image and give an indication of the bubble sizes and therefore an indication of the fineness and distribution.

3.4 Image analysing techniques

To measure the fineness and the bubble size distribution it is important to analyse the bubble size. From conversations with Wouter Nijland and Jelmer Kuiper & Hedzer vd Kamp (lead engineer), some ideas to measure fineness and distribution came to light which could be useful to implement in the analysing method.

3.4.1 Particle analysis

To analyse the particles in a segmented image, the particle analysis tool in Fiji could be used[43]. For this analysis a binary image is needed. This image format is achieved by thresholding. When the binary image is created with a set threshold, the program scans the image for edges and uses the wand select tool to automatically select the whole object that is enclosed with that edge. Then it uses a measuring tool to measure the area of that object. That measurement is given in total amount of pixels that is occupied by that objects. The recognition of the objects could be altered with size and circularity thresholds to specify the sort of object that the program needs to find. Since the size of the measuring cup is known and the macro lens is fixed, the number of pixels in an image could give more information about the sizes of the object. The number of pixels that are occupied by the area of the bubbles give the size of the bubbles and therefore the fineness and distribution.

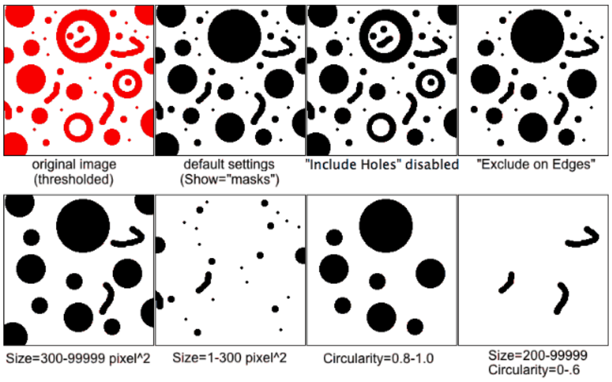


Figure 22 ***Particle analysis with Fiji***

3.4.2 Sound analysis

The bubbles of the milk foam rise to the surface and will eventually pop and make a very subtle sound that could be measured by a high-end microphone. The size of the bubbles could influence the frequency of this sound. Creating a sound map of different kind of milk foams in combination with computer sound analysis could give a categorisation.

3.4.3 The Weka workbench

The Weka workbench is designed to quickly try out existing methods on new datasets in flexible ways. It provides extensive support for the whole process of experimental data mining, including preparing the input data, evaluating learning schemes statistically, and visualizing the input data and the result of learning [44]. This tool has multiple image filters that can be used to extract features from scored images. The tool can apply different algorithms on this data to learn more about the connections between these attributes. This can be used to make prediction on new unscored images and classify their fineness and distribution scores. The workbench also contains an Experimenter tool in which it is possible to test which methods and parameter values work the best of our problem. Using this workbench can give a lot more insight in how machine learning can be in order to classify milk foam images on their quality.

3.5 Conclusions of Ideation

It is important to look at these ideas with a critical point of view while keeping the scope of this project in mind. Macro photography is for this project the best suiting technique for image creation because of its availability, the computing time and the follow up potential. A robotic arm in combination with video processing is expected to be too complicated for this project and does not fit the goals of the curriculum. Thermal imaging is an interesting technique that could tackle multiple problems, however at the current stage of this project the investment costs are too high. Micro-CT is the most promising and challenging technique. Even though this device could help PCV Group with other projects, it does not fit the project at this moment because it is too expensive.

The image optimisation techniques that are described in the state-of-the-art research will be examined at a later stage together with thresholding and uneven background correction. Almost all the researched techniques are easy to incorporate and are available through Fiji which makes this software the main software that is used. Testing the techniques is necessary to gain more insights in which technique contributes the most to a reliable analysis.

For the analysis of the images both the Weka workbench and the particle analysis technique could be interesting for the analysing method. Particle analysis is promising because of the simplicity and the availability. The techniques used in the Weka workbench are expected to have a longer computation time and need a large training dataset. However, the reliability could be higher because when trained sufficient, it is assumed to be less vulnerable to outliers and noise. This depends highly on the given problem and therefore needs to be tested.

It is important to know the possibilities of these techniques and to know the pitfalls. In the next chapter we give an explanation about what is expected from these techniques through the use of a requirements capture and a specification.

4 Requirements Capture & Specification

4.1 Introduction

In this section of the research the choice of testing workflow and the first analysing method are specified. This is done with the help of a list of requirements and a short stakeholder analysis. The requirements that are set in collaboration with the stakeholders helped with the specification of the desired analysing workflow and with the first analysing method.

4.2 Stakeholder analysis

Before we created a list of requirements, it was important to have a good understanding of the scope of this project. In order to create this, we conducted a stakeholder analysis. It is important to know who is directly or indirectly influences by this project. This is done through the use of a stakeholder analysis toolkit [45]. The stakeholder of this project can be found in *Table 2*.

Table 2 *Stakeholders of the research*

Connection	*Stakeholder*
Directly affected	Student (creative technology student)
	Supervisor of graduation project of university
	Critical observer of graduation project
	Supervisors of graduation project of PCV Group
	Members of Team Florian
	Milk foam analysts of PCV Group
Indirectly affected	Shareholders of PCV Group
	Lead project manager of PCV Group
	PCV Group's client
	Competitor of PCV Group

Family and friends
Coffee department partners of PCV Group
Milk company
Healthcare departments partners of PCV Group
Multinational’s client
Coffee shopkeeper
Computer vision specialists
Milk foam specialists
Members of other researching teams of PCV Group

Some of these stakeholders must be taken along while performing a requirements capture. The stakeholder has different levels of interest in- and power over the project therefore, all the stakeholders have their own level of importance which is associated with different kinds of approaches. These approaches, interest level and power level are shown in *Figure 23*.

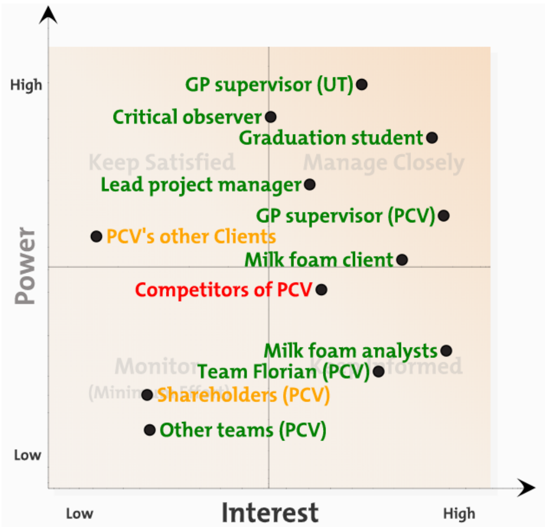


Figure 23 ***Stakeholder analysis***

The stakeholders with high power and high interest are the most influenced by this project. The supervisor from the university, the supervisor from PCV Group, the lead project manager of Florian and the Graduation student are the most important when capturing the requirements of this project and are therefore involved in this process.

4.3 Requirements capture

We began with creating a list of requirements (Appendix 9.1). This list is formulated in cooperation with Job Zwiers (Supervisor UT), Wouter Nijland (Supervisor PCV Group) and Jelmer Kuiper (Lead project manager). These are the important stakeholders that came out of the stakeholder analysis. The list of requirements is based on the MOSCOW method [46] which is a prioritization technique that is used in project management.

The important aspects that came out of the list of requirements are the following:

1) The method must be able to analyse the milk foam fineness reliable by classifying three different levels of fineness.
2) The method must be able to analyse the milk foam distribution reliable by classifying three different levels of distribution.
3) The method must include computer vision based analysing techniques
4) The method must be able store results and save the measurement for further investigation.
5) The method should combine the result of the analysis into one clear data visualization.
6) The method should create results autonomous after placing the sample in the installation, without additional actions of the operator.
7) The method should be able to analyse multiple images in a batch without the need of actions of the operator.
8) The method should not take more than 20 minutes per foam sample.
9) The method should fit in the testing environment at PCV Group
10) The method will not be able to analyse the temperature, volume, foam to liquid ratio, consistency and weight of milk foam.

Next to these requirements, we kept in mind that computer vision is a new domain to PCV Group and we think it is valuable to learn more about the possibilities of integrating computer vision in analysing methods.

4.3.1 Workflow specification

After the requirements capture it was possible to create a functional specification of the method workflow reference. This workflow could be implemented in the analysing protocol of PCV Group. The workflow consists of 4 different actors: the observer, the foaming machine, the analysing installation and the computer. During the analysing process it is important that the observer has minimal influence on the outcome of the method. This project aims on giving more insight in the feasibility of this workflow through the testing of different techniques. The tested methods must be able to classify the fineness and the distribution in classes that are previously used by PCV Group as scores.

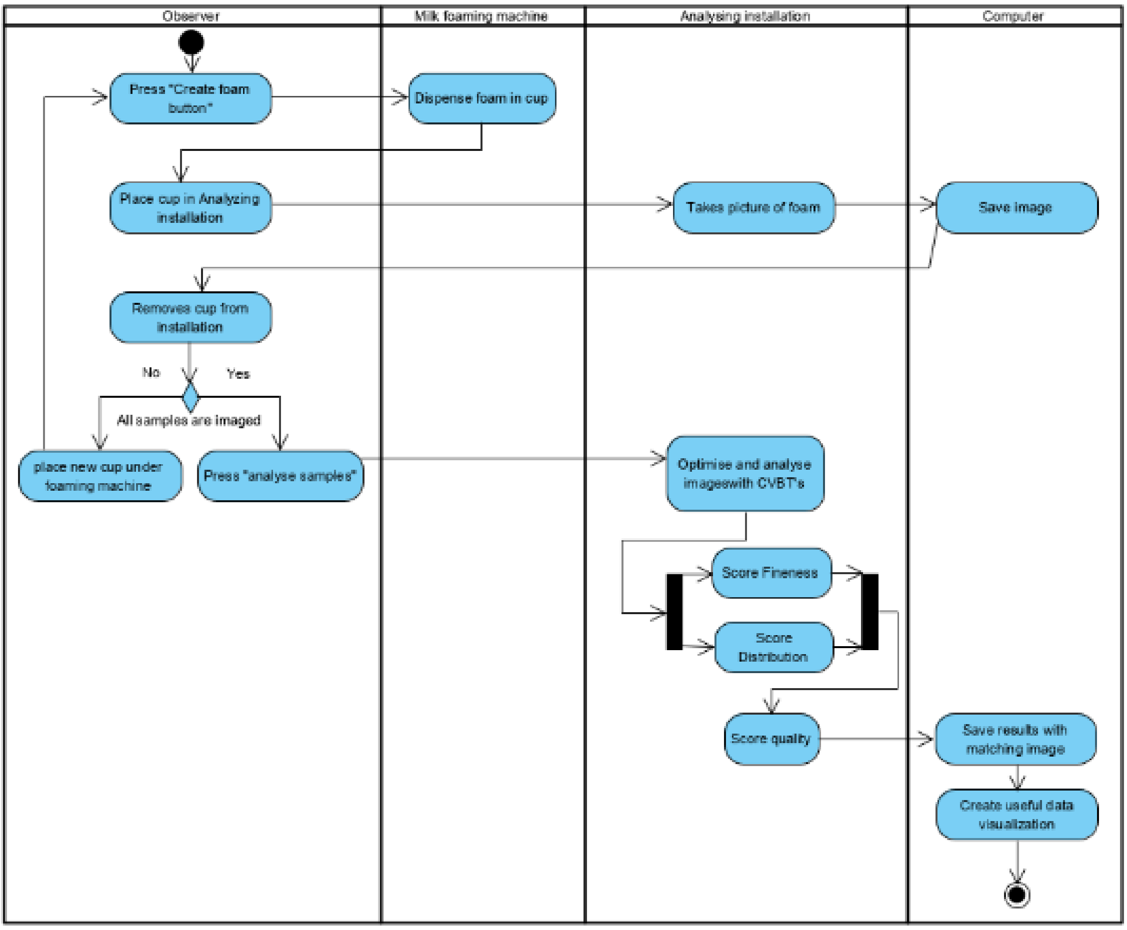


Figure 24 ***Workflow of preferred analysing method based on stakeholders' preference***

4.4 Conclusions of requirements capture and specification

A list of requirements for the analysing method is computed and a workflow in which this method can be adapted is presented. The ability to analyse fineness and distribution has the focus during the testing phase. The analysing method must be able to classify these features within a reasonable time (max 20 minutes per image). Different techniques are investigated and tested in the realisation phase to design an analysing method that meets these requirements.

5 REALISATION

5.1 Introduction

This chapter consists of the realisation of an iterative design process[47]. During this designing process we tested different techniques that could helped with the creation of a method that meets the previously stated requirements. First, an overview of the standard testing conditions will be given. Then, the first iteration will be explained and evaluated. The learnings from the iteration will be used to create a new iteration test set up. This iterative design process is continued until the requirements specified in the previous chapter were met or until there was enough evidence that using CVBT's in this analysing method is not feasible.

