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Investigation into the Use of a Fourier Based Edge Detection Image Processing Approach for Assessing Cocoa Pod Stem Cut Quality

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Abstract: *As the cocoa industry continues to grow, there is an increasing need for greater efficiency and higher levels of quality in all areas. The objective assessment of pod stem cut quality is one such critical area, as it not only directly impacts productivity but wider industry economics. Despite this, and the significance of cut quality in other agricultural applications, there is little done in the area of developing an objective and reliable assessment method. This work proposes, develops and tests a Fourier based image processing approach for assessing cut quality. The proposed Fourier Peak Index (FPI) method is implemented in MATLAB 2013 via a series of algorithms. Further, a windowed FPI (WFPI) is also developed and implemented in the same environment. Both methods are tested using a set of 40 images, comprising of 10 reference images, 15 poor cut images and 15 good cut images. The results obtained showed that the FPI method had a 93% accuracy in categorising good cuts, 60% accuracy in categorising poor cuts and an overall accuracy of approximately 77%. It was particularly noted that poor cuts with long, smooth excess bark material attached to the stems, were poorly categorised by the FPI method. Additionally, the method's effectiveness was found to be significantly influenced by image lighting, as this determined the amount of data loss during the image binarisation step. Notwithstanding, the WFPI method was found to be effective in categorising the images that were incorrectly categorised by the FPI method. The combined efforts of both methods had the potential to increase detection and categorisation accuracy to a maximum of 97%.*

Keywords: *Cocoa; cut quality; Fourier; Image analysis*

1. Introduction

Theobroma cacao, or cocoa, is a tropical evergreen agricultural crop that is cultivated for its significant commercial value. The seeds of the cocoa fruit (known as cocoa beans) are the main ingredients in the production of chocolate and other related confectionaries. They are used in the production of cocoa butter fat, which has in recent years found increasing applications in the areas of pharmaceuticals and nutraceuticals. Cocoa beans are a heavily sought after commodity. The global cocoa market has grown steadily over the past few decades, with estimated production levels of 4.78 million tonnes in 2018/2019; approximately 280% higher than 1980 levels (ICCO, 2020; Statista, 2020). As is the case with many other agricultural markets, this continuous growth in production has seen a commensurate rise in the standards of quality in the production and post-processing of the cocoa. It is expected that this trend will continue into the future, as the industry seeks to become more competitive and sustainable.

The harvesting of the cocoa fruit or pod is a very critical process in the production stages of any cocoa related product. As is well known, the cocoa plant is rather unique in that it bears the majority of its flowers along the main trunk of the tree and not the branches. In keeping with this, the cocoa pods are generally distributed vertically along the tree's length. More importantly, the seed cushion of the cocoa plant is known to be rather sensitive and is susceptible to damage once exposed to unnatural forces (Wood and Lass, 1985).

The harvesting process is generally conducted by skilled personnel who utilise sharp, bladed tools to cleanly slice the cocoa pods at the stems (Wood and Lass, 1985). The primary aim is to achieve a good quality cut. Conversely, incorrect cutting techniques such as pulling, bending or twisting the cocoa pod, or the use of dull cutting tools often result in the removal of a portion of the bark of the tree. Accordingly, the end result is generally considered as a bad or poor cut. Once this occurs, the seed cushion is irreversibly damaged and

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the tree will bear no further fruit in this location (Wood and Lass, 1985). Skinned barks and cuts on the trunk of the tree have been known to become sites for fungal growth and disease development (Wood and Lass, 1985; Theobroma, 2005). Thus, incorrect harvesting techniques result in poor quality cuts, which in turn lead to a decrease in the tree's yield capacity and severely diminish its productive life and commercial value. This places a high requirement for precision and careful management in the harvesting of cocoa pods.

Interviews conducted by the authors with local cocoa farmers have revealed that considerable care is invested into the maintenance of harvesting tools and that it can account for a substantial proportion of the total harvesting cost. As farmers continue to seek the highest levels of productivity from their fields, there is an increased need to minimise these associated costs, without jeopardising the long-term capacity of their trees to yield pods. Currently, the maintenance and replacement of cutting tools are done on a periodic basis by most farmers as a matter of practice and is not based on an objective assessment of tool sharpness or the resulting cut quality. However, an objective assessment of cut quality can potentially optimise tool replacement times, thereby minimising harvesting costs and ensuring high product yield. The assessment of cut quality can be considered as the implementation of precision agriculture practices for the cocoa farming industry and is well aligned with the industry's projected direction.

