OPTIMIZATION OF LIGHTING PARAMETERS FOR EDIBLE BIRD'S NEST VISION INSPECTION SYSTEM

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LIST OF ABBREVIATIONS

1. EBN Edible Bird's Nest
2. EPP Entry Point Project
3. ETP Economic Transformation Program
4. 2DGE Two-dimensional Gel Electrophoresis
5. ELISA Enzyme-linked Immunosorbent
6. PCR Polymerase Chain Reaction
7. ToF Time of Flight
8. CMOS Complementary Metal Oxide Semiconductor
9. CCD Charge Coupled Device
10. VGA Video Graphic Array
11. LED Light emitting Diode
12. CNN Convolutional Neural Network

ABSTRAK

Sarang burung walit merupakan salah satu pengeluaran makanan yang agak penting di Asia Tenggara kerana manfaat perubatannya. Pengilang sarang burung walit memandang penting ke arah mekanisasi untuk meningkatkan produktiviti kerana proses pembersihan sarang burung walit sekarang banyak bergantung kepada buruh dan memerlukan masa yang panjang. Oleh sebab itu, sistem pemeriksaan visi mesin untuk sarang burung walit semakin diperkenalkan tetapi ia masih dalam penyelidikan. Sistem pemeriksaan visi mesin yang diamalkan secara meluas dalam pelbagai jenis produk pertanian yang lain tidak sesuai untuk pemeriksaan sarang burung walit kerana struktur sarang burung walit yang kompleks dan tidak merata telah memberikan kesan negatif kepada transmisi dan pemantulan pencahayaan semasa pengambilalihan imej. Oleh sebab itu, projek ini adalah untuk mengoptimumkan parameter pencahayaan untuk sistem pemeriksaan sarang burung walit. Faktor-faktor yang mempengaruhi keadaan pencahayaan seperti jenis lampu, sudut pencahayaan, panjang gelombang pencahayaan (warna pencahayaan) dan intensiti pencahayaan telah dieksplorasi untuk menningkatkan nilai kontras antara kekotoran dengan sarang burung walit. Parameter pencahayaan optimum untuk sistem pemeriksaan sarang burung walit telah ditentukan dengan menggunakan cara statistik faktorial sepenuh di mana keadaan pencahayaan yang optimum terdiri daripada lampu merah yang diletakkan pada 60˚ dari spesimen sarang burung walit dengan menggunakan 255 intensiti pencahayaan. Seterusnya, imej yang diperolehi dengan parameter pencahayaan yang optimum telah digunakan untuk segmentasi. Dalam segmentasi, bilangan kekotoran yang dibezakan dengan sarang burung walit telah dibandingkan dengan bilangan kekotoran yang dikesan oleh pakar manusia. Selain itu, rangkaian saraf konvolusi telah dilatih untuk mengklasifikasikan imej kepada kelas yang berbeza megikut kebersihannya. Kemudian, kedua-dua kaedah telah dibandingkan. Keputusan kajian ini menunjukkan bahawa kadar pengesanan ialah 84.44% manakala kadar kesalahan pengesanan pula sebanyak 19.84%. Kadar klasifikasi rangkaian saraf konvolusi pula ialah 76.47%. Berbanding dengan kajian sebelum ini, kajian ini telah menyumbang kepada sistem pemeriksaan sarang burung walit dengan peningkatan dalam kadar pengesanan kekotoran dan keturunan dalam kadar kesalahan pengesanan.

ABSTRACT

Edible bird's nest production is an important food industry in South East Asia with increasing demands owing to its medical benefits. The edible bird's nest manufacturer looking into mechanization to increase the productivity because the existing cleaning process of the edible bird's nest is labour intensive and time consuming. Therefore, machine vision inspection system on the edible bird's nest was introduced but it is still in research. This is because, up to date, the details of a complete and optimised edible bird's nest vision inspection system, especially the system setup, is still not stated in detailed. While the machine vision system setup that is being practised widely in a various type of agriculture products is not suitable for the edible bird's nest inspection due to the complex, random and uneven structure of edible bird's nest which greatly affect the transmittance and reflectance of the lighting during image acquisition. Thus, this project is to optimize the lighting parameters for the edible bird's nest vision inspection system. The lighting parameters such as the type of lighting, the angle of lighting, the wavelength of lighting and the intensity of lighting are explored to obtain large contrast value between the impurity features and the edible bird's nest during the image acquisition. The optimal lighting parameters for the edible bird's nest vision inspection system is selected by using the full factorial design. The optimal experimental setup is made up of the red front lighting that placed at 60˚ from the edible bird's nest specimen with 255 intensity of lighting. The images acquired under the experimental setup with the optimal lighting parameters are used for segmentation. The adaptive threshold is used to segment the impurity features from the EBN which is then compared to the impurity features that detected by a human expert. Besides that, a convolutional neural network is trained for classifying the images according to its cleanliness. Then, both proposed methods were compared with their performances. The results show that the optimal edible bird's nest vision inspection system successfully achieved a detection rate of 84.44% with the false detection rate of 19.84% by using adaptive threshold while the correct classification rate of the neural network is 76.47%. As compared to previous works, this research shown an improvement in the impurity features detection with the optimal lighting parameters.

CHAPTER ONE: INTRODUCTION

1.1 Introduction

Edible bird nest (EBN) as shown in Figure 1, are the food product that produced by Swiftlet birds [1]. Swiftlet birds are small insectivorous birds which breed throughout Southeast Asia and the South Pacific [2] where it produces EBN from the secreted saliva during breeding seasons. Malaysia, located in Maritime Southeast Asia, were discovered to have seven Swiftlet species, namely Aerodramus francicus, Aerodramus vestita, Aerodrames brevirustis, Aerodramus fuciphaga, Aerodramus maximus, Collocalia esculenta and Hydrochous gigas [2]. However, only the nests of white-nest swiftlets (Aerodramus fuciphagus) and black-nest swiftlets (Aerodramus maximus) which are mainly constructed by saliva can be harvested as commercial EBN. The EBN found in a natural cave is categories as cave EBN, whereas another type of EBN is the house EBN where found in the artificial house that built by a human to resemble the natural habitat for Swiftlet bird to roost [3].

Figure 1 Raw unclean EBN

EBN production is an important food industry in Southeast Asia [4] where it is consumed by human since 400 years ago [5] as an important health supplement. In a study of medical benefits of EBN [2], it is revealed that the EBN is rich in protein, collagen, amino acids, essential sugar for the human body, and essential elements traced such as calcium, sodium, magnesium, potassium, phosphorus, zinc and iron. The advantages of consuming the EBN include enhance brain development of infants, increase fertility, control blood coagulation, acts as an immune system moderator, act as an anti-ageing agent [6], preventing severe memory problems, improve bone strength and reducing arthritis and cartilage degeneration.