5.2 Overview of experimental set-up

5.2.1 Introduction

Before we tested the different CVBT's it was important to create a reliable and reproducible testing set-up. Therefore, we tried to keep several conditions of the testing set-up constant. Given that our tests and therefore our results are based on our test set-up, it is important to report the set-up and to specify the used equipment.

5.2.2 Milk sample creation

For this test we used the "Lang Lekker" milk of Campina. The milk foam is created by a milk foam machine provided by PCV Group and operated by Emmy van Adrichem (Graduation Internship of PCV Group). This machine makes it possible to create milk foams with desired fineness and distribution scores (*Figure 25*).

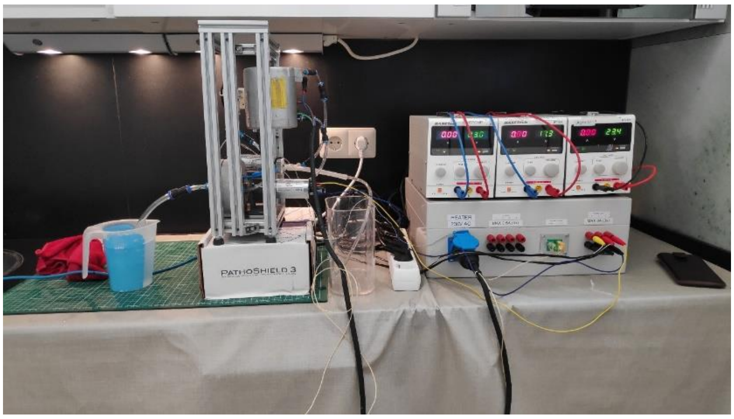


Figure 25 ***milk foaming machine***

The milk flows from the machine into a measuring cup. The specifications of this measuring cup can be found in the appendix (Appendix 9.2).

We aimed at a constant volume of the total sample. The total volume should not exceed the maximum volume of the measuring cup (250ml), but in the meantime there should be enough volume to give a reliable result. The volume of the sample during this experiment was between 200ml and 250ml.

5.2.3 Image creation

The images are created with a Nikon D5300 [48]. The lens that is attached to the camera is a Sigma 105mm macro lens [49]. The tripod that is used is the Slik U6600 and it is set to the lowest possible position. This gives a distance of 31 cm from the lens to the top of the measuring cup which makes the whole surface of the sample visible on the image.

5.2.4 Image optimisation

The images are optimised in an open sourced image processing software program called Fiji [50]. The version that is used is the 64-Bit Windows version. This program is easy to use and has a wide range of plugins that can be used for image optimisation the specific plug-ins and techniques that are used are further described in the specific iterations.

5.3 Iteration 1 Analysing method through edge detection and Watershed

5.3.1 Introduction

For this iteration it was important to test whether the analysing method that comes from the literature could be useful for the analysis of the important features of milk foam.

5.3.2 Requirements planning:

The initial requirements planning is constructed in the previous chapter and is used as base of the first test. The most important requirement is the ability to measure bubble size distribution and bubble fineness therefore, these requirements will have the focus during the design of the test.

5.3.3 Analysis and design

The test can be divided in four components: Image creation, image optimisation, image analysis and data visualisation.

5.3.3.1 The camera set-up

With imaging techniques, it is important to capture as much details of the foam as possible with the least amount of noise. Minimizing the camera movement decreases the noise on the image and helps with maximizing image details. This is achieved by placing the camera on a tripod and changing the shutter mode to remotely controlled. This removes the need of pressing the shutter button on the camera and prevents the camera from shaking while creating an image. The images are saved as standard NEF-file on the camera.

5.3.3.2 Lighting of the foam sample

From the literature is found that lighting of the sample is very important. Uniform lighting is preferred and expected to improve the quality of milk foam images. Uniform lighting can be achieved through the use of a ring light. This ring light is a StudioKing Macro LED ring light [51]. This will enlighten the bubbles from different angles and diminish the shadowing on the sample. This tends to be useful in capturing the foam as a hole and illuminating the bubbles completely. This light is equipped with a blue, white and orange diffusing filter on the light. The effect of different colours of lighting are investigated in this test.

5.3.3.3 Choice of focussing method

In the context of operator actions, it is important to address the way of focussing during image creation. There are two different methods: automatic focus and manual focus. Because of the operators actions it is more desirable to create a method that uses automatic focus. However, for testing at this stage it is important to know whether the image analysing methods could work and to test this, the quality of the image should not be the determining factor. Therefore, during testing manual focus will be used, but in order to have the possibility to investigate whether the analysing method works with automatic focus, the same foams samples will be captures through both types of focus techniques.

5.3.3.4 Computer programme

The images taken with the camera will be saved on a memory card which can be inserted in the computer to transfer the data from the camera to a folder that can be processed by the computer.

Image optimisation is the second step in this analysing method. In this step the image will be optimised through CVBT's. To maximize testing opportunities, a software program should be used that has multiple build-in filters and algorithms that could be used for processing. The two programs that are suggested from the literature are Microsoft Image-Pro[52] and Fiji[50]. Both software programs could be useful for this method, however Fiji has more open sourced techniques and algorithms that could be used for this type of analysing method and it is easier to use. Therefore, Fiji has the overall preference. Image-pro could be used for later testing if the technique is not available in Fiji.

5.3.3.5 Image optimisation

In the first test, the image optimisation techniques that are used are histogram equalisation [53], grey scaling[54], binary imaging[54], watershed segmentation[55] and Canny edge detection[56]. These techniques are previously explained in the state of the art.

5.3.3.6 Image *analysis*

The image analysis is done through particle analysis. This previously explained in the state of the art. The data of the bubble sizes data is visualized through a histogram and a table the average size, maximum size, minimum size and total amount of bubbles. This data is presented in a CSV File.

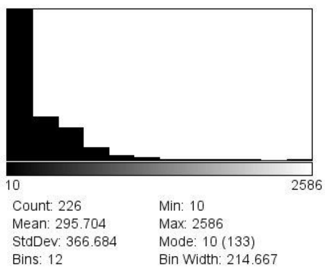


Figure 26 ***Example of Histogram of bubble sizes through participle analysis***

5.3.4 Implementation

The final workflow of the first test is described in a workflow diagram (Appendix 9.3). During the test we look at the results to create design opportunities and optimize the current techniques. The first test set-up is seen in *Figure 27*.

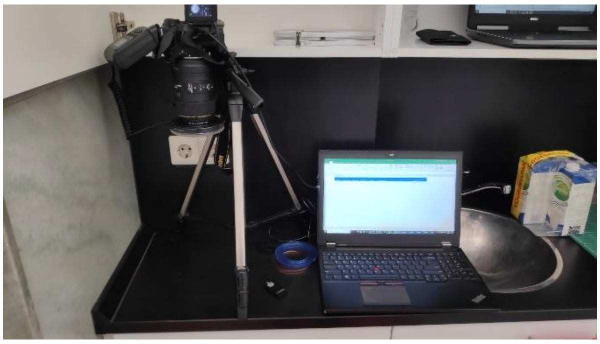


Figure 27 ***Test setup of first iteration***

5.3.5 Testing and results

Taking the images with the set up as described earlier gave the following results: The first images are taken with the standard ring light settings and a manual focus. During the test we used three colour filters. These filters diffuse the ring light slightly and create blue, orange and white lighting. The colour filter of the ring light is altered to test which colour would contribute the most to valuable data. The combination of these settings gave the following images (*Figure 28*).

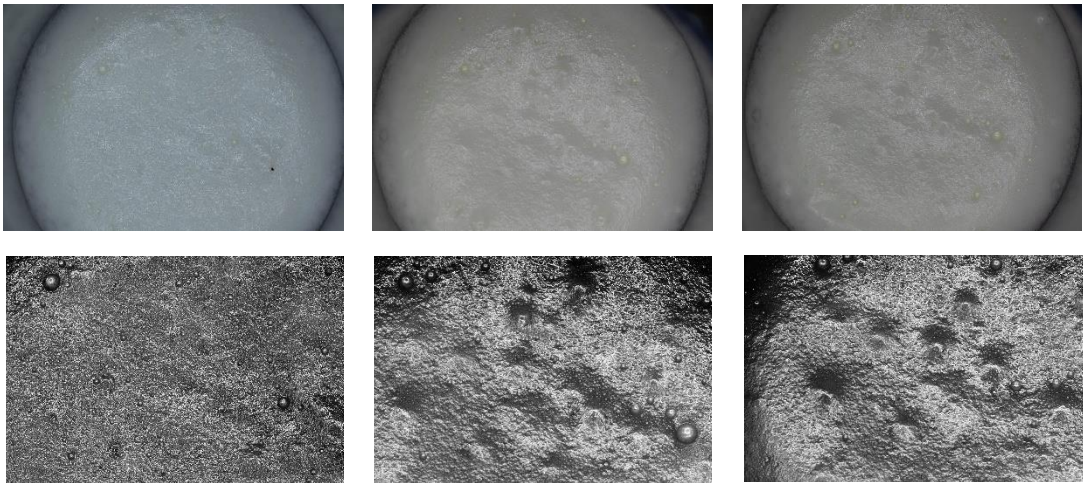


Figure 28 ***a) blue light b) orange light c) white light d) blue light with HE & greyscale e) white light with HE & greyscale f) orange light with HE & greyscale***

Processing these images with histogram equalisation, grey scaling and binary imaging techniques as described in the method gave promising results. These results were examined by the operator and with the blue diffusing light filter, the difference between bubbles and liquid were best visible. Therefore, this filter will be used for the remaining of the test.

From this image a sample is taken to improve the computation time of the analysis. This sample is taken from the centre because the lighting was the most consistent in that area. The bubble distribution and the fineness are also taken into account with the choice of this sample. The operator observed that this area has an interesting bubble size distribution and fineness. This sample is further optimized with Canny edge detection and after that analysed with the particle analysis of Fiji. The analysed particles and their areas are used to create a histogram (*Figure 29*).

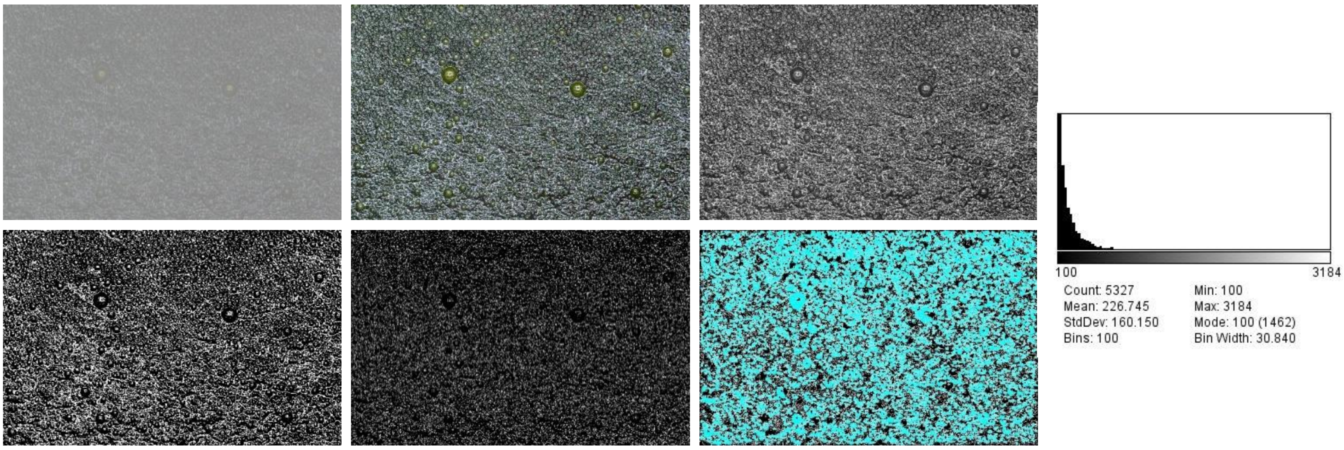


Figure 29 ***Result of literature based analysing method; (a) original sample (b) histogram equalisation (c) grey scaling (d) binary image (e) Canny edge detection + Watershed method (f) particle analysis (g) size distribution histogram***

5.3.6 Evaluation & learnings

5.3.6.1 Set up and image quality

The quality of the images turned out sufficient, the noise was minimal and even most of the smaller bubbles on the image could be recognized with the operator's eye. This was mainly thanks to the manual focus point. The transfer time from the camera to the computer was slow and could be improved by using a direct connection cable from the camera to the computer. An extra program was needed to convert the automatically saved NEF-files to JPEG- files. This took extra time and could be prevented by automatically saving the files as JPEG.

5.3.6.2 Lighting of foam sample

The Ring light worked as expected in case of enlightening the sample and created a good brightness level. The choice of the blue filter on the lights helped the most with increasing the foam details in the picture. Because of this, the blue diffusing filter will be advised to use in further tests.

5.3.6.3 Image optimisation

The image optimisation techniques did not have the desired outcome. The ring light introduced a new unforeseen problem in the images. The ring light reflects its light in the bubbles which results in small inconsistent light circles in the bubbles. These circles made it more difficult for the Canny edge detection technique to operate as desired. The main principle of edge detection is based on abrupt contrast changes and due to the ring light reflections there are too much contrast changes in the sample. Changing the parameters of the edge detection algorithm did not have the desired result. This makes this optimisation method not advisable for further testing unless the reflection of the ring light could be minimized.

