Image Entropy as the Quality Metric in Automating Agricultural Imaging Tasks

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Abstract : Image pre-processing is an important step in any of the machine vision task. Pre-processing involves application of certain techniques of digital image processing so as to enhance the image. Images that are captured may contain noises due to various factors and hence there is a need to enhance them before any image classification/analysis task can take place. However, in order to apply a suitable pre-processing step, we need to have a parameter that measures whether we are applying the right method or not. Image quality metrics play a vital role in this regard. Present paper discusses the available image quality metrics and a detailed review of their application in various agricultural imaging tasks. Goal of the present survey is to provide an insight into the available image quality metrics as far as post-harvest processing of agriculture images is concerned. The study also presents a detailed survey on need for using Image Entropy as the metric that can be effectively considered in order to assess the image quality in the agriculture domain.

Index Terms— Automation in agriculture, Image quality in agriculture, Machine vision in agriculture, Quality metrics for image.

1. INTRODUCTION

Measurement of visual quality is of fundamental importance to numerous image processing applications. The quality of an image can be defined as the subjective blend of all of the visually important attributes in an image. There are various factors that influence the image quality such as the sharpness, noise, color accuracy, dynamic range, distortion, uniformity, chromatic aberrations, flare, compression, artifacts, color gamut etc. [3].

There are basically two methods to assess the image quality: subjective and objective. Subjective methods are centered on the perception assessment of a human observer, about the characteristic attributes of a set of images. The objective methods are centered on computational representations that can forecast the perceptual image quality. However, there are various drawbacks of subjective measurement of image quality. They are: the subjective assessment is cumbersome, expensive. Moreover they cannot be fused with the automated systems where in the systems may need to work in real time. In the agriculture domain, where the domain itself is characterized by uncertainty, such subjective assessments are not preferred at all. Therefore the goal of the quality assessment is to design algorithms for objective evaluation of the image quality. And such evaluations should be consistent enough with the subjective evaluation. Objective evaluations also help significantly in the arena of testing, bench-marking, optimization of imaging systems and monitoring solicitations [1], [2].

II. MACHINE VISION IN AGRICULTURE DOMAIN

Quality inspection of agricultural products presents definite challenges when compared to that of industrial products as the aspect such as appearance is inconsistent and imprecise [4] (Deepa, P., & Geethalakshmi, S. N., 2011). Food industry is amongst the top ten industries that expansively make use of machine vision. Its role is irreplaceable in the field of automated sorting and grading of agricultural, horticultural and food products. There are many problems that the agricultural industry experiences. These include subjectivity, high losses in post-harvest, tediousness, inconsistency, labor requirements, availability etc. Experimentations have revealed that such problems can be overcome by incorporating computational intelligence and digital image processing techniques in the process.

A. IMAGE ACQUISITION IN AGRICULTURE DOMAIN

With the expansions in the areas of Digital Image Processing and Intelligent Control technologies, Machine Vision is widely used in agriculture. Various domains of agriculture that widely make use of the machine vision include crop detection, germs detection in crops, classification of agricultural products, agricultural Robots, robotic applications including visual navigation for fruit picking robot, non-destructive information monitoring for crops etc.

In order to pursue aforementioned purposes in agriculture, we need to have a dataset of images. The agriculture image data set can be collected either synthetically or real time. Almost in all cases, real time images are acquired and a dataset is built rather than synthetic images. However there are few exceptions to this. To mention, Bossu, J. et.al, [5] generated a simulated synthetic images in order to differentiate crop and weeds. However the task of image acquisition is inevitable in every application involving machine vision.

The task of image acquisition can be done in two ways. Images can be acquired either in field or in a laboratory environment such as a closed environment with light sources. Table I summarizes the image processing tasks in which images are acquired in field. Table II summarizes the image processing tasks in which images are acquired using laboratory conditions.