Owing to all the medical benefits, demand for EBN is increasing all around the world where the exportation of the EBN is gradually contributing toward Malaysia's economic growth [7]. In the era of rapid growth of exportation of the EBN, the development of Malaysia standards is being strict on defining the standards of the EBN to prevent any ethical problems occur [8]. The standards is defined based on its crescent shape, dimensions, cleanliness, natural colour, authenticity, harvest time, filament, fragment and fine grain content [9] to make sure that the exported EBN are of high standard and quality. The qualification and grading of the EBN depend on three main factors which are authenticity, characteristic, and cleanliness of the EBN. The EBN must go through the quality assurance processes in order to be certified for exportation.

Among the three main factors, the cleanliness is the most important as it is in conjunction with the Malaysia food safety regulation to ensure that the EBN is safe to consume. The cleanliness of the EBN is identified based on the percentage of impurity features in the EBN where the impurity features included feathers, sands particles, eggshells, and paints [10]. EBN is defined as a raw clean EBN when it has undergone the processes of sorting, drying, soaking, picking of impurities, moulding, second drying, grading and packing and results in zero visible impurity features [9]. In order to achieve a high-quality EBN, the EBN cleaning process is very important.

Nowadays, 90% of EBN cleaning process [11] still greatly relies on skilled human forces to manually remove the different size impurity features. This is a very tiring process because the process required high concentration over a long period which may cause a risk of the EBN is not being fully clean. Also, the limited working hours of human forces in cleaning the EBN has affected the continuous production rate. Besides that, it is also a time consuming process where it is estimated that, on average, a trained operator takes about eight hours to clean 10 bird's nests per day [12].

In the fact of high demand but the low productivity of qualified EBN, in order to sustain the exportation of the EBN, Edible Bird's Nest Swiftlet Farming is introduced as one of the entry point project (EPP) under agricultural sector in Economic Transformation Program (ETP) [11]. The project focuses on the mechanization from 10% to 60% in the EBN processing line by implementing more rapid and higher accuracy technologies to replace the human force in EBN cleaning process.

In past few years, there are many researches on rapid, accurate and non-destructive EBN cleaning method are done, such as the EBN machine vision inspection system, to replace the human forces in the inspection tasks. However, currently, machine vision inspection system in EBN industry is in the research stage.

Previously, the researchers [13] [5] focused on segmentation of different sizes impurity features from the EBN and the design of a robotic arm to remove the impurity features from the EBN. The results from previous works show unsatisfied results because the shadows and holes between the structures of the EBN were wrongly recognized as impurity features. This is because not appropriate system setup was used in the researches.

This research focuses on the development of an EBN vision inspection system. Every stage in the development process is important where start from physical system setup, image acquisition, image processing until the segmentation, all stages must have careful considerations. The project can be divided into 4 stages where it starts with the investigation on the factors that affect the image acquisition as a good image acquisition can achieve the desired result by simple segmentation method. Then the optimal lighting parameters are selected by the Design of Experiment (DOE). Thirdly, for the images acquired under the optimal experimental setup is then used for segmentation to highlight the impurity features from the EBN. Lastly, an application to classify the EBN according to the cleanliness was developed which is then compared to the segmentation's performances. At the end of the research, it is expected to contribute an experimental setup with optimal lighting parameters that achieved a high detection rate and low false detection rate in the segmentation of the impurity features from the EBN.

1.2 Problem statements

Currently, the EBN cleaning process is still a labour intensive and time consuming process, thus, it requires a rapid, accurate and non-destructive EBN inspection method. There are researches on the EBN machine vision inspection system were done to focus on the segmentation of different sizes impurity features from the EBN and the design of a robotic arm to remove the impurity features from the EBN. However, the result is unsatisfied where the detection rates are only 59.96% and 80% respectively for both researches [5, 13]. Also, in previous work, the false detection rate is up to 70% as the shadows and holes were wrongly recognized as impurity features during segmentation owing to the not appropriate system setup was used. Thus, a research on the optimization of the lighting parameters of the experimental setup which can achieve high detection rate and low false detection rate in the segmentation of the impurity features from the EBN may leave a significant impact to the EBN vision inspection system.

1.3 Objectives

1. To investigate the type of lighting, wavelength of lighting, angle of lighting and intensity of lighting for optimal lighting solution of the EBN inspection system.
2. To optimize the image contrast value between the foreground (impurity features) and the background (the EBN) by using DOE.
3. To analyze the adaptive thresholding for segmentation.

1.4 Hypothesis

The EBN is a translucent material which allows light penetration through the EBN to make it possibly become invisible on the image where it seems like the EBN has merged with the white background will have a high intensity of background (brighter). While the light is absorbed by the impurity features, due to its absorptive and opaque characteristic, will have a low intensity of foreground (darker). The difference between the intensity of foreground and background is known as the contrast [14]. With high contrast value, a foreground can be easily segmented from the background, meaning that it is defined as a good image that reduces the difficulty and complexity in image segmentation.

1.5 Scope of project

In this research, the primary goal is the optimization of the lighting parameters of the experimental setup for the EBN vision inspection system by using DOE. In order to achieve that, the effect of each factor on the response variable and the effect of interaction between the factors on the response variable will be studied to discover the optimal lighting parameters of an experimental setup. The factor variables are the type of lighting, the angle of lighting, the wavelength of lighting and the intensity of lighting while the response variable is the contrast value. The optimal experimental setup will be validated through the detection rate and false detection rate of the segmentation by using the adaptive thresholding as well as the correct classification rate of the convolutional neural network.

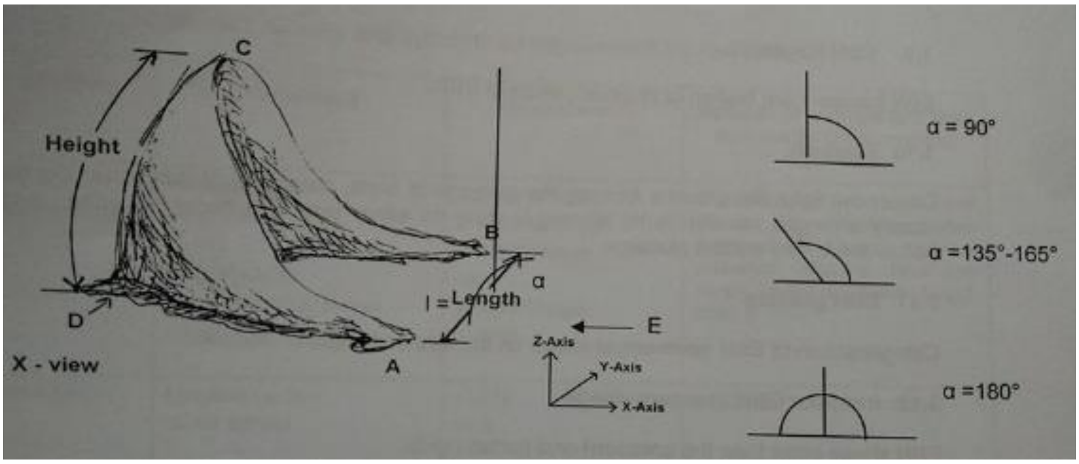
CHAPTER TWO: LITERATURE REVIEW

The quality and standard of EBN are highly depends on its authenticity, characteristic and cleanliness [9].