5.3.6.4 Analysing method

Because of the detection of many contrast differences due to the ring light, the Canny edge detection did not work sufficient and therefore the particle analysis suffered from over segmentation which creates an unreliable result.

Even though the image processing techniques did not work sufficient, they did lead to a remarkable finding. Increasing the contrast in the image increases the colour difference between the bigger bubbles and the liquid between the bubbles. This colour difference could be a determining factor in the segmentation of bubbles and is interesting to look at for further testing.

5.3.6.5 Conclusion

This method is not good enough to be accepted as the new analysing method. The quality of the image is good, the ring light illuminates the sample multi directional without shadows on the sample which resulted in a high-quality image. However, the bubbles had too much reflection which reduces the quality of edge detection and the segmentation. This reduces the quality of the analysis and makes further testing needed to know whether the reflection could by removed while maintaining the quality of the image. This iteration did not reliable analyse the fineness and distribution and therefore a second iteration is needed.

5.4 Iteration 2 Colour Thresholding

From the previous iteration we learned that image processing can improve the colour difference between milk foam bubbles and the milk foam liquid. Whether this difference is sufficient to achieve good bubble segmentation is tested in this iteration.

5.4.1 Requirements planning:

The most important requirement of this test is that the method needs to distinguish bubbles and liquid through colour differences. This method should make it possible to segment the bubbles and use particle analysis to measure bubble size distribution and fineness.

5.4.2 Analysis and design

For this test the earlier acquired images will be used. A new technique is implemented in the method. This technique is called colour thresholding [57] and is tested on the histogram equalised images. Colour thresholding is a technique that is based different pixel intensities. This technique uses a manually defined range of pixel intensities of the hue, saturation and brightness. When a pixel falls within this range, the pixel gets replaced with a red pixel. If only the colours of the bubbles are in this range and not the colours of the liquid, it is possible to segment the bubbles. After this the image is binarized to make it possible for the particle analyses to measure bubble sizes. The new workflow of the method is shown in Appendix 9.4.

5.4.3 Testing and results

The histogram equalized image of the previous iteration is used as a test sample. The colour thresholding plug-in is used on this and we set a pixel intensity range manually so that the bubble segmentation looked the best.

As seen in *Figure 30* colour thresholding method in combination with particle analyses; a) manual colour thresholding; (b) binary image of colour thresholding result; (c) noise reduction + edge exclusion + particle analysis (d) overlayed result; (e) Bubble size distribution histogram after colour thresholdingthe larger bubbles are recognized with this technique. The smaller bubbles did not have a sufficient colour difference in respect to the liquid and therefore were not detected properly by this technique. Binarizing the tresholded image gave the result showed in 16b. Simple noise reduction [58] is used on this image to prevent small inconsistencies influencing the particle analysis. The large white border is neglected when analysing the particles. The analysed bubble sizes are shown in a histogram *Figure 30*.

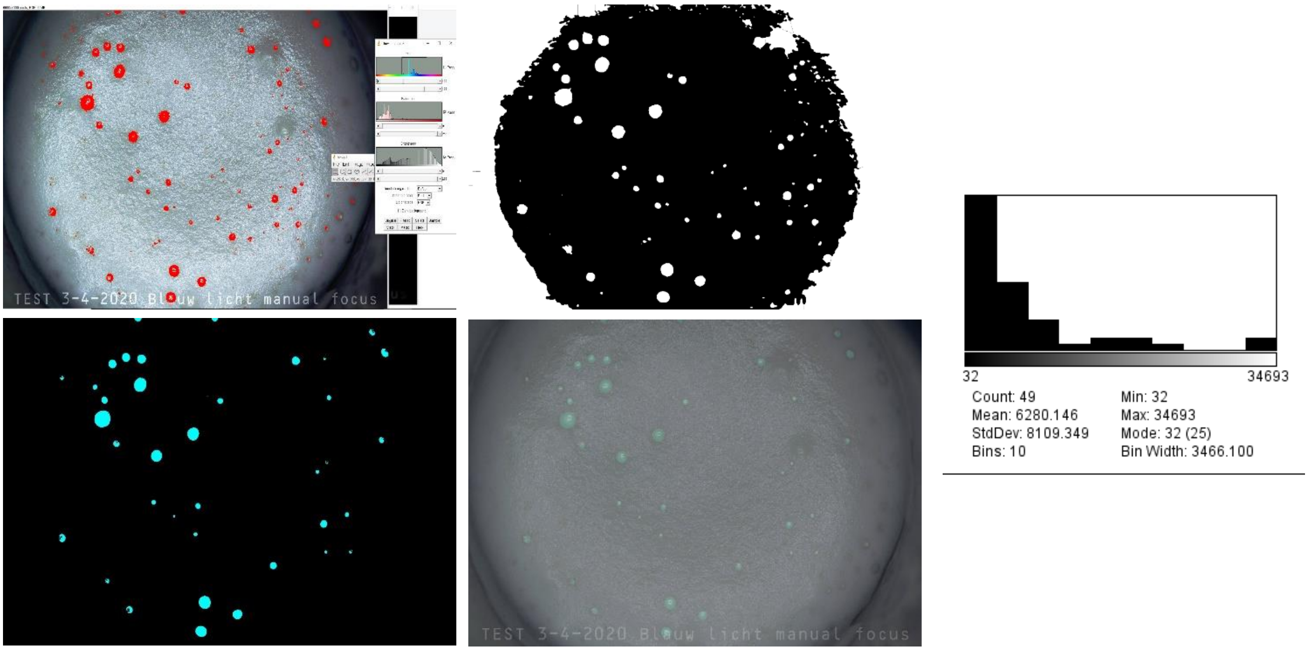


Figure 30 ***colour thresholding method in combination with particle analyses; a) manual colour thresholding; (b) binary image of colour thresholding result; (c) noise reduction + edge exclusion + particle analysis (d) overlayed result; (e) Bubble size distribution histogram after colour thresholding***

When overlaying the particle image on the original we could see that most of the bigger segmented bubbles correspond to bubbles we could recognize ourselves. The bubbles on border of the sample are not recognized but that is understandable because of the brightness difference between the middle and the edge of the sample. Because of this brightness difference it is difficult to set a good threshold that includes all the bubbles while excluding the liquid.

We tested the set range on other images but this did not work sufficient. In every image the bubbles are a slightly other colour due to lighting and reflection inconsistencies. We also tried automatic thresholding but this only worsen the result.

In extreme cases like showed in *Figure 31* the particle analysis through colour thresholding does not work properly. When the bubbles are too large, this technique will lose data bubbles due to a wide

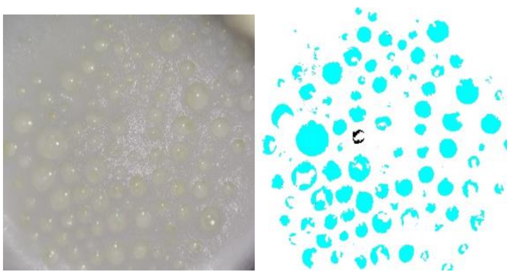


Figure 31 ***Extreme sample with large bubbles***

color variation in the bubbles itself. This influenced the particle analaysis and could underestimate the size of the bubbles. Holes in the bubbles appear in the segmented images which makes this method unreliable for extremely large bubbles.

5.4.4 Evaluation & learnings

From these results we concluded that for bigger bubbles colour thresholding is a promising way of analysing the bubble size distribution. At this moment the colour threshold needs to be set manually, but automation is preferred. With extreme large bubbles the technique does not work correctly. This is not a problem at this stage because this is only a problem in really extreme cases which will not be treated in this research. However, when these foams are considered valuable it could be interesting to look at the Fill Holes function of Fiji.

The brightness of the edges of the sample deviate from the centre of the image which resulted in the exclusion of outer bubbles. Using uneven background correction[40] could help with including the outer bubbles to this analysis and is suggested to use in further testing. Colour thresholding is a sufficient method to measure the bubble size distribution, however it needs manual input per image which is not preferred according to the requirements. It is also not capable of scoring the fineness of a foam which makes another iteration desirable.

5.5 Iteration 3.1 Polarizing filter and other lighting alterations

5.5.1 Requirements planning

For this iteration, we tested whether changing the imaging technique makes it possible remove the reflections of the ring light in the bubble while maintaining the lighting quality.

5.5.2 Analysis and design

The ring light reflection is creating problems with during the analysis of bubble sizes. From the literature [15] is found that a polarizing filter could help with minimizing the reflection in the bubbles. During this iteration we also tried to decrease the analysing time by directly uploading the images to the computer via a direct connection cable. The workflow is described in the Appendix 9.5.

5.5.3 Testing & Results

During the test, the polarizing filter is used but did not have the desired result. The bubbles still had reflections of the ring light as seen in *Figure 32*. It is interesting to see that the polarizing filter filters only some part of the reflection of the ring light but not the complete reflection.

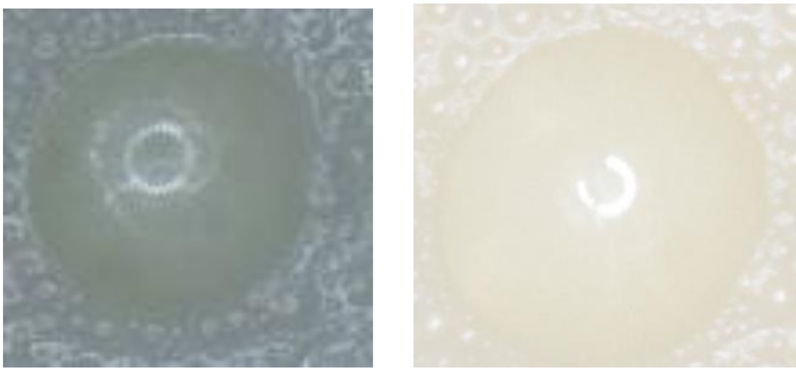


Figure 32 ***Ring light reflection in bubble a) normal b) with polarizing filter***

An additional polarising filter did not help with eliminating the reflections. Instead it did only blur the image as seen in *Figure 33*. We tried to make the data more useful by enhancing the contrast in images where multiple polarizing filters were used but even this enhancement was not enough to make the image suitable for analysis.

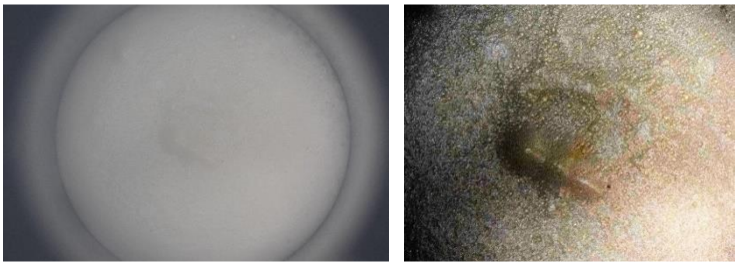


Figure 33 ***The use of multiple polarizing filters; a) the original image with 2 polarizing filter***
(b) a sample of the centre of the image with histogram equalisation

Because the polarizing filter did not work, we tested changing the lighting angles. The result from these tests and their advantages and disadvantages can be found in the table below:

Lighting method	*Resulting Image*	*Advantages*	*Disadvantages*
Dimmed lights		Evenly distribution of brightness	Not enough light to create a high-quality image and perform bubble segmentation
Lighting from the side		Bubbles are better visible and have a clear difference in contrast and colour in comparison to the milk	The lighting source has to be set manually and only one side is correctly lighten up.
Direct spotlight		The sample has an overall good brightness	The bubbles are only illuminated from one side which could result in overshadowing and therefore give an unreliable bubble segmentation.

5.5.4 Learnings and evaluation

Using the polarizing filter did not have the expected result. The ring light reflection was not completely removed. This is probably because it only filters the light that comes from a specific direction. The ring light creates multidirectional light and only a part of this reflected multidirectional light is removed. A reason for this could lay in how a polarizing filter operates because it only filters uniform light. The other lighting angles that we tested were not suitable for this method. The lighting technique has to be improved in order to use the analysing method.

5.6 Iteration 3.2 Axial lighting

5.6.1 Requirements planning

The aim of this test is to prevent ring light's reflection while still maintaining sufficient lighting. In this iteration we tested a lighting technique called Axial lighting [59]. This lighting technique uses indirect light from a light source that enlightens a transparent light reflecting surface *Figure 34*. This test will provide different alterations of the use of axial lighting to research whether this technique is promising enough to adapt as imaging technique in the new analysing method.

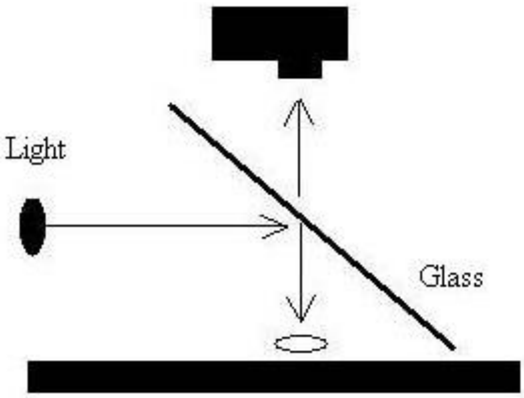


Figure 34 ***Axial lighting technique***

5.6.2 Analysis and design

In this experiment a Plexiglas plane is used in combination with a solder assistant to keep the glass in its place. We used the brightest available lamp as a light source. After the imaging we used the same analysing techniques as described in earlier iterations. The complete experiment workflow can be found in the Appendix 9.6.