Table I: Image processing tasks with images acquired in field

Sl. No	Citation	Objective of the study
1	Youwen, T et.al, [34]	Recognition of cucumber diseases
2	Yao, Q et.al,[35]	Detection of rice diseases
3	Wu, S. G et.al, [36]	General purpose leaf recognition for plant identification
4	Camargo, A., & Smith, J. S. [40].	To identify visual symptoms of banana and plantain
5	Meunkaewjinda, A et.al, [41]	Detection of grape leaf diseases

Table II: Image processing tasks with images acquired under laboratory conditions

Sl. No.	Citation	Objective of the study
1	Liming, X., &Yanchao, Z. [6]	Developed a closed environment in order to capture and grade strawberry fruits
2	Kurtulmuş, F., &Ünal, H. [7]	Used a CCD scanner in order to acquire rapeseed images and discriminate among their varieties
3	Jamil, N et.al, [31]	To automatically grade palm oil fresh fruit bunches
4	Unay, D., & Gosselin, B. [32]	Grading of apples
5	Omid, M et.al, [33]	Grading of raisins
6	Font, D et.al, [37]	Verification of in-line nectarine variety
7	Rocha, A et.al, [38]	Automated classification of fruit and vegetables
8	Mizushima, A., & Lu, R. [39]	Sorting and grading of apples

In case when the image processing tasks with images acquired in field following are the parameters that affect the image quality:
• Position of the camera
• Variations in the outside light
• Type of image acquisition unit
In case when the image processing tasks with images acquired in a simulated environment, characteristics of the light source present plays a crucial role in determining the image quality. Following are the parameters that affect the image quality:
• Position of the camera
• Characteristics of the light source
• Type of image acquisition unit

In case of post-harvest quality assessment of agriculture produce, the images are captured under a simulated environment. Such an environment may consist of a closed box/chamber with light source and cameras mounted inside and the objects (i.e., agriculture produce) are imaged. There can also be a moving conveyor belt on which the produce is put and it is imaged, mimicking the industrial fruit lines.
Whether we are acquiring images in field or a simulated environment, we need to apply few of the image pre-processing techniques. However the techniques that we need to apply will vary depending on whether the images are acquired in field or in chamber.

In case if the images are acquired in a simulated environment, the light has effect on the results out of machine vision task. Therefore, we need to properly pre-process the images before further tasks, such as feature extraction, are applied on the images.
When we pre-process the images, the image quality may change. The information present in the image may change. In order to know the whether the image quality has changed, we have various metrics available in the image processing domain. In this

regard, aim of the present work is to give a comprehensive study on the available metrics for measuring the image quality in the field of agriculture imaging tasks. The survey presented here also throws a light on various recent works pursued by the researchers and the quality metric employed by them. The work also presents informational entropy as a quality metric which is applied a far less in the field of agriculture. A motivation to use the same has been presented with the evidence.

III. IMAGE METRICS/FACTORS

As discussed in the previous section, image quality can degrade due to distortions during image acquisition and processing. Examples of distortion include noise, blurring, ringing, and compression artifacts. In every image processing task image preprocessing is must and should in order to remove any distortions. Image preprocessing plays a crucial role because it inspirits the further imaging processing and classification and decision tasks. Therefore, we need a form of metrics/factors that allow us to objectively conclude that the image after preprocessing has been enhanced.

There are few advantages of having quality metrics. Viz. (1) for many application the quality metric associates well with the subjective perception of quality by a human observer. (2) Quality metrics can track unobserved errors as they disseminate through the image processing pipeline and (3) the metrics are used to compare various algorithms of an image processing task.