Researchers have recognised the significance of blade sharpness and the resulting cut quality, in other agricultural applications. Toledo et al. (2013) have investigated the impact of blade type and orientation on cut quality in the cutting of sugarcane stems. In their work, they proposed a damage index as a means of evaluating the quality of a cut and a rudimentary image assessment approach to implementing it. The construct was based on the establishment of three distinct levels of damage, which were predefined and categorised based on commonly occurring cuts. Each level of damage was represented by a reference image that most aptly described it and captured the elements of that level. Consequently, new cuts were placed into one of the three levels based on how closely these cuts resembled the reference image.

Momin et al. utilised a similar approach in assessing different types of blade arrangements (Momin et al., 2017). Though their approach utilised a greater level of categorisation, the image analysis approach was the same. In both instances, the allocation of cuts to a specific category was determined by human judgement. This approach was limited due to its subjectivity and the inherent constraints on assessing large numbers.

Computer vision and image analysis approaches have been used with a high level of success in agricultural applications within recent times (Kakani et al., 2020). Many researchers have utilised image analysis approaches in assessing food quality (Delwiche et al., 2013; Hosseinpour et al., 2013), fruit or crop ripeness and the presence of diseases in crops (Kakani et al., 2020; Tian et al., 2020; Tripathi and Maktedar, 2020).

Notwithstanding the challenges of managing lighting conditions, these assessments are generally easier to implement via an image analysis approach because they are based on first order statistical methods of assessment of the images obtained. Some researchers have been able to utilise more involved image analysis constructs to assess fruit or crop properties. Mu et al. (2020) used colour-based data as the basis for the development of an end-effector for a kiwifruit picking robot. Nouri-Ahmadabadi et al. (2017) used five colour parameters in the development of a grading system for peeled pistachios. Xie et al. (2019) utilised six colour parameters and six shape parameters as indicators in the grading of carrots. In a similar vein, Ireri et al. (2019) also developed an image analysis system for the grading of tomatoes. Their work utilised a histogram thresholding approach to perform calyx and stalk scar detection. In related works, Habib et al. (2020) used the colour parameter data in the development of a system for identifying diseases in papaya fruits.

Perhaps of greater interest are the approaches that have examined fruit/crop shape or the presence of localised faults; an area that has seen significant development in recent years (2012). Xie et al. (2019) utilised an image analysis approach to identify surface cracks and broken edges in carrots, both of which are known to be somewhat difficult to identify visually. Their technique combined primary colour parameter data with more refined colour data obtained from binarisation, segmentation and edge detection. Gongal et al. (2018) used a pixel-size estimation technique, to determine the actual size of apples. Their approach combined both 2-D and 3-D image sets. Blok et al. (2016) also developed a machine vision system for harvesting broccoli. As texture is a defining feature in broccoli, the researchers used a number of colour-based algorithms for differentiating broccoli heads from the leaves and other image features. Their method was quite successful. In a related area of work, Jafari et al. (2014) identified a correlation between skin surface coarseness and skin thickness in oranges. Using a moving average filter approach, they were able to estimate skin thickness in oranges via computer vision. Collectively, these approaches are of great value as they indicate the potential of an image analysis approach in assessing a parameter such as cut quality.

Despite the aforementioned works, a review of the literature has yielded very few results on the use of Fourier based techniques for feature extraction in agricultural image analysis approaches. Additionally, notwithstanding its significance, the literature has been generally silent on the use of computer vision or image analysis approaches in assessing cut quality. Further, in reviewing the literature, the authors have recognised a dearth of information regarding the use of image analysis techniques in the cocoa industry or in related areas that consider the unique requirements of cocoa.

This work seeks to propose a Fourier based image analysis approach to assessing the cut quality of cocoa pods. It is of the view that the Fourier Transform methods are able to assess the feature of cut quality, due to their ability to identify geometric features in image processing effectively. Moreover, the work sought to assess the approach via in-situ testing in a local cocoa farm as a case study. The proposed approach would form the basis for the computer-vision system assessment of cut quality in cocoa pods and in other agricultural applications.

2. Definition of Problem and Theory of Approach

The removal of cocoa pods from the cocoa tree is the primary intent of the harvesting process. Generally, in a correctly cut cocoa pod the stem is usually short and also has a straight or smooth profile at the point where it was severed (i.e., the end of the stem). High quality cuts are vital to the safeguarding of the tree's flower cushion and ultimately, the productivity of the cocoa tree. However, cut quality often decreases as harvesting blades become dull with time, leading to poor quality cuts. These are generally characterised by stem-ends that are not smooth but are jagged and uneven. Often, the jagged profile of these stem-ends is characterised by the presence of long strips or protrusions, which are the result of excess bark material that is still attached to the stem (see Figure 1).

