SUGAR CENTRIFUGE IMAGE CLASSIFICATION

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Abstract

Sugar production from sugarcane is a complex industrial process involving multiple stages, with centrifugation playing a crucial role in separating sugar crystals from molasses. Accurate control of water addition during centrifugation is essential to minimize sugar loss and optimize efficiency. Traditional image analysis techniques, such as Otsu thresholding, have been used to monitor sugar quality but are highly sensitive to lighting variations, leading to inconsistent results. This work from the study group presents an improved sugar centrifuge image segmentation algorithm based on k-means clustering to enhance the accuracy and reliability of sugar quality assessment. The methodology involves preprocessing through contrast-limited adaptive histogram equalization (CLAHE) to improve image contrast, followed by k-means clustering for pixel classification. A sugar ratio metric is introduced to estimate sugar purity by analyzing intensity distributions near the rim of the centrifuge basket. Results show that k-means clustering outperforms Otsu thresholding, providing more reliable segmentation and accurate estimation of sugar content. Future work will focus on correlating the sugar ratio with lab-measured purity to develop a robust real-time monitoring system for sugar milling operations.

1 Introduction

Sugar production from sugar cane is a complex industrial process that involves multiple stages, each of which plays a critical role in obtaining high-quality sugar. These stages

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include preparation, extraction, evaporation, boiling, and centrifuging. Understanding the intricacies of each step is essential for optimizing efficiency and ensuring a consistent final product. In the preparation stage, harvested sugarcane is shredded into small pieces to facilitate juice extraction. The extraction stage involves washing out the sugar and other dissolved solids from the shredded cane using a diffuser. The extracted juice, however, contains impurities and requires further processing to achieve the desired sugar concentration.

During the evaporation stage, the extracted juice is thickened using a series of evaporators that remove excess water. This process increases the sugar concentration and prepares the juice for crystallization. In the boiling stage, vacuum pans further evaporate water, allowing sugar crystals to form. Finally, the centrifugation stage separates the sugar crystals from the mother liquor, yielding raw sugar and molasses.

The centrifugation process is a crucial final step in sugar production. The mixture of sugar and molasses, known as massecuite, is introduced into a centrifuge basket that rotates continuously at approximately 2,000 revolutions per minute. Due to the conical shape of the basket, the massecuite migrates toward the rim, while the molasses passes through a screen, leaving behind purified sugar crystals. Ideally, when the sugar reaches the rim, it should be free of molasses. Water is introduced to facilitate this separation, and the efficiency of the process depends directly on the quantity of water added. Excessive water use can lead to sugar losses, whereas insufficient water results in poor separation and the need to reprocess non-sugar materials.

A fundamental challenge in this process is determining the optimal amount of water required, which necessitates real-time monitoring of sugar quality. To address this, the Sugar Milling Research Institute has developed a camera-based system designed to optimize water addition during sugar centrifugation. This system features a camera mounted atop the centrifuge, focused on the screen inside the machine. A stroboscopic LED light is triggered to freeze frames, allowing for clear observation of the sugar flow on the screen. The system's primary objective is to analyze these images to assess sugar quality and generate automated control actions that enhance the centrifugation process. Consequently, the system heavily relies on its ability to analyze images efficiently and accurately.

The study group believes that a robust image segmentation technique can effectively address this challenge, improving the current Otsu thresholding image analysis. Accurate segmentation and analysis of centrifuge images are essential for developing a reliable control system that ensures operational efficiency while minimizing sugar loss.

The rest of this article is structured as follows. Section 2 discusses the challenges associated with sugar centrifuge image analysis. Section 3 provides a review of existing image segmentation techniques and relevant research. Section 4 introduces a proposed algorithm based on k-means clustering. Section 5 presents the results of this approach, followed by the conclusions in Section 6.

2 Problem statement

The Sugar Milling Research Institute has been developing a camera-based system to control the quantity of water added to a sugar centrifuge [2]. The system consists of a camera mounted above the centrifuge, focused on the centrifuge screen. A stroboscopic LED light is triggered to freeze frames, enabling clear observation of the sugar flow on the screen. The goal is to use image analysis to assess sugar quality and generate appropriate control actions based on the results.