A. FULL-REFERENCE QUALITY METRICS

In case of availability of the original image in its undistorted form, we can use it as a reference in order to assess the quality of other images. To illustrate, in case of image compression, the uncompressed form of the image serves as the reference. We can directly compare the other images with reference to this original image. Following are the full-reference quality metrics (Anonymous, 2018):

i) Peak signal-to-noise ratio (PSNR): The PSNR is used to compute the peak signal-to-noise ratio between two images. PSNR is derived from the mean square error. It indicates the ratio of the maximum pixel intensity to the power of the distortion. Higher the PSNR, the better the quality of the compressed, or reconstructed image.

ii) Mean-squared error (MSE): MSE measures the average squared difference between actual and ideal pixel values. It signifies the cumulative squared error between the compressed/reconstructed image and the original image, whereas PSNR signifies a extent of the peak error. Lower the MSE, lower the error. This metric may not align well with the human observation of quality. MSE is given by the formula (1) and PSNR is given by formula (2).

$$MSE = \frac{\sum_{M,N}[I_1(M,N) - I_2(M,N)}{M*N} \text{............} (1)$$

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \text{........ ....} (2)$$

Where, M,N are the number of rows and columns. I_1andI_2 are the original and reconstructed images. R is the maximum fluctuation of the data type of the input image.

iii) Structural Similarity (SSIM) Index: The SSIM metric represents a single score of quality comprising local image structure, luminance and contrast. Since the human visual system is good at distinguishing structures, this metric settles more closely with the subjective quality score. It is calculated using the formula (3)

$$SSIM = \frac{(2\mu_X\mu_Y + C1)(2\sigma_{XY} + C2)}{(\mu_X^2 + \mu_Y^2 + C1)(\sigma_X^2 + \sigma_Y^2 + C2)} \text{..........} (3)$$

Here, μ_X,μ_Y,σ_(X,) σ_Y and σ_XY are the local means, standard deviations and cross covariance for images x,y. C1 and C2 are the constants.

B. NO-REFERENCE QUALITY METRICS

If a reference image without distortion is not available then we can go for a no-reference image quality metric. These metrics calculate the quality scores depending on expected image data. They compare statistical features of the input image in contradiction to a model trained with a large dataset of images that are acquired naturally. Following are the metrics:

i) Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE). A BRISQUE model is trained on a database of images with known distortions. Limitation of this method is that we can evaluate the quality of images only with the same sort of distortion.

ii)Natural Image Quality Evaluator (NIQE). NIQE can measure the quality of images with random distortion.

Liu, S., Zhang, Z., Qi, L., & Ma, M. (2016) presented a fractal image encoding in order to compress the agriculture images. The results were demonstrated by considering PSNR as one of the quality attributes of the images before and after compression. Al-Amri, S. S., Kalyankar, N. V., & Khamitkar, S. D. (2010) used PSNR and MSE as the statistical measures in order to compare the noise removal methods using various filters applied to Saturn remote sensing images. Garg, A. et.al, (2014) attempted to increase the resolution of the satellite images using discrete wavelet transform (DWT) and the results were compared using PSNR as the metric. This indicates that, the image information is not lost when DWT is applied to the images. Valliammal, N., & Geethalakshmi, S. N. (2011) made use of PSNR and MSE as the evaluation criteria in order to assess the quality of the reconstructed images applied to leaf recognition and characterization. Lili, N. A., Khalid, F., & Borhan, N. M. (2011) analyzed the image restoration performances using PSNR and MSE as the metrics in noise removal of the herb plants for the purpose of disease classification. PSNR is used as the filtering efficiency criterion by Ponomarenko, N. et.al, (2009) in pre filtering the multi channel remote sensing data applied to classify and extract data related to bare soil erosion of agricultural fields. Various image segmentation and classification techniques in the filed of agriculture extensively make use of PSNR and MSE as per the survey conducted by Jayanthi, M. G., & Shashikumar, D. R. (2017).

However in certain circumstances PSNR may not be a suitable evaluation criterion for analysis of reconstruction image quality as suggested by Zhang, R. et. al, (2012). The SSIM has proven to be useful in extracting the structural information of a scene, out of the HSV channel. The supportive work has been carried out by Wang, Z. et.al, (2004). However it may fail to work for the badly blurred images as indicated by Kai-zhi et. al, (2006). And there are improvements that are done to SSIM and variations of the methods have been proposed. Lin Zhang et.al, (2011) proposed a novel method called as Feature Similarity (FSIM) Index with appropriate validation results. Wang, Z. et.al, (2003) proposed Multi Scale Structural Similarity (MS-SSIM) index for quality assessment of images. Li, C., & Bovik, A. C. (2009) proposed Three Component –SSIM (3-SSIM) and Three Component –SM-SSIM (3-SM-SSIM) as alternatives to SSIM and MS-SSIM that can effectively handle the noisy and blurred images.