Figure 1. Example of a Correctly Cut (above) and Poorly Cut (below) Cocoa Pod

The stem-end profiles of actual pods can range between these two conditions, often influenced by the factors of harvesting skill and/or tool sharpness. Though extremely poor cuts (as in Figure 1) are immediately visible to the harvester, less obvious cases of poor cut quality may go undetected. As the quantity of pods that are harvested increases, the likelihood of identifying poorly cut pods or tracking the number of poor cuts often diminishes only to be identified when the situation exacerbates. Much damage to the trees can occur before the situation is recognised and arrested. Consequently, a method to assess and evaluate cut quality can lead to earlier detection of deteriorating cut quality and ultimately result in greater productivity and financial benefit.

As identified by other researchers, cut quality can be assessed by means of visual inspection and thus lends itself to an image analysis approach. In a correctly cut cocoa pod, the diameter of the stem is considerably smaller than the length of the cocoa pod. The irregularities associated with poor cuts generally occur along the width of the cut stem-end. Consequently, the image analysis problem at hand is the assessment of the stem-end profile.

Having identified the stem-ends, their profiles must be assessed for smoothness and the absence or presence of irregularities. The level of smoothness present must be objectively evaluated and quantified. Besides, an indicator must be developed that can effectively represent the quality of the cut. Such an indicator can be used not only to differentiate between good cuts and poor cuts, but can also serve to track cut quality over time, with the intent of identifying when quality control interventions are necessary.

In an image of a cut cocoa pod, the stem-end is visible as an edge and thus, any assessment of cut quality would require the recognition and/or manipulation of the image data associated with this edge. This problem is highly geometric in nature and thus an effective image analysis approach must be able to address this. The Fourier transform, which is implemented digitally by a Discrete Fourier Transform (DFT) algorithm, is well known for its abilities to identify geometric patterns in image analysis. Equation 1 shows the general form of the DFT for an M x N image.

$$F(k,l) = \sum_{i=0}^{M-1} \sum_{i=0}^{N-1} f(i,j) e^{-i2\pi\left(ki/_M + lj/_N\right)} \tag{1}$$

In converting an image from the spatial to the frequency domain, the DFT allows for repetitive patterns in an image to be represented by the coefficients of the sinusoidal basis functions or frequencies. The form of the DFT used here is 2-dimensional and generates M sets of frequencies in the x-direction and N in the y-direction, where M and N are the number of pixels in the respective directions. For simple patterns, a small subset of frequencies is predominant as indicated by the magnitude of their coefficients.

For edge effects or places where there is a stark contrast in the gray colour content between segments of an image, the DFT has a unique response. It has been found in DFT analyses that edges and other similar linear patterns are characterised by a large range of frequency values with high magnitudes (Smith, 1999). This response can be leveraged to identify both the presence of stem end profiles and the quality of the profile in an image analysis approach.

3. Materials and Methods

Trinidad and Tobago is an island located in the Caribbean with geographical coordinates 10.69°N and 61.22°W, and is renowned for its world-class, fine-flavoured cocoa varieties. For the purposes of assessing the practicality and relevance of the work, the authors believed that a real-world implementation of the method would have been most instructive. Consequently, as a case study the authors worked with a small group of farmers whose farm was located on the western side of the island of Trinidad.

The conditions of the local farm were incorporated as key constraints and considerations in the development and implementation of the approach. The study was conducted in three main steps. The first step involved the acquisition of the images from the fields of local farmers. Given that the FFT had not been previously used in this context, its key characteristics for assessing cut quality were undetermined. Consequently, the second step involved the use of a set of images with known straight edges to determine key FFT response characteristics and ultimately, the identification of a suitable indicator. Having determined these characteristics, the final step of the work entailed the testing of the FFT approach developed on a set of stem-end profiles.

In the first step of the work, a 12-MP camera was used to take images of cocoa pod stem ends after harvesting. No specific camera settings or lighting controls were used during the image acquisition process. It is expected that the image acquisition process would be conducted by the harvesters in the field, to ensure that the true stem end profiles are obtained and that they are not modified during transportation or storage. As such, the process simply involved taking a photograph of the cocoa pod and stem, as the harvesters would not readily have access to specialised equipment or tools in the field. In total, 30 pod stem images were collected. The set of pod stem images comprised of 15 poor cuts and 15 good cuts. These cuts were classified as poor or good based on the feedback of farmers on the local farm.

For the second step, a set of 10 reference images were collected. These images were taken under similar conditions to those of the pod stem-ends. The reference set comprised of images taken of a smooth rectangular block of wood and of a metal metre rule against various backgrounds. Due to the machined edges of both objects, their edges and respective end profiles were smooth and were representative of ideal cut quality. Accordingly, the set of reference images were taken to assess the proposed method and to determine a range of values for the property indicator when a smooth edge was obtained. Figure 2 presents examples of images from the reference set.