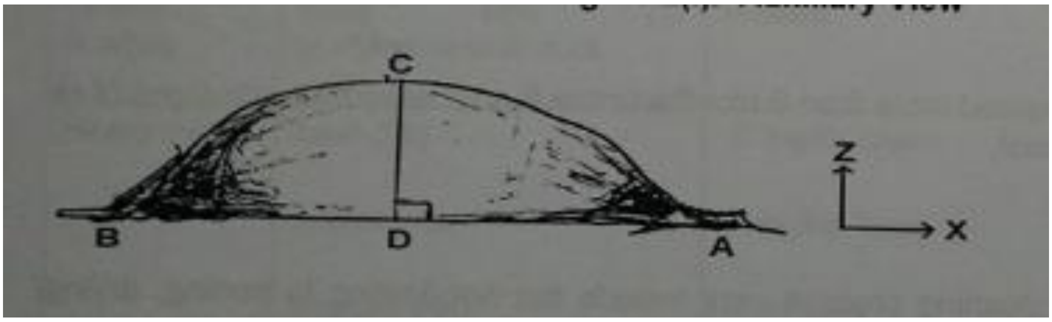
The authenticity is to identify the adulterants that mixed in the EBN. The adulterants included Tremella fungus, karaya gum, pork skin, red seaweed, gelatin, milk powder, rice, starch, agar, jelly and egg white. Currently, some chemical authentication methods [15] were introduced to differentiate the adulterants in the EBN such as Enzyme-linked immunosorbent assays (ELISA) methods, and Polymerase Chain Reaction (PCR), protein-based two-dimensional gel electrophoresis (2DGE) method and a chromatographic that ionized compounds and subsequently identify their mass by using hyphenation. All the identification methods are rapid but it is destructive because the chemicals are used.

Secondly, the EBN was qualified based on the characteristic such as crescent shape, dimension, shape, natural colour, filament, fine grain content, fragment, and harvest time [8]. The crescent shape is defined by the angle of contact planes, α. where formed when the EBN was built in its natural form with the converging point of the two planes as the centre as illustrated in Figure 2. There are four types of crescent shape which are α180˚, α165˚, α135˚ and α90˚, as specified in Figure 3.

Figure 2 Angle of contact plane



(a)



(b)

Figure 3 The crescent shape of EBN (a) auxiliary view; (b) axial view [8]

The grading of a raw clean EBN depends on the crescent shape and curve height of EBN is tabulated as in Table 1 as follows:

Table 1 Table of grading for raw clean EBN

α	α180	α165	α135	α90
L > 3.5 cm	A large	A large	A large	A large
2 ≤ L ≤ 3.5cm	B medium	B medium	B medium	B medium
L < 2cm	C small	C small	C small	C small
(others)	Others	others	others	Others

Grading also according to the characteristic of filament content, fine grain content and fragment content of the EBN [9]. The EBN filaments are the strands of the EBN that obtained when handling, dampening, soaking, picking, sieving, drying and packing of the EBN while the EBN fine grain is the tiny pieces of the EBN that acquire during harvesting, handling and processing. The EBN fragment describes the EBN chipped pieces of the EBN. The filaments, fine grain and fragment of EBN will definitely degrade the EBN. Besides, the late harvested EBN, where more than 6 months, with reshape signs will have the low grade as well [9]. After that, for a high grades EBN, its colour should be the colour of the nest occurring in its natural form without any colour additive [8].

The qualification of the EBN based on cleanliness is the most important factor to ensure that the EBN is safe to consume. The cleanliness of the EBN is identified based on the percentage of impurity features in the EBN including feathers, sands particles, eggshells, and paints [9]. According to the food safety regulation of Malaysia [16], the EBN can only be qualified as a food that safe to consume when it has zero visible impurity features after undergone the processes of sorting, drying, soaking, picking of impurities, moulding, second drying, grading, and packing.

Nowadays, the cleaning process of EBN is still relying on human forces. The impurity features in each of the EBN sample have to be visually identified and then removed from the EBN by using tweezers with the sharp end. The slow cleaning process of the EBN leads to very low continuous production rate. Hence, an automation system to increase the productivity and efficiency of the EBN cleaning process is required [11].

Therefore, the EBN vision inspection system by using an industrial machine vision system is gradually introduced. An EBN vision inspection system is expected to increase the accuracy and efficiency with comparably lower cost than the advanced technologies. Nowadays, machine vision in detecting the defects and impurities features in the product is being practiced widely in the agriculture industry, however, due to the complex, random, and uneven structure and the translucent characteristics of the EBN that differs from other agriculture product, majority machine vision inspection system such as impurities detection for wheat [17], rice mixture [18], cotton and soybean [19] are not suitable for the EBN vision inspection system.

Currently, there are two researches on the vision inspection system for the EBN were conducted where the first study is about the size characterization of the EBN impurity features by using machine vision [13] while another is the EBN processing using machine vision and robot arm [5].

The former, the paper proposed to detect the impurity features of various shapes and sizes by comparing between K-mean clustering and Fuzzy C Means clustering. The experimental setup used is the optimal setup for the citrus [20] where it uses a red colour front lighting, which radiated from the side of the EBN sample, with a black background in a black chamber while the camera was position at the front of the EBN sample. As the result, holes and shadows in dark intensity were formed and wrongly recognized as impurity features which cause a 70% false detection rate. Besides that, the detection rate also unsatisfied which is 59.96% only.

After that, the latter, the research is to design an automated EBN impurity features inspection and removal system by using machine vision and robotic arm. The setup configuration included a GigE network, 50 frames per second specification camera, white front lighting, and white background. Then, by using an algorithm, the images were processed to identify the position of the impurity features which then removed by a 6 axis robotic arm embedded with tweezers with a sharp end. As the result, it shows that the percentage of the impurity features that were detected and removed is 80%.

In fact, in machine vision application, different arrangements or configurations of the system setup will greatly affect the quality of the images acquisition stage where a poor image leads to failure in the image processing stage [21]. Hence, select the optimal image acquisition techniques is an important initial step in developing the machine vision system where the factors that affect the selection of the optimal image acquisition techniques include the type of camera, the color of the background, the type of lighting, the lighting technique, the number of light source, the wavelength of lighting and the angle of lighting.