Figure 35 ***Iteration 3 set-up Axial lighting a) side view b) top view***

5.6.3 Testing and results

We used a 45 degrees lighting angle because this is advised by an axial lighting experts [59]. During the implementation we found that it is important to use a light absorbing cloth to prevent the environment from disrupting parts of the milk foam sample due to reflections *Figure 36*a. The transparent top part of the cup which is not filled with milk foam caused refraction and light inconsistencies that were visible on the sample *Figure 36*b. Adding light blocking tape to the sides solved this problem. Based on this this finding a non-reflective cup is advised. These settings resulted in the following images.

Figure 36 ***Minimizing light inconsistencies on sample a) normal b) with taped sides c) wit taped sides and black cloth***

We did not use a ring light during this iteration so there was no ring-shaped reflection in the bubble. However, these images are of a significantly lower quality as the images created in previous iterations. Using HDR settings of the camera is tested on recommendation of Job Zwiers, however the camera needed a longer processing time and did not positively influence the result. It looks like the milk foam gets darker when using the HDR function and when zoomed in, the contrast differences are less visible then not using the HDR function.

Figure 37 ***HDR testing a) HDR low b) HDR high***

The imaging technique of this iteration is used to create images foams with different fineness and distribution values to see whether analysing these images could result in classification of the foam samples. To test whether the decrease in quality makes classification difficult, we made different foams and scored these on fineness and distributions (Appendix 9.6). We later analysed some of these different samples with the previous used analysing techniques and the results can be seen in *Table 3*. From this table we did not see a correlation with the average size of the bubbles and the fineness.

Table 3 ***Data from particle analysis on Axial lighting samples***

Fineness	*Distribution*	*Count*	*Total area*	*Average size*
0.5	1	4465	484209	108.445
1	1	5750	466710	81.167
2	1	4450	493854	110.978
3	1	2904	270446	93.129

5.6.4 Evaluation and learnings

This lighting technique does not use a ring light while still creating a decent enlighten image. The lighting technique could be further improved by using a half mirror. This enlightens the sample even more and could decrease the noise in the image caused by automatic compensating the underexposure. This underexposure made some of the samples not as sharp as hoped. Blocking the that shines directly from the light source in the camera lens could also help with improving the quality of the image. [59].

The lighting technique from this iteration are at this moment not sufficient. Because of this, the lighting technique of the first iteration will be used for further testing. Even though the reflection of the ring light is visible in these images.

5.7 Iteration 4 Weka segmentation tool

The previous imaging techniques in combination with the used image optimisation and image analysis techniques did not have sufficient results. Instead of changing the imaging technique again, we looked at changing the segmentation technique in order to get the preferred results. This iteration focusses on using the trainable Weka segmentation [42, 60] plug-in in Fiji to research the possibilities of a machine learning based segmentation method. We chose a machine learning based segmentation tool because with this kind of tool the segmentation does not only dependant on contrast differences but it has other image features that can be extracted and used for segmentation. We expected that the use of multiple image features, the high contrast difference caused by the reflection of the ring light would have a smaller influence on the segmentation. The Weka segmentation tool is capable of extracting these different image features and is very easy to use.

5.7.1 Requirements planning

We expected that the Weka segmentation tool could help with a better segmentation method. A better distinction between the bubbles and the liquid makes it easier for the particle analysis to analyse the bubbles and give precise bubble sizes. With these more precise sizes, the score of the fineness and the distribution can be determined with more precision.

5.7.2 Analysis and design

Because we expected that the ring light has a smaller influence on this segmentation, we used the high-quality images of the first iteration. We cropped these images to decrease the computation time. After that we separately identified bubbles and liquid in the first cropped image. After a few identifications the classifier is trained and the programme created an overlay of the segmentation as described in the state of the art. The trainable Weka segmentation tool has a lot of different training features. We looked at all the different features and selected the ones we thought could help with the segmentation. For our training we used the Gaussian Blur, Sobel filter, Hessian, gaussians difference, membrane projections and Lipschitz training features. We tried multiple combinations of features to get the best result. Then we visually examined the results and classified more bubbles and liquid in areas where the segmentation did not work sufficient. When this segmentation was good enough for the first image, we used another sample to increase the size of the training dataset. This second sample came from the same foam sample image but from another location of the image. This is done to make sure that the lighting of the sample was equal and only the exact bubbles were different. This sample is used to further train the classifier. When the segmentation of this image was successful, we used the classifier to segment a part of a new image which was located in the training dataset. We analysed the images with the particle analysis from Fiji to get the bubble sizes.

5.7.3 Testing and results

First the trainable segmentation is tested on one sample of an image *Figure 38*a. To give the programme useful data, multiple bubbles are selected and added to the bubble class. This can be seen in *Figure 38*b. The red areas are identified as bubbles and the green areas are identified as liquid. The bubbles that are selected differ from size and shape to cover a wide range of bubble variations. Training on a varied dataset improves the classifier and makes the segmentation more reliable.

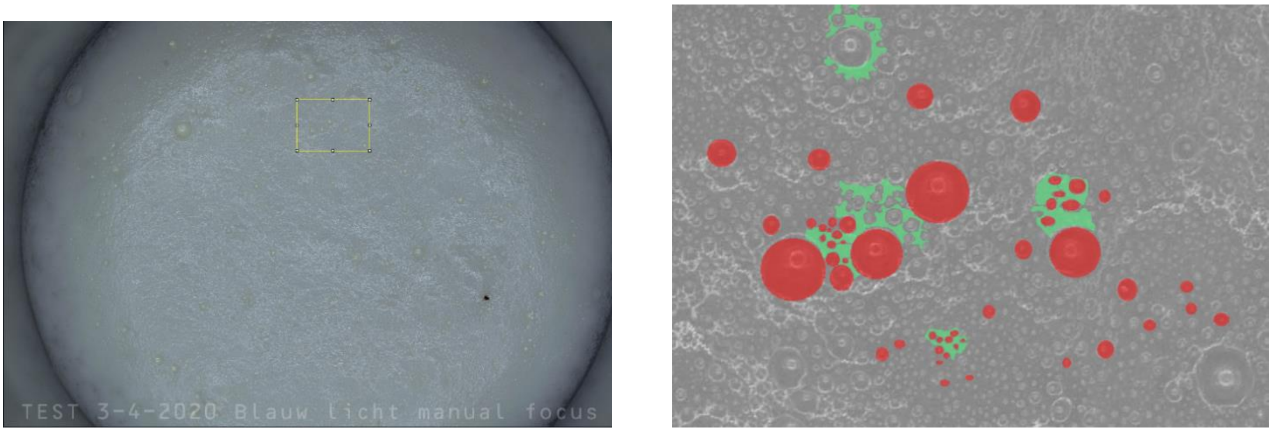


Figure 38 ***(a) first Weka segmentation sample (b) first training data***

While creating the labelled training data we found that distinguishing a bubble from a liquid is hard sometimes. Even when the image is zoomed in, the operator struggled with identifying the liquid and the foam is some areas. Some areas are very bright and it is hard to see whether this is liquid or an odd shaped bubble with strange light reflections. Because we wanted to have the most reliable training data, only the areas of which it was clearly visible to what class it belongs were given as training data to the programme.

After the classifier was trained for the first time, the overlay result was not what we were hoping for as seen in *Figure 39*a. We hoped that the program could segment the bubbles from the liquid correctly, however a lot of pixels that belong to liquid areas are wrongly classified as bubble.

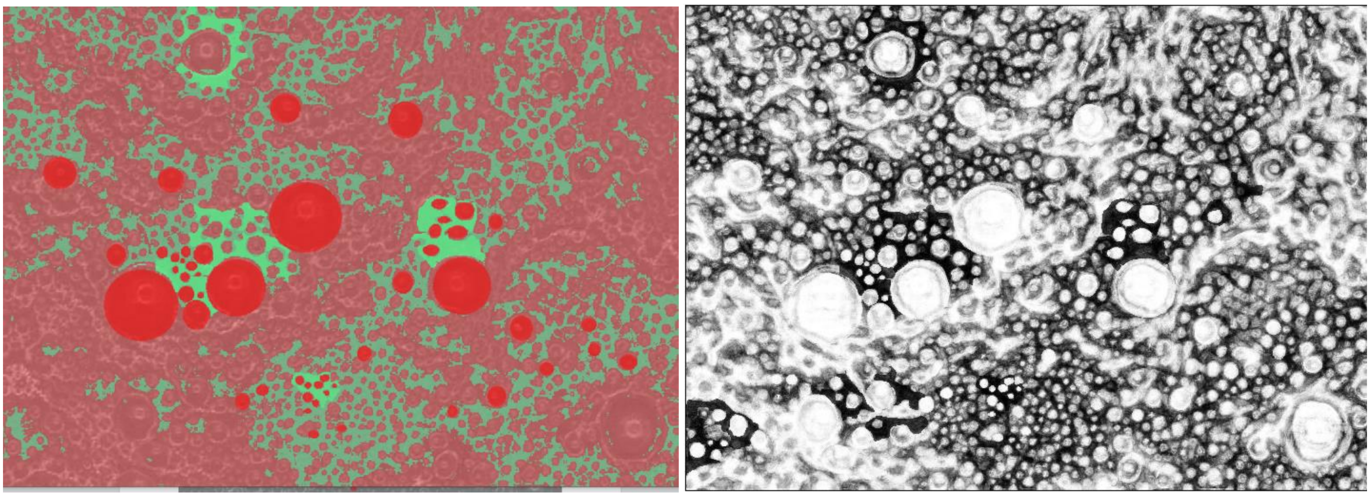


Figure 39 ***(a) overlay of segmented image (b) probalility map***

To get more insight in how big this problem was, we used a build in technique to create a probability map of the segmentation of the image *Figure 39*. This probability map looked a lot more promising than the initial overlay of the image. In this map we saw a clearly visible bubble structure. This probability map is later used to measure exact bubble sizes, but first we were interested in how this classifier would perform in another sample.

The image of the other sample can be seen in *Figure 40*a. We tried to segment a part of this image with the classifier from the previous sample. The result of this can be seen in *Figure 40*b. It was interesting to see that the classifier did segment a portion of the bubbles but definitely not enough to give a reliable segmentation.

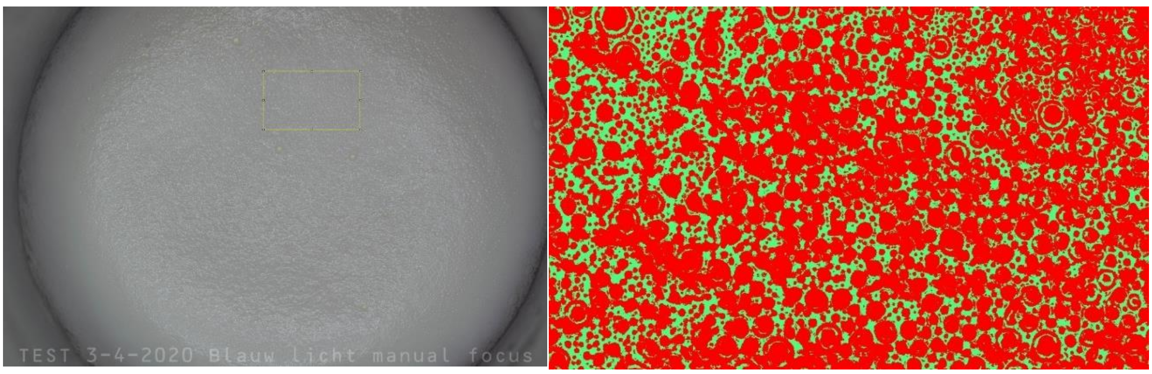


Figure 40 ***Result of first Weka segmentation on untrained image***

To improve this classifier, we added multiple labelled bubble and liquid to the training data set. We expected that more training data would improve the result significantly. The areas we labelled can be seen in *Figure 41*.

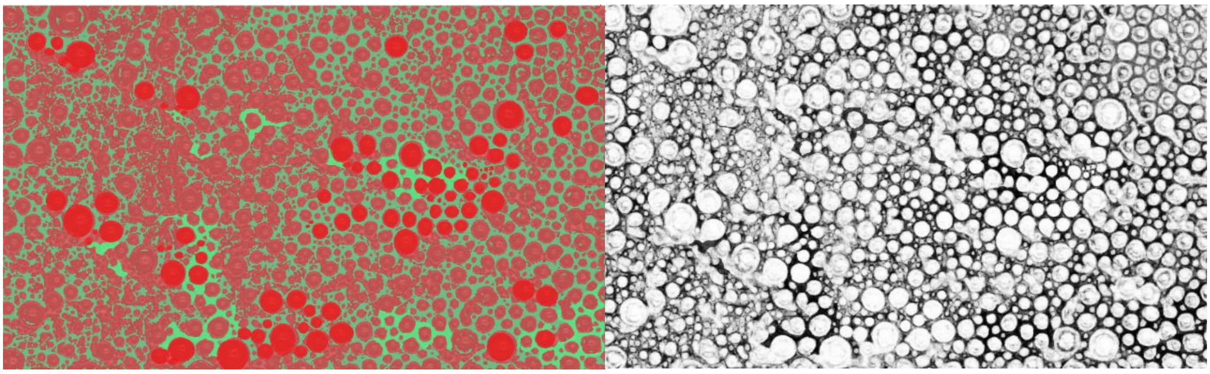


Figure 41 ***(a) Additional training and (b) probability map***

The bright red and the bright green areas are the one that are labelled manually. We gave the classifier a large amount of training data to improve the segmentation as much as possible. The probability map of this training is shown in *Figure 41*b.