A typical frame captured by the system is shown in Figure 1. The massecuite, which appears predominantly dark, enters the basket at the hub and migrates up the screen. Ideally, clean sugar remains in the basket while non-sugar material is expelled over the rim of the centrifuge. However, depending on the nature of the feed, finger-like patterns may form on the screen surface. If too many of these patterns reach the rim, excess non-sugar material is reprocessed, reducing efficiency. Conversely, if the sugar appears excessively clean, it may indicate an overuse of water, leading to the undesired dissolution of sugar into molasses. To strike the right balance, the control system must accurately analyze the images and determine the optimal water quantity.

The current system employs Otsu thresholding to binarize the images, simplifying the analysis process. The control action is derived by calculating the sugar ratio, which is determined by counting the number of white pixels within a defined rectangular region adjacent to the basket rim. However, the effectiveness of this method is heavily influenced by lighting conditions and threshold settings. Poor illumination at the edges of the image can result in the false detection of massecuite, leading to inaccurate control actions. Additionally, the binarization process struggles to differentiate between fully dark and fully light images, reducing its reliability.

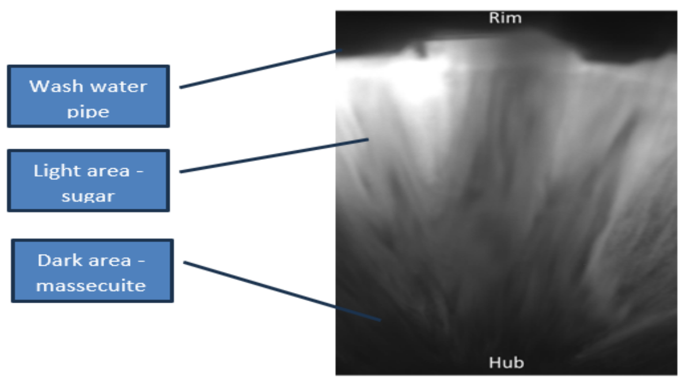

Figure 1: A typical centrifuge image

Due to these limitations, industry representatives have expressed the need for a more robust image segmentation technique that is resilient to variations in lighting conditions. Developing an improved approach that enhances accuracy and reliability is essential for optimizing the centrifugation process and minimizing sugar losses.

3 Literature review

Thresholding is a fundamental technique in image processing used for segmentation, where an image is divided into foreground and background regions based on pixel intensity values. Several thresholding methods have been proposed, each offering different advantages in terms of computational complexity and segmentation accuracy.

One of the most widely used thresholding techniques is the method proposed by Otsu [3], which is a nonparametric and unsupervised approach. Otsu's method selects an optimal threshold by maximizing the inter-class variance between object and background regions. A key advantage of this method is that it does not require prior knowledge of the image's histogram distribution, making it a robust choice for various applications. The algorithm computes the optimal threshold using the zeroth- and first-order cumulative moments of the histogram, identifying the point that minimizes intra-class variance while maximizing class separability. Due to its computational efficiency and effectiveness in bimodal histogram segmentation, Otsu's method is extensively used in medical imaging, document binarization, and industrial quality inspection. However, its performance deteriorates under uneven lighting conditions, which has led to the development of adaptive and hybrid variations to improve robustness in complex environments.

Beyond thresholding techniques, clustering-based segmentation methods have gained traction in image processing due to their ability to partition images into meaningful regions. One of the most widely adopted techniques in this category is k-means clustering, an unsupervised learning algorithm that classifies pixels based on their intensity values. Dhanachandra et al. [1] proposed an improved approach by integrating k-means clustering with subtractive clustering to enhance segmentation accuracy. Their method begins with image pre-processing using partial contrast stretching to improve quality, followed by subtractive clustering to determine initial cluster centers. These centers are then used in k-means clustering to achieve more precise segmentation. Finally, a median filter is applied to refine the segmented image, reducing noise and unwanted artifacts. Inspired by this approach, our study adopts a similar strategy for segmenting sugar centrifuge images, aiming to improve segmentation reliability under varying lighting conditions.