In machine vision, depth camera is widely applied to three-dimensional reconstruction for a translucent object [22]. The depth cameras were used for shape recovery by collecting the shadow regions of the transparent objects from different viewpoints. Furthermore, a skewed stereo time of flight (ToF) depth camera is useful in detecting a translucent object with single foreground and background and recovering its distortion depth [23]. However, both cameras are at a high cost, hence, cheaper approaches, such as Complementary Metal Oxide Semiconductor (CMOS) or Charge Coupled Device (CCD) camera, are commonly used for the two-dimensional imaging of the agriculture products in the industry. CMOS camera has the advantage of the simple structures, multi-function, high yield, low price and more flexible and faster in transferring signals because each pixel can be read individually which is more suitable for high speed online industrial inspection imaging [24]. In contrast, CCD camera has the advantages of high sensitivity which produces a high-quality and less noise image. It has great potential in the inspection of agriculture products [25].

The selection of the colour of the background is based on the colour of the object. The research [20] claimed that, when a light colour object is selected, the intensity distribution of the foreground and background in the intensity histogram become closer when proceeding from darker to a lighter background. In other words, the segmentation becomes more difficult. In contrast, if the background colour is in contrast with the foreground, the segmentation is easier [26]. In the previous work regarding the detection on the impurity features of various shapes and sizes by comparing between K-mean clustering and Fuzzy C Means clustering that discussed previously, a black background was used in the research resulted in high false detection rate, up to 70%, because the spaces between the structures of the EBN became dark and it was wrongly identified as impurities [13].

In machine vision system for the agriculture industry, a front lighting is commonly used for opaque objects for the detection on the surface features or textures [19] while a backlighting is widely used for a transparent object which silhouettes the structure of the object for critical edge dimensioning or for sub-surface features analysis such as the crack detection [25].

The lighting technique affects the image acquisition. The directional lighting is a good choice for generating contrast and enhancing topographic detail but it provides shadows whereas the diffuse lighting is ideal for an object with uneven surfaces [27]. Bright field illumination is the simplest optical illumination technique which is suitable for fixed, stained and the object with the high natural absorption of visible light [28] where the image produced by this illumination technique will have relatively large internal structures and outline can be seen.

The uniformity of the lighting depends on the illumination sources where a non-uniform lighting affects the robustness of the image preprocessing. The research [29] claimed that the effective illumination is more uniform with increasing number of light sources but the effect of location of multiple sources of light to produce uniform illumination is minimal. In the previous work regarding the EBN vision inspection system [13], the only light source was located at the side of the EBN specimen which has caused a serious shadow.

Currently, a wide range of spectrum was applied in the machine vision system including both of the non-visible spectrum, for instance, X-ray (0.01-10nm), Ultra-violet (UV) (200-400nm), and Infrared red (IR) (700-2500nm), as well as the visible spectrum (400-700nm) such as the red light (620-750nm), green light (495-570nm) and blue light (450-495nm) [24]. The different wavelength of lighting allows it to penetrate through the different type of surfaces. Also, the wavelength of the lighting affects the contrast of an image where, by referring to the colour wheel as in Figure 4, the light of an opposing colour makes the features apparently darker while the same colour makes features apparently lighter. In simple words, if the feature you want to make darker is red, use a green light. In contrast, use a green light to make a green feature appear lighter [30].

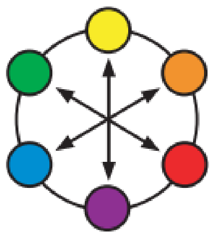


Figure 4 The colour wheel

Low angle lighting is where the lights are aimed nearly parallel to the image surface of the target object which enhances the contrast of surface features, casting the shadows that emphasize changes in elevation and typically used to check engravings and to highlight edges, holes and cracks.

An optimal machine vision system produces high-quality images so that the essential information can be extracted from the image while there are five factors contribute to the overall image quality which are the resolution, noise, depth of field, threshold value and contrast [17].

Contrast is defined as the difference between the luminance or intensity of the background and the foreground that is distinguishable by the machine vision system. One of the examples is Weber contrast [14] which is defined as shown in Equation 1:

$$\frac{I-I_b}{I_b} \qquad \text{(Equation 1)}$$

where I and I_b are representing the intensity of the foreground features and the background, respectively. The value range is from -1.0 to + ∞. . It usually used in the cases where small target feature is present on a large and uniform background whereas it is not applicable to the case with many target features.

In order to choose the optimal experimental setup, a Design of Experiment (DOE) can be used to determine the relationship between the factors that affect the experimental setup. There are many available DOE methods for the experimenter to use includes screening design, full factorial design and fractional factorial design such as Taguchi. A full factorial design requires that every factor under consideration be tested against every other combination of factors in the experiment so that the accuracy is comparably higher than the other methods. While a fractional factorial method such as Taguchi is a simple version of the full factorial design which emphasizes the use of orthogonal arrays so that it tests only a fraction of the possible combinations of factors which help in solving the time-consuming problem of the full factorial design but the accuracy is comparably low. Hence, which methods are better depends on the experience, available times and available resource of the researcher and the consideration of how accurate must be the results [31].

In overall, there are two researches are conducted for the EBN vision inspection system with different approaches where one of them is focused on the algorithms that used for segmentation while another is focused on removal of the impurity features by using the robotic arm. The result is unsatisfied where the detection rate for the former research [13] is 59.96% with a false detection rate of 70% because the system setup used is not appropriate. On the other hands, up to date, there is no research on the optimization of the EBN vision inspection system configuration for good image acquisition was found. Thus, a further research about the optimization of the EBN vision inspection system setup configuration may significantly improve and increase the state of art of the EBN vision inspection system.

CHAPTER THREE: METHODOLOGY

The research divided into four stages where the first stage focuses on selecting the lighting parameters for the experimental setup. The factors that affect the lighting conditions are the type of lighting, the angle of lighting, the intensity of lighting and the wavelength of lighting. The second stage is to optimize the lighting parameters by using the full factorial design. The effect of each factor variable on the response variable and the effect of interaction between the factor variables on the response variable will be studied to identify the optimal lighting parameters. The response variable is the contrast value. The third stage is to segment the impurities from the EBN by using adaptive threshold where the performance of segmentation is based on the total detection rate and the total false detection rate. Lastly, a convolutional neural network application was conducted to classify the images according to the cleanliness of the EBN.