Figure 2. Examples of Reference Images (Top: metre rule; Bottom: wooden block)

Once obtained, the images were processed in the third step of the work using a series of algorithms developed and executed in MATLAB 2013. Figure 3 provides an overview of the sequence of steps conducted in the method. The images were first cropped to focus solely on the stem end profiles. This removed excess material from the images and led to expedited processing times by the subsequent steps in the algorithms. The cropped colour images were then converted to binary images using a fixed level value of 0.3. Once converted, the binary image was then further refined using an edge detection algorithm. The Sobel algorithm was selected as it is one of the more fundamental and reliable methods, and it is known to be relatively less computationally demanding than other algorithms. Collectively, the binarisation and refinement steps served to segment and filter the image. The final step of the method involved the implementation of a DFT algorithm. The refined images were first transformed using the DFT command.

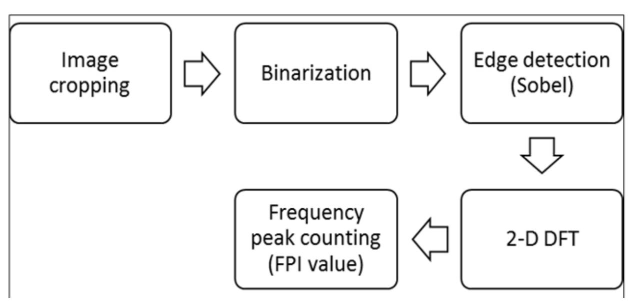

Figure 3. Sequence of Image Processing Steps in Proposed Approach

Given that the DFT is 2-dimensional, but the stem-end profiles were generally found in the x-direction, a scan of the y-directional coefficients was conducted for a fixed x-directional frequency. Subsequent to the scan, the total number of peaks was determined. In keeping with the nature of the DFT, this number was representative of the nature of a straight edge in an image. The number derived here was referred to as the Fourier Peak Index (FPI) and is proposed as an indicator of cut quality. Figure 4 shows the results obtained for each step for a sample image of a stem-end profile.

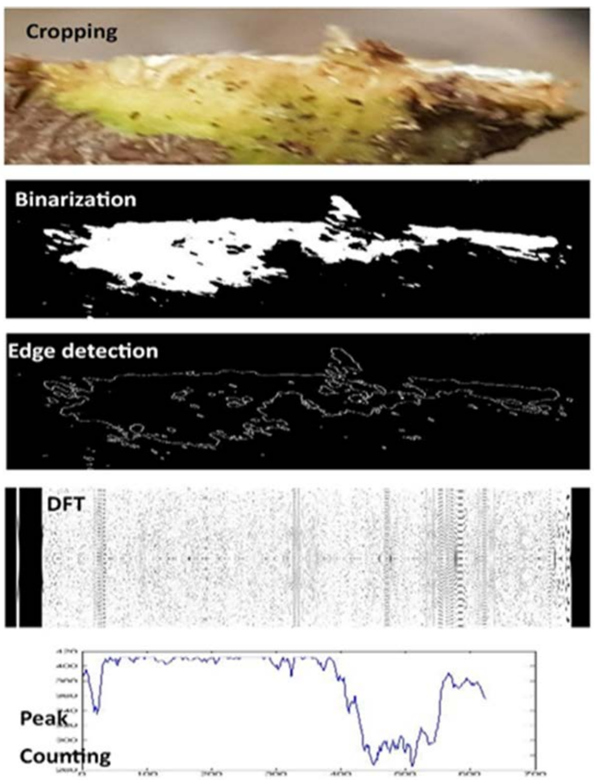

Figure 4. Example of the Images Produced by Each Processing Step of the Proposed Approach

The binary conversion step served to segment the image and the level value used determined what data was omitted and what was carried forward. It was necessary to assess the impact of using different level values upon the magnitude of the FPI indicator. The method was conducted for each image in the image sets, using a range of level values. A total of five level values were assessed ranging from 0.3 to 0.7. The results of these assessments and the overall method are presented in the subsequent sections.

4. Results and Discussion

4.1 Establishment of Cut Quality Indicator Reference Values

Table 1 presents the results for the cut quality analyses conducted for the set of reference images. The most immediately notable result concerns the magnitude of the FPI value. The lowest FPI value observed was 97, while the highest value was 238; both of these values were obtained for the metre rule images. The mean value of the FPI for all five level values was 149 and 157, for the metre rule and wooden block images, respectively. Moreover, the median values were 143 and 162, for the metre rule and wooden block images respectively. Moreover, it would be noted that over the five level values assessed, only one FPI value was found to be less than 100 (i.e., 97).