This probability map looks sufficient regarding the segmentation. We used a greyscale threshold to change this image into a binary image and Watershed to separate bubbles that were connected because of this threshold. This new binary image is analysed by the particle analysis and the visual result van be seen in *Figure 42*.

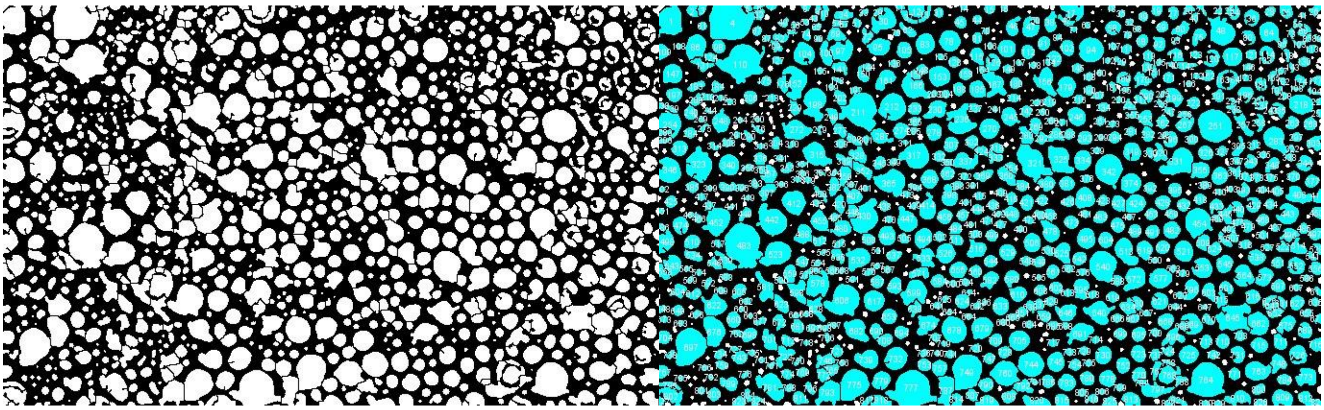


Figure 42 ***(a) binary image of probability map and (b) analysed particles***

This analysis looks sufficient based on visual observation. The particle analysis analysed the bubbles and was able to measure the bubble sizes and created a bubble size histogram. This data was not fully reliable given that there were some small segmentation errors on the edges of some bubbles. These errors could be minimised in a later stage of the project, but for now this method looks promising and we did not find these errors significant.

We moved on to see how this classifier would perform on another foam sample that was not implemented in the training data. This new image sample is cropped to the image shown in *Figure 43*. We applied the previous trained classifier without any additional training on this new sample.

This probability map is also binarized through a greyscale threshold and analysing with particle analyses. This gave the following result *Figure 43*.Some errors occurred. In the top right corner of the image there is undersegmentation. This gave a less reliable analysis. Also, the particle analysis did not analyse all the bubble particles, there are some white areas on the image. These errors together are expected to result in a smaller average size than the sample has in reality.

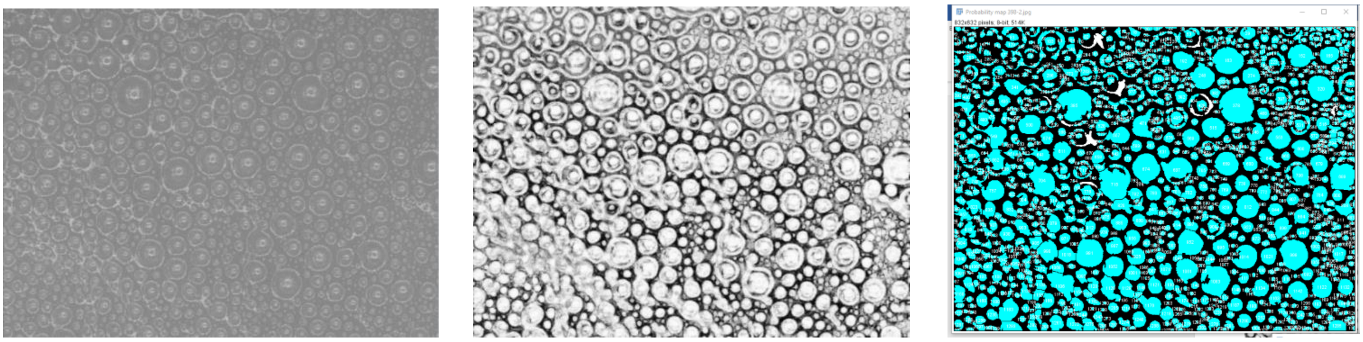


Figure 43 ***Applying classifier on untrained data***

After this result we tested the same classifier on another part of the sample. This part has slightly other lighting and a more complicated structure. The probability map that came out of this segmentation contains a higher number of grey pixels. This means that it was more difficult for the tool to classify these pixels in bubble or liquid. Because of this uncertainty, the binary image that came from this probability map and the particle analysis that came from this binary image is not yet reliable enough to determine the exact bubble measurements of this foam. Extra training could improve this segmentation but when trying this we had difficulties with labelling the images ourselves because of the earlier explained problem of seeing strange white light reflections.

5.7.4 Evaluation and learnings

As seen in the first results of this iteration, with a low amount of training the Weka segmentation tool does a decent job in segmenting the bubbles from the liquid. When the training dataset is increased the quality of the result increases significantly. The segmentation of a small cropped sample however took a lot computation time (5 minutes). The creation of a probability map, which is needed to create a higher quality binarized image took even longer (5 min). This computation time for a small part of a foam sample in not preferred. When we tried to segment an image without cropping the computer crashed multiple times. Using this technique for multiple full-size foam images would require a lot more processing power. We set the full-size segmentation aside and continued with the cropped samples.

A trained Weka segmentation can segment bubbles in a cropped image where it is not trained for. However, the segmentation tool is really reliable on the consistent imaging technique. Applying a classifier on earlier seen sample but a new part of this sample works correctly, but a applying it on a whole new image requires extra training. This method is very useful to get exact bubble sizes and very detailed information about a single sample. However, with this method it is not possible to classify a large amount of foam samples without a lot of extra training and manually labelling. To be able to classify a large number of samples without extra training and manually labelling, we thought it was interesting to look at direct classification. This is tested in the next iteration.

5.8 Iteration 5 The Weka classification workbench

The Weka classification workbench is a tool that is used a lot for testing the feasibility of classification through machine learning. In this tool it is possible to test different feature extraction filters and different machine learning algorithms. This tool can give useful information about the usability of machine learning in a project.

5.8.1 Requirements planning

During this iteration we focus on classifying the fineness and distribution in different classes and being able to do this for a large sample without the need of extra operators' actions for every individual sample.

5.8.2 Analysis and design

For this iteration it is important to have a lot of high-quality images of milk foam samples to create a good training dataset. Therefore, we used the imaging setup of the first iteration to create new milk foam sample data. We made 41 individual milk foam samples which together include all the regularly occurring combinations of fineness and distribution scores. After the first image is taken from the sample the samples are rotated and slightly shaken to achieve a different image with the same fineness and distribution properties. This way the dataset is bigger and varied which could improve the training program. We tried to have the same lighting, the same placement of the cup and the optimal focus point for every image. This way a total of 232 images are taken during this iteration. The foams are scored by two operators to have a more reliable result. These scores are written down in an excel sheet together with the file name of the image. The images are transferred to the computer and the data in the excel sheet is made into a file that can be read by the machine learning tool (ARFF).

We installed the open sourced image filter program[61] for Weka. In the Weka workbench we used multiple Image filters to test which filters contribute the most to the classification of the fineness and distribution of milk foam. When the features were extracted, we used different machine learning algorithms to look for relations between the extracted features. To test the full potential of the combination of the filters and the algorithm we used the Weka experimenter to determine the reliability of these different classification approaches.

5.8.3 Implementation

Before we tested the image filters, we researched the available image filters. There were multiple filters which were available and were expected to be useful in our segmentation method.

- **Colour Layout & simple colour histogram**: The identified colour differences between big bubbles, small bubbles and liquid is earlier used for analysing the distribution. This technique had a lot of potential and was therefore interesting to test.
- **Edge Histogram**: the contrast differences that are identified earlier were previously not resulting in good segmentation. The amount of edges that are detection in an image could say something about the quality of the foam but that is important to test. This was not yet tested in classification which makes it interesting to see how this technique influences this process
- **Fuzzy Colour and Texture Histogram (FCTH):** This technique is based on the texture of an image and in the images that are created during this test the milk foam surface has a very important texture that could be extracted. It was interesting to see whether this texture analysis could help with identifying the quality scores of the foam.
- **Binary Pattern Pyramid:** This filter is based on a pattern structure in the image. In milk foam images the bubble pattern is really important for the fineness of the foam. This makes this filter interesting for testing.

There are multiple algorithms available in the Weka classification Workbench. These algorithms have to be tested to know which one performs the best. This testing is done through the experimenter of Weka. Here it is possible to validate the combination of image filter and algorithm with a k-fold cross validation[62].

5.8.4 Results

First, we created and scored new images of different milk foam samples. We made different quality milk foams to get a varied dataset. We made a total of 232 images of 41 different milk foams. During the test we classified the fineness and the distribution of the sample in 5 classes: 1,1.5,2,3,4. The number of images per combination of scores is shown in the table below.

Table 4 ***Number of samples with Fineness and Distribution scores***

	Fineness 1	*Fineness 1.5*	*Fineness 2*	*Fineness 3*	*Fineness 4*
Distribution 1	14	22	10	24	7
Distribution 1.5	7	26	14	0	6
Distribution 2	4	6	7	14	5
Distribution 3	4	18	12	4	3
Distribution 4	0	10	0	4	12

We created an ARF file with the image file name and scores of each sample appendix. This file is used in the Weka workbench. We started with testing all the available image filters from the standard ImageFilter package [61] individually in the Weka explorer. After applying an image filter we used the random forest algorithm [63] on the extracted features. We tested the classifier with a standard 10-fold cross validation. This validation gave us a correctly classified instances percent which we used as an evaluation of effectiveness of the filter.

From the individual image filters in combination with the random forest algorithm, the colour layout filter (CLF) gave the best results. This classifier had correctly identified the fineness in 90.5% of the instances and distribution in 88.7% of the instances.

We tried to improve this result by adding other image filters. We added all the filters individually to see what influence the addition of that filter had on the correctly classified instances

Image filters	*Fineness*	*Distribution*
CLF	91.8	82.7
CLF + Colour histogram	87.2	81.6
CLF + Fuzzy Opponent histogram	87.4	82.0
CLF + FCTH	82.5	81.1
CLF + Edge detection	76.2	72.8
CLF + PHOG	84.7	82.3
CLF + Auto colour correlogram	78.3	82.6

Table 5 ***Image filters with percentage correctly classified instances***

Because we saw no improvement when combining different image filters, we used only the colour layout filter for further testing.

We thought it would be interesting to see whether image optimisation techniques could improve the result of the program. While choosing which image optimisation techniques we would use, we kept in mind that it should be implemented in a large sample of images at the same time without the need operators' actions. We started with using histogram equalisation. This is done through the batch processing option of Fiji. We used the same filters and algorithm but the results were worse than without the histogram equalisation. We looked at the wrongly classified images and found a possible explanation for this result. The size of the black border in the image influences the histogram equalization. The histogram equalisation changed the colours in the images differently per image due to the different amount of black areas. To get rid of this influence we cropped the images so that only the middle of the image remains. This way the result was less influenced by slightly misplaced cups. By cropping the images, we lost some data from the outer area of the foam and that resulted in an even worse result. Therefore, it was important to have a second look at each cropped image and change the scores of the images based on the cropped image. This created the problem that the outer areas of the foam are not taken into account while classifying the foam. However, we were interested in whether this improves the result. A total of two samples were scored differently in this new scoring process. Both these samples had a deviation of 0.5 from the original distribution score. The fineness as expected stayed the same for every foam. The second scoring of the cropped image also did not improve the results so we renounced histogram equalisation for this stage of testing.

Another way to possibly improve the classification is by testing different tree-based algorithms. We tried all the tree-based algorithms that were provided in the standard Weka Workbench to improve this result. The result of these algorithms can be found in the table below.