3.1 Experimental setup

The system is equipped with an industrial camera which mounted with lens extension tube and lens, EBN specimens, retort stand, white background and light. A Toshiba TELI V2030CBU camera was used where it provides Video Graphics Array (VGA) OF 744X480 pixels and the frame rate of 125 frames per second. A lens that mounted on the camera is to properly direct the light incident to the camera's sensor so that the captured image captured is clear and recognizable. The lens used is a VS Tech lens with an aperture of f/1.4. However, due to the maximum focal length of the lens is 35mm, hence a 10mm extension tube was used. An extension tube helps to get the lens further from the focal plane of the camera and make the minimum focusing distance smaller so that it can get closer to the specimen for better focusing and magnification. The camera was fixed at a distance of 31cm from the EBN specimen. The lighting used was a directional square illumination where there are 4 lighting bars combine into one lighting. The directional lighting was used due to its directionality nature which enhances the topological details as compared to diffuse light. There are three different models used which are LBRQ-00-160-3-R-24V, LBRQ-00-160-3-G-24V and LBRQ-00-160-3-B-24V that provide red lighting, green lighting and blue lighting respectively. While the spotlight used is YN16011 Pro Light-emitting diode (LED) video light. The EBN specimens are in the “biscuit” size, as shown in Figure 5, with different thicknesses. A white colour background is chosen so that the dark impurity features can be easily recognized during segmentation where the background is made up of four pieces of A4 papers.

Figure 5 The "biscuit" size EBN

There are three different setup configuration for each type of lighting. Figure 6, Figure 7 and Figure 8 show the setup for front lighting, backlighting and front lighting with a spotlight as backlighting respectively.

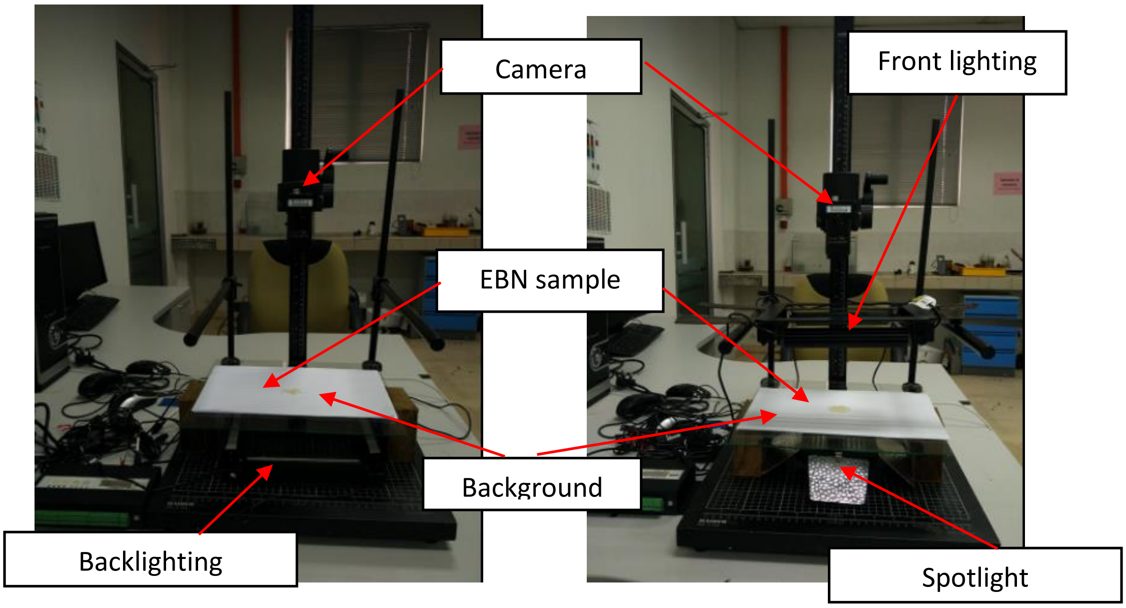


Figure 6 The backlighting setup configuration

Figure 7 The front lighting with spotlight as backlighting setup configuration

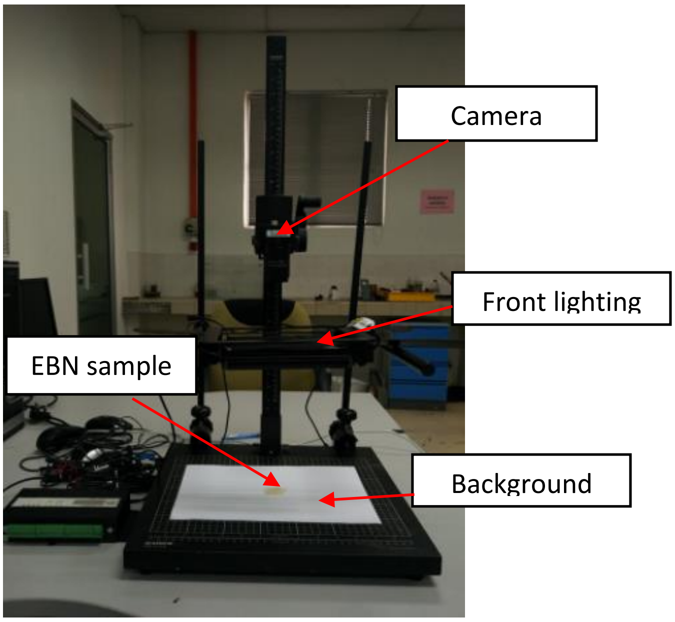


Figure 8 The front lighting setup configuration

3.2 Factor affecting the image acquisition

There are four lighting parameters are considered in this research which are the type of lighting, the angle of lighting for both front lighting and backlighting respectively, the wavelength of lighting and the intensity of lighting.

There are three types of lighting were used which are the backlighting, front lighting and front lighting with a spotlight as backlighting. For front lighting with a spotlight as backlighting, the backlighting is used to enlighten the holes between the structures of EBN so that the intensity of holes was lowered which leads to less false detection.

The angle of lighting was divided into two part which is for the front lighting and also the backlighting. The angle of lighting shows no much effect on the backlighting in previous works hence only 2 variables are used which are 45˚ and 90˚. For both cases, the distance between the lighting and the EBN is fixed at 12cm. While for front lighting, there are 4 variables which are 30˚, 45˚, 60˚ and 70˚. Low angle lighting of 30˚ and 45˚ are the lighting that located almost parallel toward the EBN. The distance between the lightings and EBN for the angle of 30˚ and 45˚ are 6.93cm and 12cm respectively. A high angle lighting of 60˚ and 70˚ are 20.78cm and 32.97cm respectively.

The intensity of lighting directly related to the brightness of lighting. The higher the intensity of lighting indicates the brighter lighting. The lighting intensity was ranged from zero to 255 where zero means no light while 255 indicates maximum lighting. The intensity was controlled by the lighting controller. In this research, the variables of the intensity of lighting are 50, 100 and 255.

The visible lights were used include the blue light with the wavelength of 450-495nm, green light with the wavelength of 495-570nm and red light with the wavelength of 620 – 750nm. The factors that affect the experimental setup for image acquisition are summarized in Table 2.