Recent advancements in image segmentation have explored adaptive clustering techniques, incorporating fuzzy logic and deep learning for enhanced robustness. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image processing tasks. One of the most effective architectures for image segmentation is U-Net, introduced by Ronneberger et al.[4]. Initially designed for medical image segmentation, U-Net has since been adapted for numerous applications due to its ability to generate highly accurate segmentations with minimal training data. Given the nature of sugar centrifuge images, the application of U-Net is particularly appealing. However, deep learning models require a well-curated dataset for training, which is currently unavailable. Although efforts were made to curate data from centrifuge video footage, the available resources were insufficient to implement and train the model effectively. As a result, despite its potential, a deep learning-based approach is currently not viable for the Sugar Milling Research Institute due to resource constraints.

Given these limitations, our study focuses on enhancing existing thresholding techniques using clustering-based segmentation. By leveraging k-means clustering with appropriate pre-processing techniques, we aim to develop a robust and computationally efficient method for segmenting sugar centrifuge images, ensuring reliability across varying lighting conditions and operational scenarios.

4 Methodology

To maximize the use of available resources, the study group aimed to improve the Otsu thresholding technique by implementing a more robust segmentation approach. A sugar centrifuge image segmentation algorithm using k-means clustering was designed to address the problem at hand. The proposed algorithm consists of three main stages: preprocessing, k-means clustering, and sugar ratio computation, as illustrated in Figure 2.

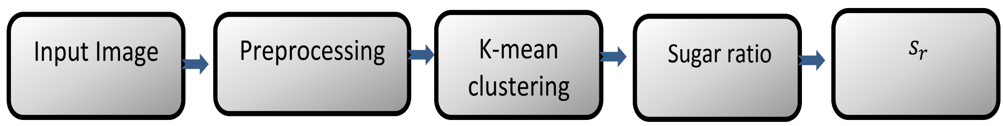

Figure 2: The block diagram of the proposed algorithm

4.1 Preprocessing

Sugar centrifuge images are often noisy, blurred, or low-contrast, with inconsistent lighting. Thus, the first step in the algorithm is image enhancement to improve segmentation accuracy. The preprocessing phase involves cropping the image to focus on the region of interest removing irrelevant areas such as the hub and rim. This is followed by contrast enhancement using Adaptive Histogram Equalization (AHE) to improve apparent contrast under uneven illumination.

AHE enhances image contrast, making it particularly useful for handling uneven lighting and low-contrast images. Unlike traditional histogram equalization, which applies a global contrast adjustment, AHE operates on smaller, non-overlapping tiles of the image, adjusting contrast locally within each region. The transformation function for each tile is defined as:

$$T_t(r) = \frac{F_t(r) - F_t(r_{min})}{F_t(r_{max}) - F_t(r_{min})}(P-1),$$

where r represents the pixel intensity, r_{min} and r_{max} are the minimum and maximum intensity values in the tile t, P is the number of possible intensity levels (typically 256), and $F_t(r)$ is the local cumulative distribution function calculated as:

$$F_t(r) = \sum_{i=0}^{r} h_t(i),$$

where $h_t(i)$ is the histogram count of intensity i in the tile, t. A pixel at position (x, y) with intensity $r = p(x, y)$ in the tile is then mapped to a new intensity $p'(x, y)$ based on the transformation function:

$$p'(x, y) = T_t(p(x, y)).$$

The transformation function $T_t(\cdot)$ normalizes the pixel intensities within each tile, stretching the contrast based on the local histogram. This localized contrast enhancement improves visibility in both dark and bright areas without distorting the overall image balance.

Since AHE applies different contrast adjustments to individual tiles, sharp intensity differences may arise at the boundaries between adjacent tiles. To prevent these artifacts, bilinear interpolation is applied to smooth the transitions between regions. The pixel intensity in the output image is computed as:

$$p'(x, y) = \sum_{i=1}^{4} w_i p'_i, \quad \text{with} \quad \sum_{i=i}^{4} w_i = 1, \quad w_i \geq 0, \tag{1}$$

where p'_i are the adjusted intensities from the surrounding tiles,w_i represents weights based on the pixel's proximity to tile centres, and i runs over the four tiles whose centres form the axis-aligned rectangle bracketing the pixel (x, y).

To avoid excessive enhancement or noise amplification in uniform areas, Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied. CLAHE introduces a clip limit (c) to constrain histogram peaks, preventing over-enhancement and ensuring more natural-looking results. By redistributing excess histogram values and normalizing the transformed histogram, CLAHE enhances contrast while maintaining noise suppression.