Table 6 ***Algorithms with percentage correctly classified instances***

Algorithms	*Fineness*	*Distribution*
Random Forest	91.8	82.7
REPTree	59	53
Random Tree	73.3	70.3
LMT	75.7	72.4
J48graft	74.1	71.5
DecisionStump	31.2	41.4

These results show that Random Forest is the best fitting algorithm of the ones that are standard available in the Weka Workbench.

At this moment we found the best classification method currently available in the Weka Workbench. This technique requires no image optimisation. It uses the colour layout filter and a random forest algorithm to classify the fineness and distribution. This results in 91.8% correctly classified fineness scores and 82.7 % correctly classified distribution scores. Even though this result is decent, we thought it was interesting to look at the incorrectly classified instances to look for other areas of improvement.

To do this we looked at the confusion matrix of this classification and examined the incorrectly classified fineness scores and distribution scores.

Not all incorrectly classified instances are equally important. When the difference between the real score and the classified score lower than 0.5 we identified that as a small error. When the difference was bigger than 0.5, we identified that as a big error. The errors can be found in the table below.

Table 7 *Errors with current best classifying method*

	Small errors	*Big errors*
Fineness	8	11
Distribution	15	25

We investigated these errors to better understand the origin of these errors. During this investigation we focussed on the big errors because these errors are important to prevent. The total of 36 big errors are divided over 29 images. This means that in 7 images there were big errors in the fineness and the distribution and in 22 images only one of the two scores had a big error.

When we looked at the 7 images with two wrongly classified scores, we saw that 6 these images had some unsharp areas. This could lead to an unreliable image feature extraction and therefore an incorrectly classification of this image. This can be a simple explanation why these errors occurred. For the other errors we did not directly find a simple solution. A reason for this incorrect classification could be the relatively small sample size. Because of this we thought it was interesting to see how the sample size influences the result.

To test this, we decreased the sample size by using only the even numbers images and trained the classification tool only in these samples. We used the current best method and came to a result of 57% correctly classified instances. This deterioration of the result with a smaller sample size supports the assumption that a bigger sample size can improves the results significantly.

5.8.5 Evaluation and learnings

During this test we learned a lot about the Weka workbench and the opportunities that lay within image classification with the use of image filters and machine learning algorithms. When using the workflow as described in *Figure 44*. We can correctly classify 91.8% of the fineness scores and

82.7% of the distribution scores. Applying the image filter on 232 images takes 4 minutes and classifying the images takes roughly 10 seconds. This is a very promising result and could possibly be improved by a larger sample size and a more consistent focussing technique during the imaging of the foams.

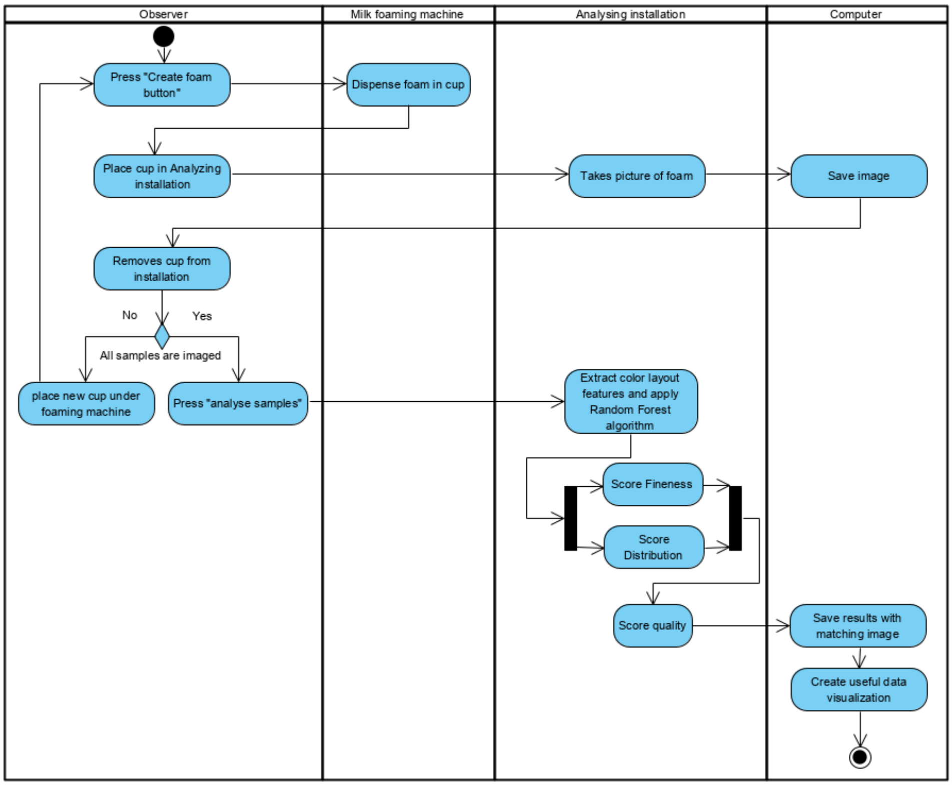


Figure 44 ***Workflow of direct classification***

5.9 Conclusions of realisation

During the realisation was found that there are a lot of different techniques that could be implemented in the new analysing method. The first iteration focussed on the imaging technique. It uses a macro lens to capture details and a ring light for multidirectional lighting. This results in a high-quality image but the reflection of the ring light makes segmentation based on contrast difficult. Multiple lighting techniques are tested to solve this problem. Axial lighting removed the ring light reflection but the quality of the overall image was not sufficient. Instead of the imaging technique we looked at the image analysis techniques. The Weka segmentation tool is used for segmentation with machine learning. This has good results for individual samples and the bubble size can be analysed. With these sizes we can precisely score the particular sample. However, this method has a high computation time and can needs a lot of computing power to be used in quantitative image analysis. The use of colour layout filter in combination with a random forest algorithm is very promising technique and could classify 91% of the fineness scores and 81% of the distribution scored correctly.

6 Conclusion

In this thesis, we researched the possibilities of a reliable computer vision based analysing method for milk foam quality. At first, we investigated which quality characteristics of the milk foam should be analysed through image processing and computer vision. We found that rheology, stability and foamability are the most important foam quality influencing characteristics. These characteristics are influenced by multiple features like bubble size distribution, bubble size in general, weight, foam to liquid ratio and temperature. Bubble size and bubble size distribution were the most interesting to analyse during this research because of their important influence on the milk foam quality and their expected analysability through CVBT's.

Secondly, we looked at what kind of imaging techniques, image optimisation techniques and image analysing techniques can be used to analyse images of milk foam. We found that the use of a DSLR camera with a macro lens created images with sufficient details when combined with a remote shutter mode and when placed on a tripod. The use of a ring light to illuminate the sample created an evenly lighted sample and prevented shadowing on the sample while still preserving the details in the image. While processing the images we found two interesting approaches: segmentation and direct classification. For segmentation, the useful techniques are mainly based on the colour and contrast differences between the bubbles and the liquid. Using Histogram Equalisation to increase the contrast in combination with Colour thresholding, makes it possible to segment and analyse most of the larger bubbles that are important for the distribution. However, this method does not analyse all the bubbles that are determining the distribution and therefore this method is not reliable enough. Edge detection does not contribute to a good segmentation with this imaging technique because of the contrast differences inside the bubbles due to the reflection of the ring light. Removing this reflection by using axial lighting or a polarizing filter did not have sufficient results. To further segment the bubbles, we used the Weka segmentation tool to extract features from the areas that we labelled as bubbles and liquid. These features are used to create a model that predicts whether an area is a bubble or a liquid. This model creates a probability map that can be used to analyse individual bubbles with decent precision. Although this can be very useful for the exact measuring of the milk foam, due to the computation time of 10 minutes per small part of a foam sample this technique needs serious improvements in speed to be used for quantitative testing.

The other approach we looked into is direct classification. For this, we used the Weka workbench. In this workbench, we used all the standard image filters to extract features direct from the foam images and several algorithms to test what has the best results. For our research, we used only the Colour Layout filter in combination with a Random Forest algorithm to get the best results. We validated this method with 10-fold cross-validation and came to a result of 91% correctly classified instances for Fineness and 81% correctly classified instances for distribution. That the distribution is harder to classify can be explained because the bubbles that determine the distribution are a lot more variable than the bubbles that determine fineness. After the error analyses we found that a constant imaging and focussing technique is very important for this method. This is currently the technique with the highest reliability. This reliability could be improved even more by increasing the size and variety of the training dataset.

From these tests, we found that there are a lot of different possibilities that could improve the reliability of milk foam quality analysis. Colour thresholding could be used to measure exact bubble sizes of distribution determining bubbles, the Weka segmentation tool could be used to measure precise bubble sizes of both fineness and distribution determining bubbles and with the Weka classification tool it is possible to directly classify the fineness and the distribution scores of foam images with decent reliability.

7 DISCUSSION

In this study, we researched and tested multiple computer vision-based techniques that could help with increasing the reliability of milk foam analysis. We researched segmentation and classification techniques and designed a method that could classify the fineness and distribution of the bubbles with decent reliability.

The literature might suggest that techniques based on contrast differences can help with bubble segmentation. However, based on the findings of our tests, this method is not reliable for our milk foam analysis. A reason for this deviating result might be our test set-up. We tried multiple lighting techniques but could not achieve enough detail in the image while solving the contrast problems that occurred because of the ring light reflection. Using a different set-up might increase the reliability of this contrast difference-based method.

Colour thresholding was also suggested by the literature. We tested this technique and found that it was only reliable for larger bubbles. The fact that this threshold is set manually due to slight colour differences in images and the finding that this threshold is not applicable for every sample introduced another operators action in the method if this technique is used. This decreases the reliability of this method and that problem should be resolved before this technique can be used.

The third segmentation technique we used, the Weka segmentation tool, is not yet totally reliable. The reliability is impacted by the lack of analysis of the measured data. The validation of the measured data of this technique is completely based on visual observations. To increase the reliability of this technique it would be useful to statistically analyse the measured data and compare this to exact measured bubble sizes.

The classification technique we used did not completely classify the samples correctly. There are multiple problems with this method. The first problem is caused by the size of the dataset. At this moment we only used 232 images of foams with 41 different foams. The appearance of a foam with a specific fineness and distribution score can look very different from another foam with the same exact score. These difference in appearance while having strong similarities in scores makes it difficult for the machine learning program to classify correctly. Increasing the training dataset with more diverse data could increase the quality of the classification. Especially the classification of the distribution score because the appearance of the distribution scores are very different.

Another problem with this classification technique is that it uses the fineness and distribution scores that operators assigned manually to the foams. These scores are operator dependant which means that the machine learning programme will use biased data as training data. This negatively influences the reliability of the classification and therefore the analysing method. Using multiple operators or scores calculated through exact bubble sizes to define the first dataset can decrease the influence of this bias.

Even though there is a lot of room for improvements, these techniques are very promising and can be the foundation for a new improved analysing method.

8 RECOMMENDATIONS

Further research is needed to establish to what level of reliability these techniques could be improved and to what extent these methods could be implemented in the overall milk foam treating analysis. In these future studies it would be useful to look at multiple research subjects. While investigating different techniques we only tried the easily accessible techniques. There are a lot more techniques that could be beneficial for this analysing method. These techniques could replace the techniques we used or complement them.

When building on the techniques investigated in this research, we recommend to work further on the direct classification technique and focussing on increasing the reliability and decreasing the big errors of this method. There are multiple ways to achieve this.

The first option is to try other image filters for feature extraction. These filters could be based on shape detection or symmetry which could help with extraction of more useful data from the images. Symmetry for example is expected to help a lot with classifying the bubble size distribution because with a big size distribution, the image is less symmetric than with a small size distribution.

Also, the machine learning algorithm that is used could possibly be improved. It could be useful to try other algorithms like CNN for classification. Trying other techniques and focussing on the combination of different image filters and algorithms could create a faster and more reliable alternative.

Another interesting approach is to step away from scoring the milk foams in a few different quality classes and give precise fineness and distribution values with a smaller step size. For the investigation of this approach it could be interesting to analyse the measurements of the Weka segmentation tool to precisely score the foams. This scored data can be used as a training set for the Weka Workbench. This Workbench contains multiple options for numeric analysis and this could give a score with more precision.

To fully integrate these methods in the natural workflow of PCV Group we recommend to create a Python or Java program that uses a GUI that is easy to use for every operator. This can be combined with an installation in which only the foam sample has to be placed and the program automatically created images and scores them with the machine learning algorithm.