Table 2 Factor that affecting the experimental setup

Factor	**Variable**
Type of lighting	Front lighting
	Front lighting with spotlight as back lighting
	Backlighting
Angle of lighting 1 (For front lighting and front lighting with spotlight as back lighting)	30˚
	45˚
	60˚
	70˚
Angle of lighting 2 (For backlighting)	45˚
	90˚
Intensity of lighting	50
	100
	255
Wavelength of lighting	Red light (620-750nm)
	Green light (495-570nm)
	Blue light (450-495nm)

3.3 Design of Experiment (DOE)

The adoption of DOE method, the full factorial design, in this research is crucial to select the optimal experimental setup, taking into account of numerous four factors affecting the image acquisition that mentioned in section 3.2. The response variables is the contrast value.

In this study, the level of each factor was different where the type of lighting, the intensity of lighting and the wavelength of lighting have three levels while the angle of lighting for front lighting has four levels and the angle of lighting for backlighting has two levels. A General full factorial design was used where a total of 90 experiments is replicated for once time. The design matrix for the experiment was attached in Appendix 1. In factorial design, the analysis not only for the individual factor but also the interaction between the factors.

The effect of each factor and the interaction between the factors on the response can be determined from analysis of variance (ANOVA) in the full factorial design analysis. The ANOVA is to determine the levels of variability and form a basis for tests of significance. The fundamental technique in ANOVA is partitioning of the total sum of squares (SST) into components related to the effects used in the model where the equation is shown in Equation 2. Hence, the significant factors can be determined based on the percentage of contribution or the value of SST.

$$SST = SSM + SSE; \qquad \text{(Equation 2)}$$

where

SST = total sum of square

SSM = sum of square of model

SSE = sum of square of error

Besides that, the F-value and the P-value provide a statistic for testing the hypothesis as follows:

Null hypothesis: $\beta=0$ (the effect is not significant)

Alternate hypothesis: $\beta \neq 0$ (the effect is significant)

Confidence level = 95%, P-value = 0.05;

When the P-value is less than 0.05 and the F value is large, there is evidence to reject the null hypothesis. Hence, the factor is significantly affect the response variable.

R squared (R^2) is another statistical measure used to interpret how close the data are to the fitted regression line. R squared value lies within 0 to 1, with 0 denotes none the variability of the response data around its mean and vice versa for $R^2 = 1$. Generally, R squared greater than 0.90 is within the acceptable range for this experiment setup up, to which at least 90 % of the variability of the data can be explained through this model.

Lastly, a main effect plot is used to determine the best level of each factors which can used to determine the optimal lighting parameters in this research.

3.3.1 DOE for thickness < 4mm

The thickness of the EBN affected the light penetration. In image acquisition, the EBN with thinner thickness resulting in apparently higher intensity value as illustrated in Figure 9. The thickness of the EBN is deviated within a piece of the EBN specimen, thus, the EBN specimens were grouped depending on the maximum thickness of each EBN. Figure 10 shows some of the images of the EBN specimen under the group of thickness < 4mm.

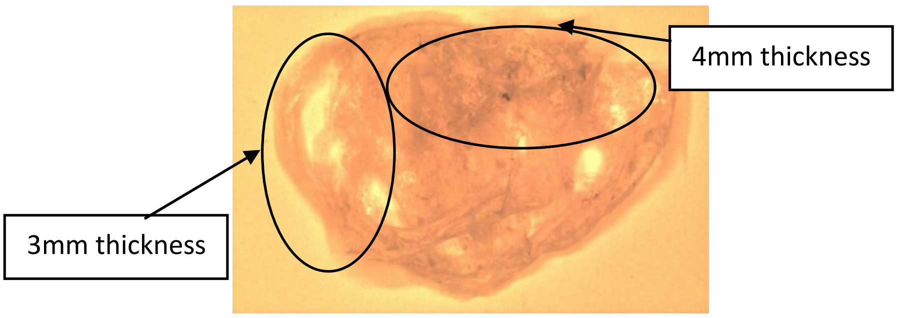


Figure 9 Image of EBN with different thickness

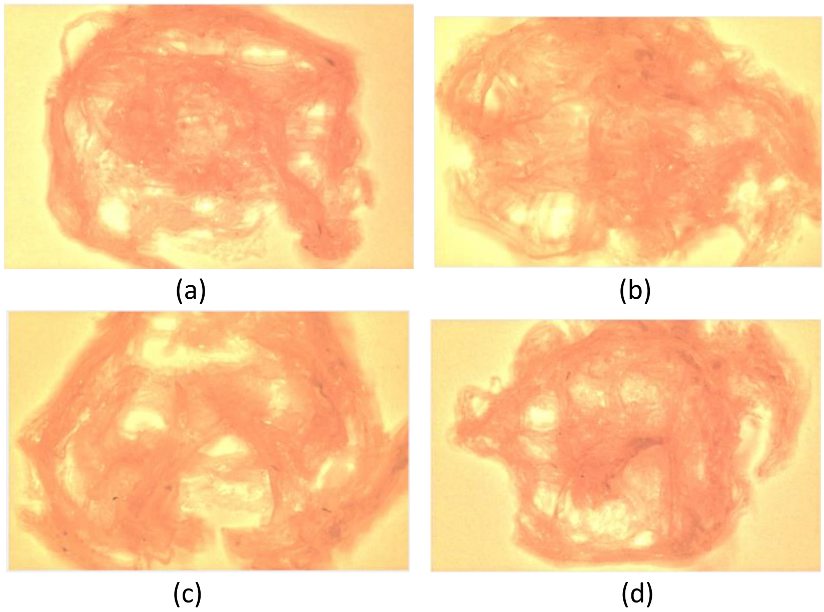


Figure 10 The image of (a) Sample 12 (b) Sample 15 (c) Sample 16 (d) Sample 30

3.3.2 DOE for thickness ≥ 4mm

In contrast to section 3.2.1, the thick EBN resulting in apparently darker under the image acquisition as shown in Figure 9. Hence, the EBN with thickness ≥ 4mm will be grouped in this group to investigate the effect of the thickness on the DOE analysis and segmentation process. The Figure 11 shows some of the images of the EBN specimen under group of thickness ≥ 4mm.