4.2 The k-means clustering algorithm

The second stage of the algorithm applies k-means clustering, a widely used unsupervised learning technique for image segmentation. In grayscale images, each pixel is treated as a one-dimensional data point, where the feature is the pixel intensity value.

The algorithm starts by randomly initializing k cluster centroids, $\{\mu_i\}_{i=1}^{k}$, in the intensity space. Each pixel is assigned to the nearest centroid based on the Euclidean distance metric. After assignment, centroids are updated by computing the mean intensity of all pixels within each cluster:

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x, \tag{2}$$

where $|C_i|$ is the number of pixels in cluster C_i, and x is a pixel's intensity value. The algorithm iteratively repeats the assignment and centroid update steps until centroids converge or a maximum number of iterations is reached. The objective function minimized by k-means is the total intra-cluster variance, given by:

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2, \tag{3}$$

where J represents the sum of squared distances between each pixel x and its assigned cluster centroid μ_i. The k-means clustering algorithm follows these steps:

1. Choose k initial centroids, $\mu_1, \mu_2, \ldots, \mu_k$, randomly.

2. Assign each data point x_j to the cluster with the nearest centroid:

$$C_i = \left\{ x_j : \|x_j - \mu_i\|_2^2 \leq \|x_j - \mu_l\|_2^2, \quad \forall l = 1, 2, \ldots, k \right\}.$$

3. Update the centroid of each cluster C_i to the mean of its points:

$$\mu_i = \frac{1}{|C_i|} \sum_{x \in C_i} x.$$

4. Alternate between steps 2 and 3 until convergence, $\|\mu_i^{(t+1)} - \mu_i^{(t)}\|_2^2 \leq \epsilon$.

Once the algorithm converges, each pixel in the image is assigned to its respective cluster, producing a segmented image where regions correspond to the clusters. The k-Means method is effective for segmenting images with distinct intensity distributions. However, the number of clusters (k) must be predefined, and improper selection can lead to under- or over-segmentation. Furthermore, The quality of the final clustering results depends on the arbitrary selection of initial centroids. If the initial centroid is randomly chosen, different results will be obtained for different initial centres. Running the algorithm multiple times to select the best clustering result increases computational complexity. To mitigate these issues, k-means++ initialization and incorporating spatial features can improve segmentation accuracy and robustness.

4.3 Sugar ratio

The sugar ratio (s_r) is a key metric used to quantify the brightness distribution of pixel clusters near the rim of the centrifuge image. This metric helps assess sugar purity by analyzing the concentration of lighter pixels in the segmented image. The sugar ratio is calculated as follows:

$$s_r = \frac{\sum_i^k \nu_i N_i}{P \times N}, \tag{4}$$

where k represents the total number of pixel clusters, ν_i is the mean pixel intensity of cluster i, and N_i is the number of pixels in cluster i. The numerator computes the total intensity contribution by weighting each cluster's mean intensity with its pixel count. In the denominator, P is the maximum possible pixel intensity (commonly 255 for 8-bit images), and $N = \sum_i N_i$ is the total number of pixels in the region of interest. Together, $P \times N$ normalizes the weighted intensity contribution, ensuring the sugar ratio remains a unitless value between 0 and 1. A higher sugar ratio indicates brighter, purer sugar, whereas a lower ratio suggests contamination with non-sugar materials.

The computed sugar ratio must be correlated with laboratory-measured sugar purity to validate its accuracy and effectiveness in quality control. This correlation will help refine the segmentation process and improve the reliability of real-time sugar centrifuge monitoring.

5 Results and discussion

In this section, we demonstrate the effectiveness of the proposed algorithm by evaluating its performance in two key areas: the impact of preprocessing and the estimation of sugar purity using the sugar ratio. The preprocessing step is analyzed in Section 5.1, where we highlight its importance in improving segmentation accuracy. In Section 5.2, we estimate sugar purity based on the computed sugar ratio and discuss the algorithm's performance in differentiating sugar from molasses.