These results are in keeping with the nature of the DFT. Straight edges are represented by a large subset of frequency values with large coefficients. This will result in a large number of peaks in the Fourier spectrum and ultimately a large FPI value. Consequently, it can be deduced that a FPI value of at least 100 is associated with a smooth edge.

Another point of interest in the results of Table 1 concerns the impact of level values on the FPI. For the metre rule images, the FPI value generally increases with increasing level value. This trend is slightly amended for the images of the wooden block. In this instance, there is a general increase in the FPI value from 0.3 to 0.5 and a decrease thereafter. These results can be attributed to the impact of lighting conditions upon the image analysis process. As the level value increases, the quantity of data that is filtered in the binarisation process increases. More specifically, a greater portion of the image is converted to black as the level value increases.

Table 1. Fourier Peak Index Values for Reference Set

Image	FPI for 0.3 level value	FPI for 0.4 level value	FPI for 0.5 level value	FPI for 0.6 level value	FPI for 0.7 level value
Metre Rule 1	110	123	140	144	169
Metre Rule 2	139	138	162	171	177
Metre Rule 3	110	143	176	177	174
Metre Rule 4	140	238	141	165	198
Metre Rule 5	105	97	103	137	155
Block 1	141	155	174	179	153
Block 2	164	180	162	150	104
Block 3	104	161	173	166	133
Block 4	173	174	156	142	115
Block 5	147	177	191	177	186

As can be seen in Figure 5, this initially leads to greater definition of the edges within the image and consequently increasing FPI values. As the level value increases further, a greater level of detail tends to be lost and the exact location and shape of the profile becomes unclear and increasingly inaccurate. The point at which the loss begins to occur depends on the image brightness and the exact details of an image. Due to the reflective nature of the metre rule, its images were naturally brighter. A general increase in FPI value from 0.3 to 0.7 was observed. Conversely, for the darker wooden block images, the FPI values generally began to decrease at level values higher than 0.5

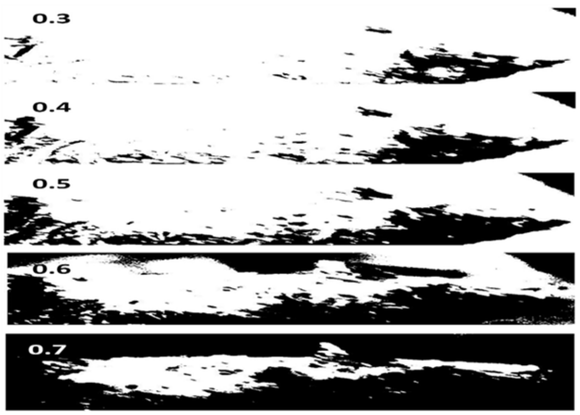

Figure 5. Impact of Level Value on Binarisation Process of Image 2

Though the proposed method is able to assess images without the use of controlled lighting conditions, it is evident that its accuracy and reliability would be increased under such conditions. The level value of 0.5 is taken as the reference value in further assessments as most of the stem-end images are more similar to the wooden block than the metre rule.

4.2 Stem-end Analyses and Method Accuracy

The cut quality analyses allowed for the establishment of a FPI value of 100 as a reference point in the analyses. In keeping with this, the proposed method categorises pod stem images having a FPI value of 100 and over as having acceptable cut quality (a good cut), while images with lower values were considered as unacceptable or poor cuts. Figure 6 shows a sample of the stem-end images assessed. Table 2 depicts the respective FPI values obtained.

The results illustrate the effectiveness of the FPI value and the proposed method (see Table 2). For Images 2 and 14, both of which were good cuts, a FPI value of greater than 100 was obtained in each case. As mentioned earlier, a FPI value of 100 or greater is associated with a smooth profile. The proposed method would have correctly categorised Images 2 and 14 as good cuts. Conversely, the analyses of the poor cut Images 1 and 21 both yielded FPI values that were lower than 100. Both of these images would have been correctly categorised as poor cuts. Moreover, the FPI value of Image 21 is lower than that of Image 1. A review of the images would show that there is a greater degree of damage in Image 21 than in Image 1.