9 Appendices

9.1 List of Requirements

System/ product requirements						Module requirements					
NR.	MSCW	User Requirements	Reference	Functional Requirements	Rationale	Installation	program	Camera Top	Camera Side		
1. Computer Vision characteristics analyses											
1.01	M	CV installation must analyze Fineness	Milk Foam scoring protocol / literature	The installation must be able to classify the Fineness of the milk foam in 3 different scores.	Giving a precise value will increase the reliability this result		X	X			
1.02	M	CV installation must analyze Bubble size Distribution	Milk Foam scoring protocol / literature	The installation must be able to classify the Distribution of the milk foam in 3 different scores.	Giving a precise value will increase the reliability this result		X	X			
1.03	S	The program must provide an understandable data visualization	previous data visualizations	The measurement must be given in numbers/words/figures which are normal for the kind of measurement	This makes it possible to revise the measurements if necessary		X				
1.04	C	CV installation must analyze Total Volume	Milk Foam scoring protocol / literature	The installation must be able to give the total volume of the milk and milk foam with a margin of +- 5ml	This is the same margin that is used with the current measurement		X		X		
1.05	c	CV installation must analyze Milk/foam ratio	Milk Foam scoring protocol / literature	The installation must be able to give the milk/foam ratio of the milk foam with a margin of +- 2,5%	This is the same margin that is used with the current measurement		X		X		
1.06	C	CV installation must analyze Consistency	Milk Foam scoring protocol	The installation must be able to give a rating of the milk foam Consistency between 0 and 3 with a step size of 0.25	The consistency is hard to measure precise so this has a lower step size (same as the current measurement)		X	?	?		
1.07	W	CV installation must analyze Temperature	Milk Foam scoring protocol	The installation must be able to give the temperature of the milk foam with a margin of 0.1°C	This is the same margin that is used with the current measurement		X	X	X		
1.08	W	CV installation must analyze Weight	Milk Foam scoring protocol	The installation must be able to give the total weight of he milk and milk foam with a margin of 5g in the same time	This is important to measure the density of the foam/liquid		?		?		
2. General Computer vision program											
2.01	M	The program must be able to save the data for further investigation		The measurement and the picture must be saved automatically in an excel file	Makes it possible to revise the measurements if necessary		X				
2.02	M	Installation must minimize the influences of the environment		The analysis should not change significantly due to environmental changes like light	creates a more reliable installation	X		X	X		
2.03	S	The resulting data must be more reliable than the previous analyzing method		The program should give less deviation than the previous way of measuring	Makes this installation more reliable than the current installation	X	X				
2.04	S	CV program must combine the different characteristic analysis into one program/ data visualization		All measured data should be presented in one dashboard	This way the measurements are easily understandable		X				
2.05	C	CV program / the installation must not slow down the analyzing process		The measurement should be available within 30 seconds	This way the measurements can be used to alter the input for the next test	X	X				
2.06	C	The CV program should be able to integrate additional information / comment of the researcher	Jelmer	Their should be a comment section for every measurement	This way the researcher can write down unusual observations / numbers of foams.	X	X				
3. General installation usability											
3.01	M	Installation must not take in too much space		Total space the installation could take in is 150 x 150 x 100 cm	This makes it possible to use the installation in the lab	X		X	X		
3.03	S	The analyzing method should work autonomous from the moment the cup is placed and the start button is pressed		the installation should work without extra actions from the researcher	this improves efficiency and reliability	x	x	x	x		
3.04	S	Installation must be able to be rebuild with a consistent outcome		Installation will give the same output if it gets the same input when rebuild	This keeps the installation objective in the long run	X		X	X		
3.05	S	Installation must be able to be build up and broken down and repaired easily		There should be instructions on how to set this up which are understandable and this would not take more than 15 minutes	This keeps the installation useful in the long run	X	X	X	X		
3.06	S	Installation must be compatible with different computers		program should be downloadable different windows computers	Multiple people need access to this program	X	X				
3.07	C	Installation must not be vulnerable to liquid damage		There should only product directly on the desk that are water/milk resistant	During the milk foam scoring this could be a problem	X			X		
3.08	C	The different parts of the installation should be integrated into one product		the different modules (except for the camera's) should be integrated in fixed one product	reduces set up time and differences in results due to building the installation	X	X				

9.2 Measuring cup specifications

Volume: 250 ml

Resolution: 5 ml

Colour: Transparent

Height: 124mm

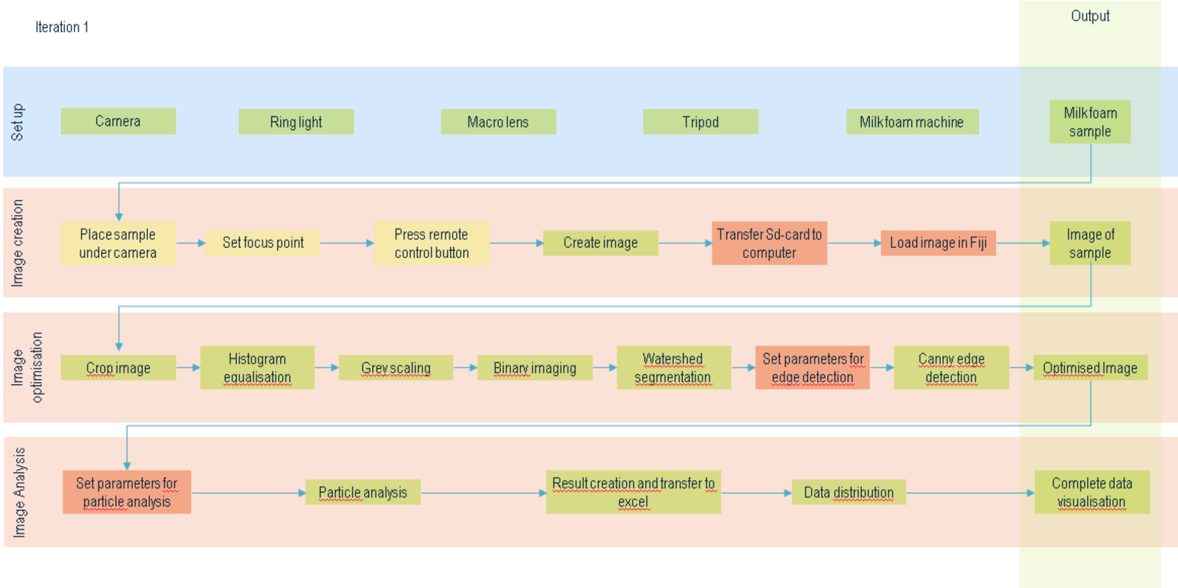
Outer diameter: 60mm

www.Efalock.de

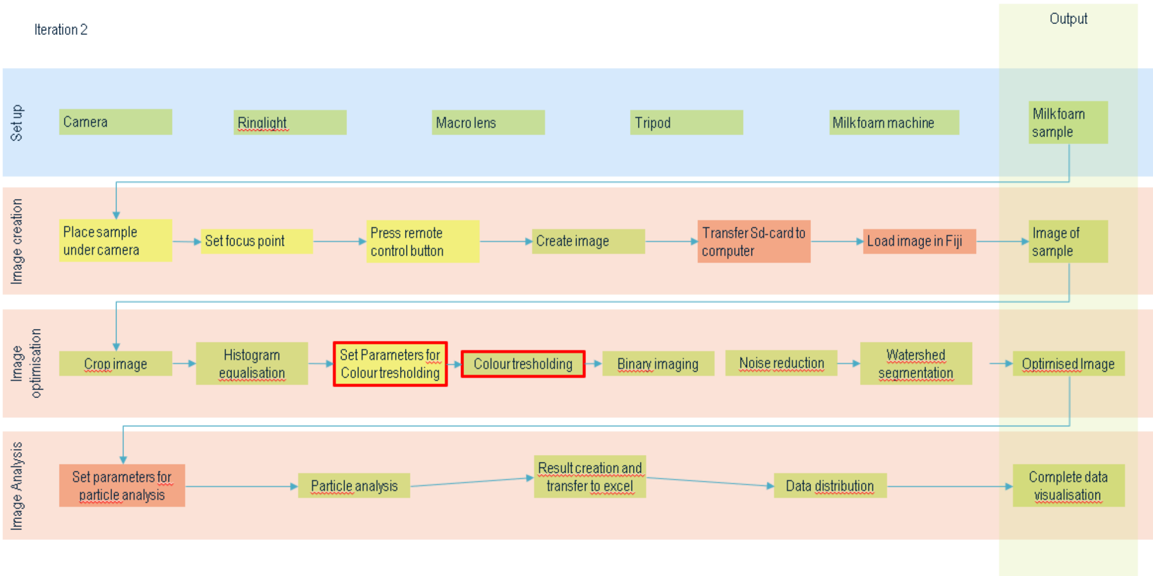
EAN no.: 4025341451102

Figure 45 Measuring cup used in the experiment

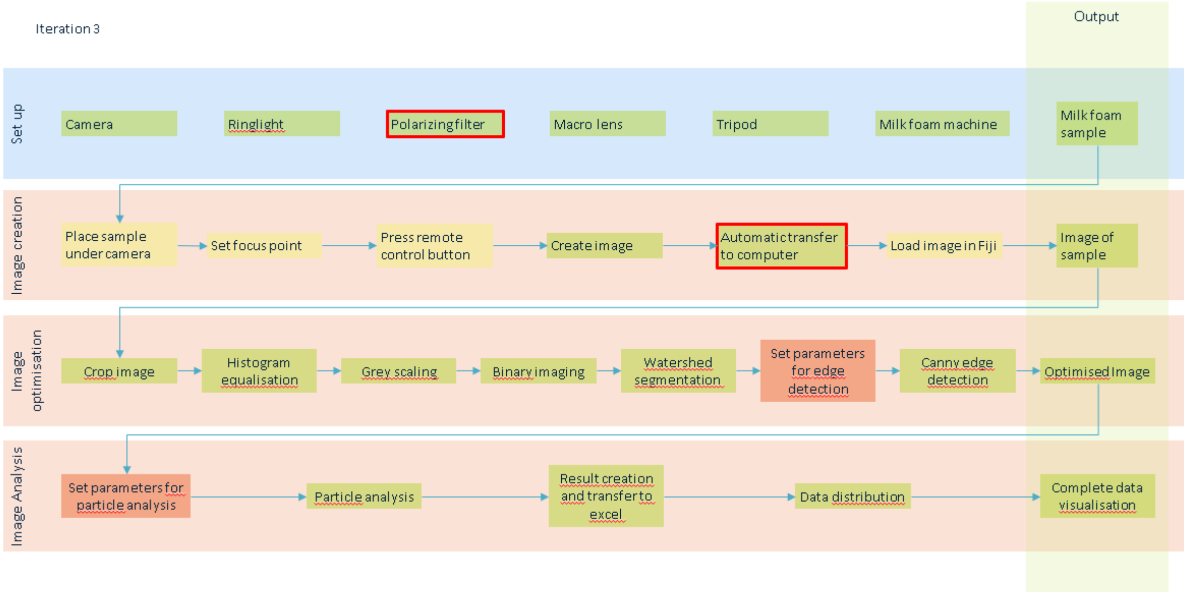
9.3 Workflow of iteration 1



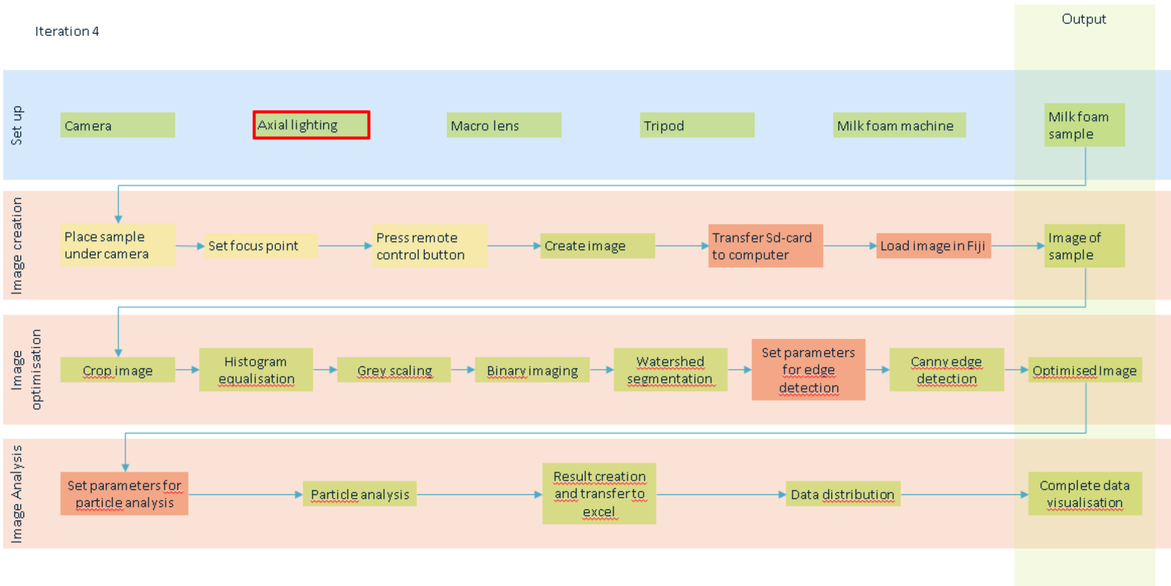
9.4 Workflow of iteration 2



9.5 Workflow of iteration 3



9.6 Workflow of iteration 3.2



9.7 Images of scored foams with axial lighting

	Fineness 0.5	*Fineness 1*	*Fineness 2*	*Fineness 3*
Distribution 1				
Distribution 2				
Distribution 3				

9.8 Personal evaluation

This section evaluates the process by looking back on the project on a personal level, the choices that have been made and the results that came with this research.