5.1 The effect of preprocessing

Preprocessing plays a crucial role in enhancing image quality before segmentation. To illustrate this, we first applied Otsu thresholding and k-means clustering (with $k = 4$ clusters) directly to the original image, Figure 3a, without any enhancement. The resulting segmented images are shown in Figures 3b and 3c, respectively.

Next, we introduced preprocessing by applying contrast-limited adaptive histogram equalization (CLAHE) in addition to cropping irrelevant areas (hub and rim). This enhancement significantly improved the lighting and contrast of the image, as seen in Figure 4a. The effect of preprocessing on Otsu thresholding and k-means clustering is shown in Figures 4b and 4c , respectively.

From Figures 3 and 4, it is evident that preprocessing significantly improves segmentation quality. Without enhancement, both Otsu thresholding and k-means clustering struggle to distinguish sugar from molasses. Otsu thresholding tends to overestimate the presence of sugar, while k-means clustering fails to form distinct clusters due to the similarity in pixel intensity values. After applying CLAHE, the segmented images reveal clearer boundaries between sugar and molasses, especially in k-means clustering, where previously indistinguishable regions become more defined.

(a) Original image (b) Otsu thresholding (c) K-means clustering

Figure 3: The results of K-means clustering after enhancing the image

In this section, we evaluate the ability of the algorithm to estimate sugar purity using the sugar ratio (s_r). The sugar ratio is computed in two scenarios: (1) an image predominantly containing sugar and (2) an image dominated by molasses.

For the sugar-dominant image, shown in Figure 5a, the sugar ratio was computed in the region of interest (20% near the rim). Using Otsu thresholding (Figure 5b), the sugar

(a) Enhanced image (b) Otsu thresholding (c) K-means clustering

Figure 4: The results of K-means clustering after enhancing the image

(a) Enhanced image (b) Otsu, $s_r = 0.7349$ (c) K-means $s_r = 0.7096$

Figure 5: The computation of sugar ratio on the image dominated by the sugar

(a) Enhanced image (b) Otsu, $s_r = 0.6747$ (c) K-means, $s_r = 0.2899$

Figure 6: The computation of sugar ratio on the image dominated by molasses

ratio was determined by dividing the number of white pixels by the total pixels in this region. For k-means clustering (Figure 5c), the sugar ratio was calculated by mapping the clusters in the region of interest to the enhanced image and applying Equation (4). The computed sugar ratio values were $s_r = 0.7349$ for Otsu thresholding and $s_r = 0.7096$ for k-means clustering. Both algorithms successfully identified the image as predominantly containing sugar, with minor variations in the computed values.

For the molasses-dominant image, shown in Figure 6a, the sugar ratio was expected to be lower due to the darker regions. The computed values were $s_r = 0.6747$ using Otsu thresholding 6b and $s_r = 0.2899$ using k-means clustering (Figure 6c). The Otsu method overestimated the sugar ratio because it only considers the binary image, whereas k-means clustering, which relates segmentation to the original pixel intensities, produced a more realistic value. This indicates that k-means clustering provides a more reliable estimation of sugar purity, particularly in darker images.

The results demonstrate that preprocessing significantly improves segmentation performance, particularly for k-means clustering, which benefits from enhanced contrast and lighting conditions. Additionally, the sugar ratio metric provides a useful estimate of sugar purity. Otsu thresholding tends to overestimate sugar content, whereas k-means clustering offers a more accurate reflection of sugar purity by incorporating intensity-based clustering. This method provides a more effective alternative to traditional thresholding techniques and shows potential for real-time monitoring of sugar centrifuge operations.

6 Conclusions

The proposed sugar centrifuge image segmentation using k-means clustering demonstrates the promising potential for achieving accurate sugar purity assessment. However, further improvements are necessary to enhance its robustness and reliability. It is important to note that sugar purity is determined through laboratory testing, whereas the sugar ratio is an image-derived metric. Therefore, additional work is required to establish a strong correlation between the computed sugar ratio and actual sugar purity.

The algorithm must be applied to a larger dataset to ensure the reliable computation of the sugar ratio across various conditions. Furthermore, validating the sugar ratio against lab-measured purity values will provide a benchmark for refining the segmentation process. These efforts will guide future research toward optimizing the algorithm for real-time sugar quality assessment, improving its applicability in industrial sugar milling operations.

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