Figure 6. Sample of Stem-end Images Assessed

Table 2. Results obtained for sample images of Figure 6

Image number	Type of cut	FPI value (0.5 level value)
1	Poor cut	91
2	Good cut	181
4	Poor cut	482
14	Good cut	153
21	Poor cut	68

Image 1 has a profile that is generally smooth, with the exception of the additional mass at the right end. It is closer to a smooth profile than Image 21. In keeping with this, the lower FPI value for Image 21 is indicative of a higher degree of distortion, while the higher value of Image 1 is indicative of its greater degree of smoothness in the profile. The FPI indicator is not only able to differentiate between good and poor cuts, but that it also has some capability to assess the level of smoothness.

The poor cut of Image 4 obtained a FPI value of greater than 100. The FPI value obtained was even higher than those obtained for the reference images. The method would have incorrectly categorised Image 4 as a good cut. Of the 15 good cuts assessed, the method was able to identify 14 of them correctly. The cut that was incorrectly categorised had a FPI value of 69 for a 0.5 level value, while its highest FPI value was 96 for a 0.6 level value. The reason for the incorrect categorisation is not certain, but it is likely a consequence of the quality of the image taken. Nonetheless, the accuracy of the method in detecting good cuts was found to be approximately 93%. The second column of Table 3 shows a summary of the calculated detection accuracies.

Table 3. Accuracy of the FPI method for pod stem-end analyses

Category of assessment	Detection accuracy (full or binarised approach)	Detection accuracy (non-binarised)
Poor cuts	60%	47%
Good cuts	93%	87%
System total	77%	66%

Conversely, the method showed an accuracy of 60% in the categorisation of poor cuts. This is significantly lower than the accuracy of identifying good cuts and warrants further investigation. Nevertheless, the overall accuracy of the method in its present form is approximately 77%.

4.3 Requirement for Binarisation

The previous results allude to the potential effectiveness of the approach taken, i.e., the use of the FPI as an indicator of edge smoothness in conjunction with an established FPI reference value. In the proposed approach, the accuracy of classification is predicated upon its ability to identify edges in the stem-end images. It was established that the level value affects the quantity of data loss in the binarisation process, and consequently the accuracy of classification. To increase the method's accuracy, the requirement for binarisation was assessed.

The method was implemented without the use of the binarisation step. Firstly, the non-binarised approach was used to assess the reference set of images to determine a reference FPI value. In this instance, it was found that the lowest value of the FPI associated with the reference set was 130. The FPI value of 130 was taken as the reference point for acceptable cut quality, i.e., good cuts were defined as those that had a FPI value equal to or greater than 130. Having defined the reference value, the stem-end profile image set was then assessed using the non-binarised approach. The results are presented in the third column of Table 3. As seen, the non-binarised approach was less effective in categorising the stem-end images than the binarised approach. This approach had an 87% accuracy in categorising good cuts and was somewhat comparable to the binarised approach. However, the non-binarised approach was particularly weaker in categorising poor cuts and had an accuracy of less than 50%.

The results allude to two key issues. Firstly, it would be noted that the binarised approach was generally better than the non-binarised approach in categorising the stem-end images. This indicates that binarisation enhances the categorisation ability of the method. This is likely the case, as binarisation allows edges to be enhanced within the image. This subsequently leads to more accurate representation of the stem-end profile and ultimately more effective categorisation. The second trend of interest concerns the poor cuts. It would also be noted that both methods were weaker in categorising poor cuts than good cuts. This suggests that correct classification of poor cuts requires a more accurate capture and representation of the stem-end profile than in the case of good cuts. This is a logical result, as the determination of a poor cut is predicated upon the recognition of asperities, unevenness in the profile and the presence of additional masses; all of which constitute greater image detail for the stem-end profile.

The absence of this detail leads to an inaccurate representation of the stem-end profile, i.e., the appearance of a smooth edge and results in the incorrect classification by the approach. Moreover, these details in the stem-end profile must be differentiated from the surrounding environment. As such, the improved performance of the binarised approach is likely due to its ability to remove the influence of background and other irrelevant details in the image that may be incorrectly incorporated in the Sobel algorithm, leading to an incorrect FPI calculation. In keeping with this, binarisation is considered to be important in increasing categorisation accuracy and consequently, the binarised approach is favoured to the non-binarised approach in the implementation of the method.

4.4 Windowed Fourier Analyses and the WFPI Method

Though the proposed FPI method was particularly strong in categorising good cuts, it was not as effective in categorising the poor cut stem-ends in the sample set. An analysis of the incorrectly categorised poor cut images reveals a critical issue, i.e., two-thirds of them share a similar feature. The incorrectly categorised stem-ends generally shared the characteristic of having long, smooth excess bark material attached to the stem-ends. An example of this is seen in Image 4 of Figure 6. The additional bark material is often positioned horizontally with respect to the image coordinate system. The excess mass is interpreted as a straight edge and leads to a high FPI value as seen in Table 2. Consequently, they are miscategorised as good cuts.