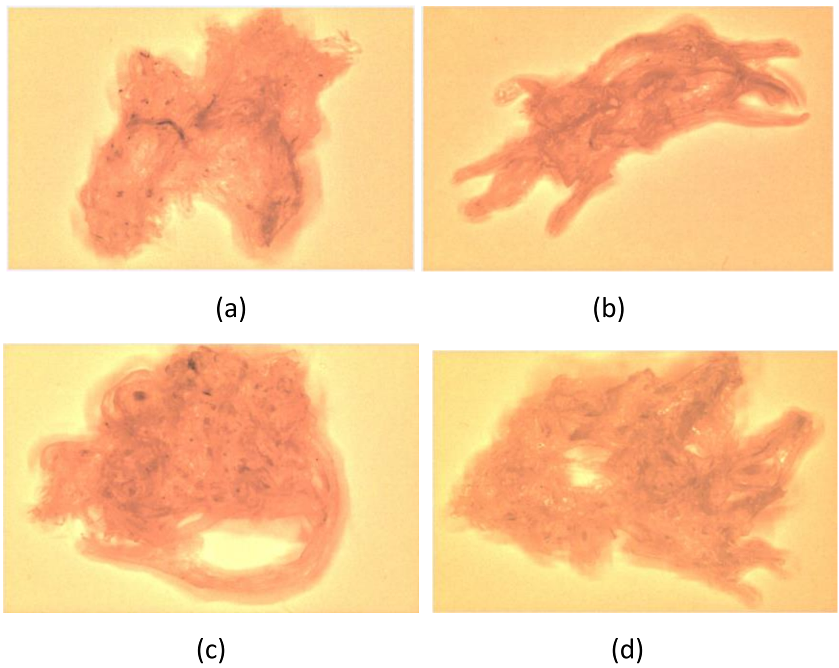


Figure 11 The image of (a) Sample 12 (b) Sample 15 (c) Sample 16 (d) Sample 30

3.3.3 Response variable

The response variable of the factorial design is the contrast value. Generally, the contrast value, the Equation 3, is the intensity of foreground divide by intensity of background where:

$$Contrast = \frac{I_{foreground}}{I_{background}} \qquad \text{(Equation 3)}$$

where I = impurity

In order to make sure that the calculated contrast value is representable the whole image, the intensity of foreground and background were determined by the weighted average of the intensity distribution in the intensity histogram of an image as shown in Figure 12. By apply the threshold value, the histogram can be divided into an area for the intensity of impurity and area of intensity for EBN and background.

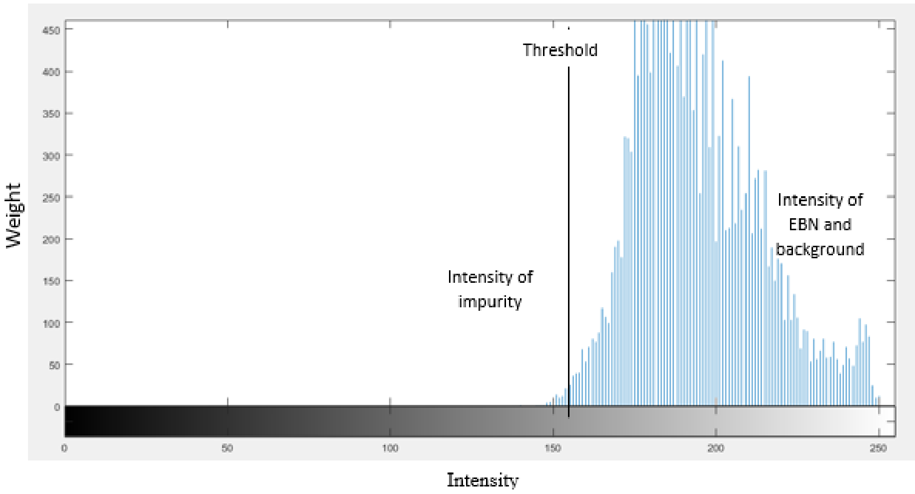


Figure 12 Intensity histogram of EBN image

The Equation 4 is the equation of the contrast value that used in this research.

$$Contrast = \frac{\left(\frac{\sum_{i=1}^{n}(I_{f_i} * w_i)}{\sum_{i=1}^{n} w_i}\right)}{\left(\frac{\sum_{i=1}^{n}(I_{b_i} * w_i)}{\sum_{i=1}^{n} w_i}\right)} \qquad \text{(Equation 4)}$$

where

I_f = intensity of foreground (impurity)

I_b = intensity of backgrounf (EBN and background)

w = weights

There are two assumptions for the Equation 4 which are:

1. The background required to be comparably larger than the foregrounds in the same image.
2. The background required to be uniform.

To make sure the assumptions are meet, the images of EBN was cropped into a region of interest of 300x300 pixel image which then divided into four 150x150 pixel sub-images. This is to ensure that the image only contains EBN and impurities with least background. For all the sub-images that located at the left upper side, right upper side, left bottom side, and right bottom side will be grouped into sub-image 1, sub-image 2, sub-image 3, and sub-image 4 respectively. While each group of the sub-image will conduct the DOE analysis separately to investigate the variability of the experiment result. The region of interest is as illustrated in Figure 13.