During the beginning of this project it was important to create a better understanding of the aim of-and the background behind this project. PCV Group had already a lot of knowledge about milk foam and milk foam analysis which helped with the first part of the background of this project. The computer vision part on the other hand was totally unexplored and therefore it was difficult to estimate how much time this would cost and what the potential results would be. The extensively background research on computer vision-based methods took a lot more time than expected but it helped a lot with getting a better understanding of the possibilities. However, all these techniques are specialised for a specific task and there was no predominate evidence that these techniques would work for this project.

Because of the lack of feasibility knowledge, this research had two different approaches. On one hand this was a feasibility-based research to get to know the potential of computer vision in this domain, but on the other hand it was important design a method and test the performance. This made it difficult to set requirements on feasibility part and the performance part at the same time. After multiple meeting with both PCV Group and the supervisor, the balance between these two approaches became clearer.

After the requirements were clear it was time to design the first tests. During this design we found that there are a lot more variables that influence the result than we initially thought of. Every problem has multiple solutions and these solutions brought new problems. Using only easily accessible basic techniques helped a lot with reducing the overall possibilities and with increasing the amount of techniques that we tested during this project.

Performing the tests did not go as expected. During the realisation phase we needed to put a lot more effort in the imaging techniques than we hoped. Because we wanted to proceed with testing the image optimisation and image analysis techniques, we did not achieve the best possible images. Fortunately, the imaging technique was sufficient for the rest of the test. This was important because for the rest of the realisation phase it was difficult to create more images because of Covid-19. Testing the computer vision-based techniques was easier than expected. Using Fiji and the Weka tools gave a good visual idea on how the technique worked and this made evaluating them easier.

When looking at the conclusions of the realisation it is important to keep in mind that machine learning is also based on a training dataset created by an operator. According to Jelmer Kuiper this is not a big problem because if this method is adapted as the new analysing method, a large dataset could be created by two researchers on the same day so that there are less operator dependant aspects in this method.

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10 REFERENCES

[1] C. M. Villanueva *et al.*, "Total and specific fluid consumption as determinants of bladder cancer risk," *International journal of cancer,* vol. 118, no. 8, pp. 2040-2047, 2006.

[2] G. M. Campbell and E. Mougeot, "Creation and characterisation of aerated food products," *Trends in food science & technology,* vol. 10, no. 9, pp. 283-296, 1999.

[3] S. Silva, A. Espiga, K. Niranjan, S. Livings, J.-C. Gumy, and A. Sher, "Formation and stability of milk foams," in *Bubbles in Food 2*: Elsevier, 2008, pp. 153-161.

[4] C. K. Lau and E. Dickinson, "Instability and structural change in an aerated system containing egg albumen and invert sugar," *Food Hydrocolloids,* vol. 19, no. 1, pp. 111-121, 2005.

[5] T. Huppertz, "Foaming properties of milk: A review of the influence of composition and processing," *International Journal of Dairy Technology,* vol. 63, no. 4, pp. 477-488, 2010.

[6] Y. Lau, N. Deen, and J. Kuipers, "Development of an image measurement technique for size distribution in dense bubbly flows," *Chemical engineering science,* vol. 94, pp. 20-29, 2013.

[7] E. A. Foegeding, P. Luck, and J. P. Davis, "Factors determining the physical properties of protein foams," *Food Hydrocolloids,* vol. 20, no. 2-3, pp. 284-292, 2006.

[8] S. Magrabi, B. Dlugogorski, and G. Jameson, "Bubble size distribution and coarsening of aqueous foams," *Chemical engineering science,* vol. 54, no. 18, pp. 4007-4022, 1999.

[9] P. J. Hailing and P. Walstra, "Protein-stabilized foams and emulsions," *Critical Reviews in Food Science & Nutrition,* vol. 15, no. 2, pp. 155-203, 1981.

[10] E. Dickinson, *Introduction to food colloids*. Oxford university press, 1992.

[11] A. David and S. S. Marsden Jr, "The rheology of foam," in *Fall Meeting of the Society of Petroleum Engineers of AIME*, 1969: Society of Petroleum Engineers.

[12] J. C. Germain and J. M. Aguilera, "Structural Image Analysis of Food Foams and Aerated Food Products," in *Bubbles in Food 2*: Elsevier, 2008, pp. 109-116.

[13] T. Florian, "Milk foam scoring protocol," Protocol, 22 January 2020, 2020.

[14] Kruss. Available: https://www.kruss-scientific.com/products/foam-analysis/dfa100/dynamic-foam-analyzer-dfa100/

[15] A. Cimini, F. Pallottino, P. Menesatti, and M. Moresi, "A low-cost image analysis system to upgrade the rudin beer foam head retention meter," *Food and bioprocess technology,* vol. 9, no. 9, pp. 1587-1597, 2016.

[16] Z. M. Ariff, Z. Zakaria, A. A. Bakar, and M. A. M. Naser, "Effectiveness of a simple image enhancement method in characterizing polyethylene foam morphology using optical microscopy," *Procedia Chemistry,* vol. 19, pp. 477-484, 2016.

[17] T. Eren, "Foam characterization: Bubble size and texture effects," *Middle East Technical University,* 2004.

[18] E. Galindo *et al.*, "Development of advanced image analysis techniques for the in situ characterization of multiphase dispersions occurring in bioreactors," *Journal of biotechnology,* vol. 116, no. 3, pp. 261-270, 2005.

[19] R. Bueno *et al.*, "Two-phase flow bubble detection method applied to natural circulation system using fuzzy image processing," *Nuclear Engineering and Design,* vol. 335, pp. 255-264, 2018.

[20] X. Zabulis, M. Papara, A. Chatziargyriou, and T. Karapantsios, "Detection of densely dispersed spherical bubbles in digital images based on a template matching technique: Application to wet foams," *Colloids and Surfaces A: Physicochemical and Engineering Aspects,* vol. 309, no. 1-3, pp. 96-106, 2007.

[21] T. W. Asegehegn, M. Schreiber, and H. J. Krautz, "Investigation of bubble behavior in fluidized beds with and without immersed horizontal tubes using a digital image analysis technique," *Powder Technology,* vol. 210, no. 3, pp. 248-260, 2011.

[22] L. Vega-Alvarado, B. Taboada, E. Galindo, and G. Corkidi, "Hough transform based method for air bubbles and oil drops segmentation in dispersions occurring in stirred bioreactors," in *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No. 03CH37439)*, 2003, vol. 1, pp. 735-738: IEEE.

[23] W. Wang and O. Stephansson, "A robust bubble delineation algorithm for froth images," in *Proceedings of the Second International Conference on Intelligent Processing and Manufacturing of Materials. IPMM'99 (Cat. No. 99EX296)*, 1999, vol. 1, pp. 471-476: IEEE.

[24] C. Citir, Z. Aktas, and R. Berber, "Off-line image analysis for froth flotation of coal," *Computers & chemical engineering,* vol. 28, no. 5, pp. 625-632, 2004.

[25] N. Sadr-Kazemi and J. Cilliers, "An image processing algorithm for measurement of flotation froth bubble size and shape distributions," *Minerals Engineering,* vol. 10, no. 10, pp. 1075-1083, 1997.

[26] G. Barker, B. Jefferson, and S. Judd, "The control of bubble size in carbonated beverages," *Chemical engineering science,* vol. 57, no. 4, pp. 565-573, 2002.

[27] S. Deotale, S. Dutta, J. Moses, V. Balasubramaniam, and C. Anandharamakrishnan, "Foaming Characteristics of Beverages and Its Relevance to Food Processing," *Food Engineering Reviews,* pp. 1-22, 2020.

[28] J. Ilonen *et al.*, "Comparison of bubble detectors and size distribution estimators," *Pattern Recognition Letters,* vol. 101, pp. 60-66, 2018.

[29] J. C. Germain and J. M. Aguilera, "Identifying industrial food foam structures by 2D surface image analysis and pattern recognition," *Journal of food engineering,* vol. 111, no. 2, pp. 440-448, 2012.

[30] S. Sudhakar. (2017). *Histogram Equalization*. Available: https://towardsdatascience.com/histogram-equalization-5d1013626e64#:~:text=level%20is%20higher.-,Histogram%20Equalization,intensity%20range%20of%20the%20image.

[31] Y. Huang *et al.*, "Contrast-enhanced ultrasound imaging based on bubble region detection," *Applied Sciences,* vol. 7, no. 10, p. 1098, 2017.

[32] T. R. Jadhav and S. M. Kamble, "Volume measurement of object using computer vision," in *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, 2016, pp. 1792-1795: IEEE.

[33] C. Aldrich, C. Marais, B. Shean, and J. Cilliers, "Online monitoring and control of froth flotation systems with machine vision: A review," *International Journal of Mineral Processing,* vol. 96, no. 1-4, pp. 1-13, 2010.

[34] P. Miché and R. Debrie, "Fast and self-adaptive image segmentation using extended declivity," in *Annales des télécommunications*, 1995, vol. 50, no. 3-4, p. 401: Springer.

[35] N. Kulkarni, "Color thresholding method for image segmentation of natural images," *International Journal of Image, Graphics and Signal Processing,* vol. 4, no. 1, p. 28, 2012.

[36] W. V. Nicholson and R. M. Glaeser, "Automatic particle detection in electron microscopy," *Journal of Structural Biology,* vol. 133, no. 2-3, pp. 90-101, 2001.

[37] M. Planck, *The theory of heat radiation*. Courier Corporation, 2013.

[38] S. Badger. (2018). *Studying Foam with Micro-CT (3D X-Ray Imaging)*. Available: https://www.blue-scientific.com/studying-foam-micro-ct/

[39] P. K. Sahoo, S. Soltani, and A. K. Wong, "A survey of thresholding techniques," *Computer vision, graphics, and image processing,* vol. 41, no. 2, pp. 233-260, 1988.

[40] (2017). *Image Intensity Processing*. Available: https://imagej.net/Image_Intensity_Processing

[41] J. Mairal, "Sparse coding for machine learning, image processing and computer vision," Cachan, Ecole normale supérieure, 2010.

[42] J. S. Verena Kaynig. (2020, 21-7-2020). *Trainable Weka Segmentation*. Available: https://imagej.net/Trainable_Weka_Segmentation

[43] (2020). *Particle Analysis (24 januari ed.)*. Available: https://imagej.net/Particle_Analysis

[44] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD explorations newsletter,* vol. 11, no. 1, pp. 10-18, 2009.

[45] M. C. c. team. *Stakeholder analysis toolkit v3.doc*. Available: https://www.alnap.org/system/files/content/resource/files/main/Stakeholder-analysis-toolkit-v3.pdf

[46] D. Clegg and R. Barker, *Case method fast-track: a RAD approach*. Addison-Wesley Longman Publishing Co., Inc., 1994.

[47] J. Nielsen, "Iterative user-interface design," *Computer,* vol. 26, no. 11, pp. 32-41, 1993.

[48] Nikon. Available: https://www.nikon.nl/nl_NL/product/discontinued/digital-cameras/2020/d5300#tech_specs

[49] Sigma. Available: https://www.sigmabenelux.com/nl/objectieven/105mm-f2-8-ex-dg-os-hsm-macro

[50] J. Schindelin *et al.*, "Fiji: an open-source platform for biological-image analysis," *Nature methods,* vol. 9, no. 7, pp. 676-682, 2012.

[51] StudioKing. Available: https://www.fotokonijnenberg.nl/studioking-rl-130-macro-led-ringlamp-dimbaar

[52] J. S. Francisco, H. P. d. Moraes, and E. P. Dias, "Evaluation of the Image-Pro Plus 4.5 software for automatic counting of labeled nuclei by PCNA immunohistochemistry," *Brazilian oral research,* vol. 18, no. 2, pp. 100-104, 2004.

[53] S. P. R. Fisher, A. Walker and E. Wolfart., "Histogram Equalization," ed, 2003.

[54] W. S. Rasband. (1997-2018, 20-7-2020). *ImageJ Image Menu*. Available: https://imagej.nih.gov/ij/

[55] D. L. Ignacio Arganda-Carreras. (2019, 20-7-2020). *Classic Watershed*. Available: https://imagej.net/Classic_Watershed

[56] T. Gibara. (2013, 20-7-2020). *Canny Edge Detector*. Available: https://imagej.nih.gov/ij/plugins/canny/index.html

[57] K. U. Barthel, "Color Threshold," ed. Berlin, Germany: Internationale Medieninformatik.

[58] E. Meijering, "Noise," ed, 2019.

[59] J. Aldred. (2018, 24-6). *HOW TO USE MIRRORS TO GET PERFECT AXIAL LIGHTING ON MACRO SUBJECTS*. Available: https://www.diyphotography.net/use-mirrors-get-perfect-axial-lighting-macro-subjects/

[60] I. Arganda-Carreras *et al.*, "Trainable Weka Segmentation: a machine learning tool for microscopy pixel classification," *Bioinformatics,* vol. 33, no. 15, pp. 2424-2426, 2017.

[61] M. Mayo, "ImageFilter for Weka," ed. GitHub, 2016.

[62] J. Brownlee. (2019, 21-7). *A Gentle introduction to k-fold cross validation*. Available: https://machinelearningmastery.com/k-fold-cross-validation/

[63] L. Breiman, "Class RandomForest," *Machine Learning,* 2001.