In light of this, a modified form of the FPI method is proposed here and will be referred to as the Windowed Fourier Peak Index method (WFPI). The WFPI is represented by Equation 2. The WFPI segments an image of M x N pixels into a series of smaller images of M x n pixels, where n is a factor of N. Having segmented the image, the usual FPI algorithm is executed. Thus, unlike the FPI which yields a single value, the WFPI yields a vector of FPI values. In dividing the image into smaller sections, the WFPI tracks the development of edges across the vertical length of the image and essentially assesses the composition of the profile for that image.

$$\begin{pmatrix} F(k,l_1) \\ F(k,l_2) \\ \vdots \\ F(k,l_a) \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{M-1} \sum_{i=0}^{n-1} f(i,j) e^{-i2\pi\left(ki/_M + l_1 j/_n\right)} \\ \sum_{i=0}^{M-1} \sum_{i=n}^{2n-1} f(i,j) e^{-i2\pi\left(ki/_M + l_2 j/_n\right)} \\ \vdots \\ \sum_{i=0}^{M-1} \sum_{i=(a-1)n}^{(a)n-1} f(i,j) e^{-i2\pi\left(ki/_M + l_a j/_n\right)} \end{pmatrix} \quad (2)$$

In a similar manner to the FPI method, the WFPI method is first assessed using the set of reference images. Some examples of the set of FPI values obtained for each type of reference image are plotted and presented in Figure 7. In addition, the WFPI is used on the subset of poor cuts. An example of the result obtained is shown in the figure. Unlike the FPI method where the key indicator of cut quality was a single FPI value, in the WFPI method the cut quality is defined by the nature of the FPI value plots. More specifically, the magnitude of the plotline gradient and the number of inflexion peak points are the primary indicators here.

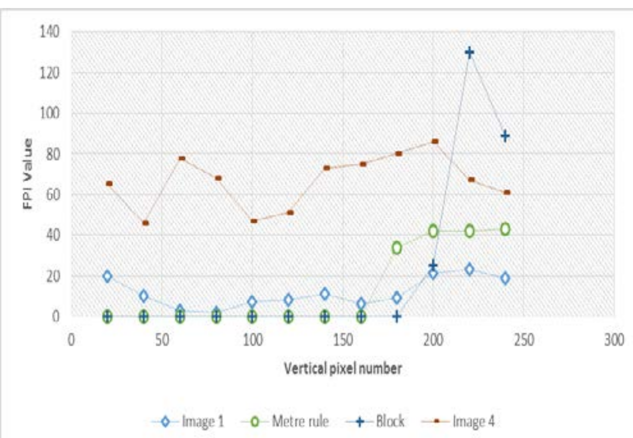

Figure 7. WFPI Plots for Various Images

Though a higher magnitude of the FPI is still indicative of the presence of a smooth profile or straight line, it is the change of FPI value across the vertical length that is more instructive. For the purposes of this work, the gradient is defined as the change in FPI value with change in vertical pixel distance. In keeping with this, rapid increases in the gradient of the FPI plot across successive image sections can be interpreted as a progression from a rough area to a smoother one. Conversely, a generally consistent FPI value across successive image sections, indicates that the level of smoothness in the image has not changed significantly over this region. In like manner, an inflexion peak point is a peak on the plot line where the sign of the gradient changes.

Having defined the two indicators of gradient value and number of inflexion peak points, it was found that the reference images were characterised by plots having no more than one inflexion peak point, while having three or more points over which the gradient is positive and usually large. In general, these plots show consistent low FPI values for the first few image sections and then rise rapidly over the remaining sections (see Figure 7). This can be explained by the nature of the image. In each case, the nature of the image above the straight edge profile is characterised by the image background. Once binarised, this results in either a completely black area or an area having a lot of irregular shapes. The associated FPI values are either zero (for completely black areas) or very low. Once the image section moves below the straight edge, this results in image sections that contain straight edges. As such, the resulting FPI values are larger. This sudden change in FPI value produces a large gradient.

Conversely, poor cuts were found to be characterised by smaller, fluctuating gradient values that were lower in magnitude, while having two or more inflexion points. This is also a result of the image composition. For the poor cuts, some portion of the excess mass generally extends beyond the profile. Thus, when the image is sectioned, portions of the excess mass can be found in several of the sectioned images. Given that the excess mass is not necessarily distributed evenly in terms of size or orientation, the resulting magnitude of the FPI value generally fluctuates across the sectioned images, leading to inflexion points in the plot line.