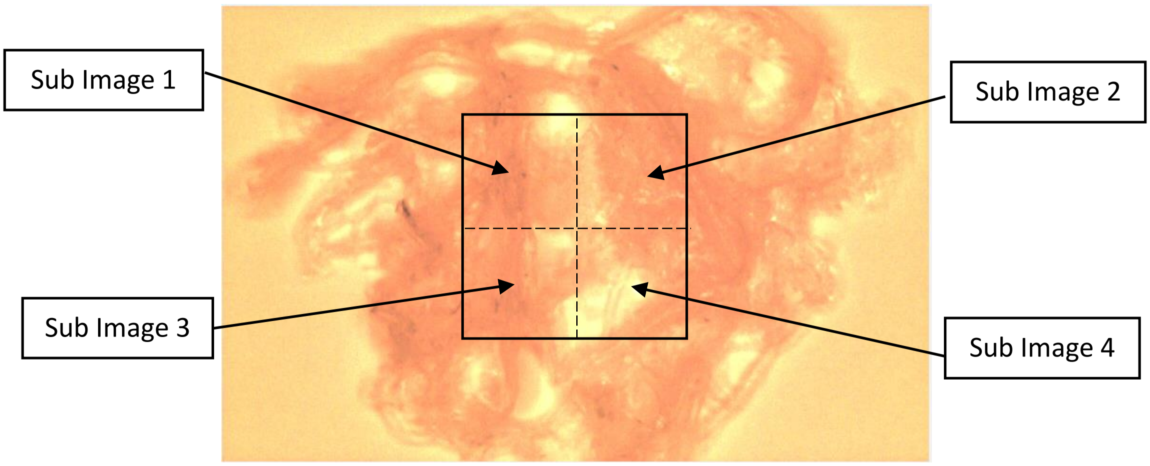
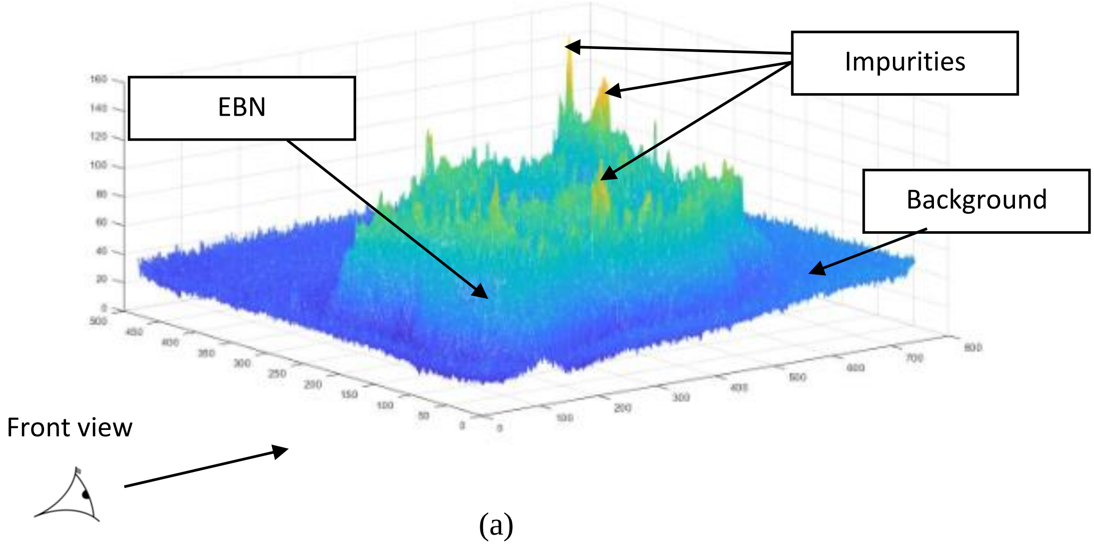
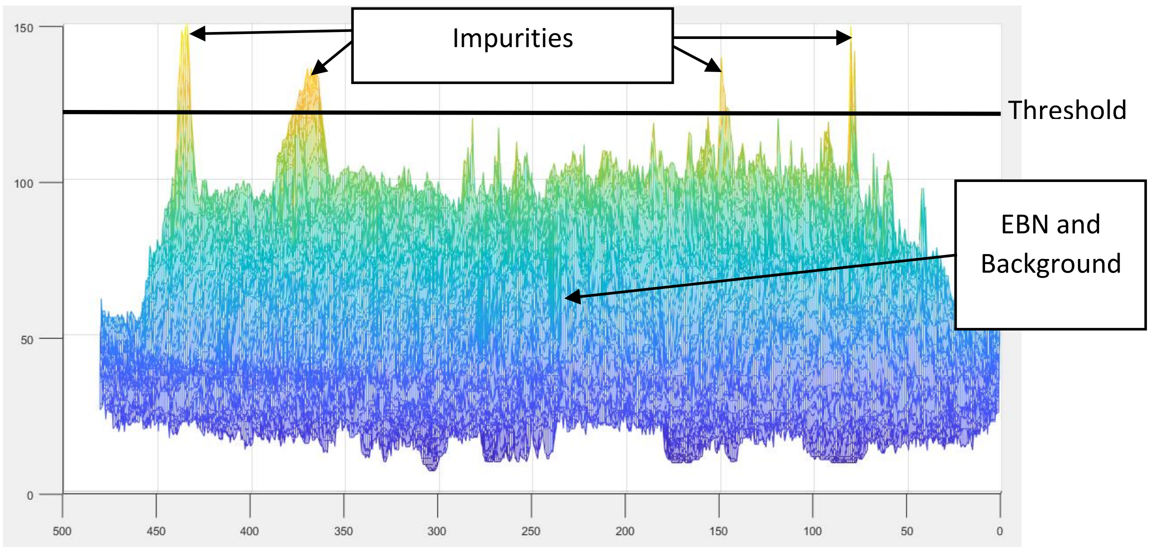


Figure 13 Region of interest

The threshold value that used to divide the intensity histogram was determined from a three dimensional (3D) intensity plots as illustrated in Figure 14. In the 3D intensity plot, the x-axis and y-axis indicate height and width of the image respectively while the z-axis represents the image intensity. The intensity of image was inverted, where the dark colour impurity features will become white in colour (higher intensity) so that the impurities can be observed easily from the plotted graph.



(a)



(b)

Figure 14 3D intensity plot of EBN sample 11 in (a) auxiliary view (b) front view

The threshold value for all images was determined and it found that the threshold value is different for each image. The range of threshold values for all images is attached in Appendix 2. Hence, in order to make sure that the threshold value is applicable to all images in this research, the highest threshold value among the range of threshold value of all images was selected. Also, the threshold value is different for different wavelength of lighting, type of lighting and thickness of EBN specimens where it was summarized in Table 3.

Table 3 Threshold value of each wavelength of light for each group of thickness < or ≥ 4mm

Threshold value		
	Thickness < 4mm	**Thickness ≥ 4mm**
Backlighting		
Blue light	55	55
Green light	55	70
Red light	75	85
Front lighting		
Blue light	80	75
Green light	95	85
Red light	155	145
Front lighting with spotlight as backlighting		
Blue light	80	75
Green light	95	85
Red light	155	145

3.4 Segmentation

The third stage is to segment the impurities from the EBN for all 210 images that acquired under the optimal experiment setup. The performance measure is the detection rate and the false detection rate between the algorithm detection and the ground truth.

Currently, the inspection of EBN was done manually, therefore, the ground truth is the number of impurities that manually identified by a human expert who has the experiences in cleaning the EBN in industry. The human expert identifies the position of impurity features on the EBN and marks it onto the image. The inspection was done at the top view of the EBN without flipping the EBN.

The image has an uneven illumination due to the randomness and unevenness structure of the EBN. Also, the intensity distribution was different for every image when the images were acquired from the same sample but under a different position. Hence, the global threshold which used a fixed threshold value for all pixels in the image is not appropriate as it results in poor segmentation. Therefore, in this research, the adaptive threshold was used. The adaptive threshold is a local threshold that selects an individual threshold based on the local statistic in the neighbourhood of each pixel.

In order to achieve good segmentation, the input arguments are important. There are four input arguments which are sensitivity, neighbourhood size, foreground polarity and statistic.

The sensitivity determines which pixel get threshold as a foreground pixel. High sensitivity values lead to threshold more pixels as foreground and it has a risk of include background pixels. After determining the sensitivity for few images, it found that the sensitivity value of 0.4 is applicable to all so that the value is chosen. The neighbourhood size is the size of the neighbourhood that used to compute local statistic around each pixel. The neighbourhood size is important to make sure there are sufficient foreground and background pixel so that a good local threshold value can be selected. There are different size of impurity found in all images, hence, the neighbourhood size is decided to be twice of the area of largest impurity among all images which is [61 93]. The foreground polarity is to define which pixel is the foreground. Bright indicates that the foreground is brighter than the background. The statistic used in this research is the local mean intensity.

By using adaptive threshold, the impurity features can be segmented from the EBN as shown in the binary image in Figure 15. The black blob indicated the impurity feature.

Figure 15 Segmented impurities by algorithm