IV. ENTROPY AS ONE OF THE QUALITY CRITERION

The afore discussed metrics i.e., PSNR, MSE and SSIM considers the difference of intensity or color values for measuring the image quality and they measure the image quality based on how much the structures of the image are distorted (Basha, G., & Basheera, S. 2014). However using the histogram of a signal to figure out the Shannon information/entropy ignores the temporal or spatial structure (Image, E. 2018) and it is simply defined mathematically as shown in equation (4).

$$\mathrm{H} = -\sum p \log_2 p \ldots\ldots\ldots (4)$$

where p contains the normalized histogram counts (Rafael C et.al, 2009). In general, the entropy of the image can be considered as one of the quality metric. Table III presents few of the research works that considered entropy as the quality metric.As far as addressing the issue concerned with the presence of light on the images, there are various works carried out in order to neutralize the effect of light. It was found that histogram equalization can be applied whenever there is a light source during imaging. The works supporting this fact are presented in Table IV.However the works presented in Table IV demonstrated that there was a reduction in the informational content of the image which was evident from the analysis of entropy. The authors have applied the techniques in order to enhance the entropy as given by the last column of Table IV. The works presented in Table IV captured images under simulated environment.Hence, from Tables III and IV, it is clearer that Entropy can be considered as one of the important quality metrics. And entropy can be considered as the metric whenever the image acquisition is performed in a simulated environment with a light source. This is because entropy presents the overall informational content of the image.

Table III: Research works that considered entropy as the met

Sl. No	Citation	Images considered	Remarks
1	Hameed, A. and Ali, M. [22]	General	Entropy of First Derivative (EFD) is considered as the as the metric.
2	[23]	Natural photographic images	Spatial–Spectral Entropy-based Quality (SSEQ) index has been developed as the quality metric
3	Soundararajan, R., & Bovik, A. C. [24]	LIVE Image Quality Assessment Database and Tampere Image Database	Reduced Reference Entropic Differencing (RRED) index has been developed as the quality metric
4	[25]	General	A new quality metric based was proposed which was based on measuring the averaged anisotropy of the image on the basis of a pixel wise directional entropy
5	Fu, J. C et.at, [26]	Medical imaging	Entropy is used as the metric to quantify the results of before and after preprocessing

Table IV: Research works that considered addressing of the light on images

Sl. No	Citation	Images considered	Methodology followed
1	Fu, J. C et.at, [26]	Medical images (gastric sonogram images)	Histogram equalization followed by wavelet post-processing
2	YIN, S. C., & YU, S. L. [42]	Infrared images	histogram equalization algorithm with the wavelet transform
3	Zhang, R et.al, [43]	Medical images (ultrasonic liver images)	wavelet denoising and histogram equalization

It is also worth to note that there are no remarkable works that are carried out on the analysis of entropy as far as agriculture imaging is concerned.

In view of this, the authors have considered entropy as one of the quality metric of the agriculture imaging. The work has been carried out using pomegranate fruit images and is available at (Kumar, R. A., & Rajpurohit, V. S., [27]).

V. CONCLUSION

The present review paper throws a light on available image quality metrics and their applications in various dimensions of machine vision. The study begun by expounding the image quality and the metrics to be used to assess the image quality. Present study explains different methods of image acquisition in machine vision tasks of agriculture domain. Goal of the Present review is to give an insight into the image quality metrics that can be considered in agriculture imaging tasks. Accordingly, the metrics and their usefulness have been provided with the sufficient literature. The paper also suggests that there is a great scope to consider Image Entropy as one of the quality metrics with supporting review on the same.

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