Based on the aforementioned criteria, the WFPI method was used to assess the set of images that were miscategorised by the FPI method. Of the seven (7) cuts that were miscategorised, the WFPI was able to identify six (6) of these correctly. The WFPI was able to correctly identify both good cuts and poor cuts that were incorrectly categorised by the FPI.

4.5 FPI and WFPI: Wider Method Applicability

If the results of the FPI and WFPI methods are combined, the combined approach would have been successful in correctly categorising 29 of the 30 stem-end images. This results in a combined accuracy of approximately 97% and is a favourable outcome for this work. The results obtained here are not limited to this study and can be replicated without attenuation in a larger context.

Though a larger sample size will be required to give a more precise evaluation of the approach's key values and overall accuracy, the principles underlying its efficacy are scalable and uninfluenced by sample size. The results obtained here allude to a number of key issues to be considered in the wider implementation of this approach.

Perhaps the first of these concerns the structure of the algorithm used.

Given the results of this work, a combined implementation would be more favourable than that of the standalone FPI method. However, any combination must consider the unique computational requirements of each method. Due to the WFPI's iterative nature, the method requires more processing time than the FPI method. Thus, its use in an in-situ or real time computer vision or image analysis system, would require either greater computational power or result in longer processing times than the FPI method.

Notwithstanding this, the nature of the combination can vary depending on the user's requirements and the quality of the input images. A second key consideration concerns the standardisation of image acquisition conditions. The conditions under which images were acquired for this work were not standardised. Though this allowed for greater ease of implementation and was more in keeping with the context of this work, a larger scale implementation may benefit from a standardised approach. Greater lighting controls combined with fixed stem-end orientations during image acquisition can result in better images for assessment.

A final point of consideration concerns the intent of the user. Accurate images present the detail leading to better analysis. A standalone FPI method implementation may be insufficient for the WFPI method. Moreover, if a cursory or preliminary assessment of an image set is required, then a standalone FPI implementation may suffice, regardless of the image quality. If greater accuracy is required, poorer image quality may require a sequential implementation, where the WFPI method is used to corroborate the results of the FPI for poor cut images. Yet, if the user is not constrained by computational capacity, the FPI may be omitted in favour of the WFPI for the images to be analysed. There exists some measure of flexibility in the manner in which the system can be implemented at the user's discretion. It must be guided by image quality, accuracy requirements and computing capacity.

The inherent flexibility of the approach significantly influences its usefulness and the manner in which it can be leveraged by users. Implementation of the approach can be tailored to achieve differing objectives, leading to a range of potential iterations. In one possible iteration, the approach can be implemented in a semi-automated manner where farmers manually review and assess images over a selected period. The sole objective may in this instance be the assessment of a harvester's cutting proficiency with the intent of making changes to personnel scheduling.

Moreover, the approach can be implemented as a part of a real-time computer vision system that assesses collected pods and makes determinations about tool sharpness and reliability, as well as recommendations about tool replacement or tree health. Such information as harvesting time, number of pods harvested per tree and origin of each pod would be coupled with the approach to develop a robust system. The approach's implementation would potentially provide farmers and field owners with insights to facilitate field management and tool maintenance interventions. These insights aid farmers and field owners in addressing the current need to minimise harvesting cost, while maximising field output.

5. Conclusion

This work is sought to examine the use of a Fourier based method for the examination of cut quality in cocoa pod stems. It proposed two methods: namely the Fourier Peak Index (FPI) and windowed Fourier Peak Index (WFPI) methods. These methods were used to assess a set of forty (40) images taken in the field, under non-specified and non-controlled conditions.

The following key findings were noted:

1. The FPI method was able to assess images using a single value as an indicator of cut quality. A FPI value of 100 was a demarcation point; values lower than 100 were associated with poor cuts, while higher values were associated with good cuts.
2. Based on the FPI value as an indicator of cut quality, the method has a categorisation accuracy of 93% for good cuts, while an accuracy of 60% was observed in the identification of poor cuts. The overall accuracy of the method was approximately 77%.
3. The WFPI was developed as an enhanced form of the FPI. In this method, the magnitude of the plotline gradient and the number of inflexion peak points were suitable indicators of cut quality.
4. The WFPI was able to identify most of the images that were miscategorised by the FPI. A combined approach increases the categorisation accuracy of the methods, with the potential for as much as 97% accuracy.

Both FPI and WFPI methods have the potential to be effectively used in computer vision or image analysis approaches for the assessment of pod stem-end cut quality. The exact nature of the implementation should be guided by the users' requirements and constraints. Notwithstanding the focus on cocoa pod stem-ends, the results obtained from this work could be adopted for applications in other assessments of cut quality. As such, this work provides a platform for further investigation and research in other areas.

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