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ANATOMICAL FRACTION SEGMENTATION IN THE BIOMASS BALES

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Abstract

According to the Bioenergy Technologies Office (BETO), creating a robust next-generation domestic bioenergy industry is an essential pathway for providing sustainable renewable energy alternatives. Using non-food feedstocks, like corn-stover and forest residue, in the biorefineries doesn't affect the food supply chain. In the commercial-scale bioenergy operations, a significant development in the technological advancements is required to determine the biomass feedstock quality at the preprocessing stage. The penetrating ability of the x-rays helps study the big biomass bales, but the feedstock heterogeneity—physical size, shape, and chemical composition—poses a significant challenge during milling, conveyance, feeding, and biofuel conversion processes. The inherent complexity introduced during harvesting and bailing makes the reconstruction and interpretation of baled biomass materials from x-ray data time consuming, laborious, and expensive. The presence of similar low-dense materials showed a small contrast difference in the x-ray images, which makes the characterization based on the x-ray attenuation values not promising. This paper focuses on using the shape and texture properties extracted with image processing techniques to characterize the different tissue samples in the biomass bales.

1 Introduction

Recently, renewable energy resources have attracted a lot of attention as countries worldwide are trying to find sustainable energy alternatives while reducing the impact on the climate. Among the resources, renewable biomass represents an abundant carbon-neutral energy source, which has the potential to meet the expanding energy needs in the transportation sector while limiting greenhouse gas emissions. According to the 2016 Billion-Ton report [1], there is a future potential of producing one billion tons of biomass resources (composed of agricultural, forestry, waste, and algal materials) available in the United States on an annual basis. It can generate 85 billion gallons of biofuels that can potentially displace 30% of U.S. petroleum consumption. Now, the Bioenergy Technologies Office's (BETO's) future looks to "drop-in" replacements such as bio-butanol or other bio-derived intermediates that can be used to replace petroleum intermediates within existing/modified refineries.

Current research is more focused on using lignocellulosic biomass materials as a feedstock at the biorefineries. Lignocellulosic materials refer to the biomass originating from plants that cannot be used for food, which recycles unused plant matter and preserves food resources. The use of lignocellulosic biomass presents a crucial step in moving toward more sustainable renewable energy systems.

Lignocellulosic biomass constituents are made of complex polymer structures that need to be broken into simple sugars before converting them to biofuels. In order to convert these complex polymers biologically, pretreatment is required. Much research has been done on understanding each constituents' behavior and optimizing the pretreatment procedures to achieve high yield.

The main constituents of lignocellulosic biomass are cellulose, hemicellulose, and lignin. During pretreatment, the cellulose and hemicellulose are broken down to glucan and xylan, then converted into biofuels. Lignin is considered to be the most recalcitrant component of lignocellulosic biomass. Acid soluble lignin fragments formed during pretreatment can cause irreversible cellulose loss during enzymatic saccharification. The remaining solid lignin restricts enzymatic hydrolysis by physically impeding cellulase's accessibility to cellulose and un-productively binds cellulose enzymes [2]. Different plant parts are composed of different carbohydrates, have different permeabilities, crystallinities, etc., and therefore do not behave the same way physically or chemically.

And other factor that affects the feedstock quality is the ash content in the lignocellulosic biomass. Ash content during the conversion process can cause problems like slagging, fouling, and corrosion in the thermochemical conversion processes and can cause displacement of fermentable carbohydrates and potential buffering capacity during pretreatment in the biochemical conversion, which increase operational costs for both conversion pathways [3]. This could increase the costs of pretreatment, handling and disposal which can affect the end-product price. A review conducted by Kenney et al. in [4] estimates that a 5% increase in soil-derived ash would increase a 227 $MLyear^{-1}$ conversion facility's costs by \$1.15 $Myear^{-1}$, which translates to a 1% increase in the minimum ethanol selling price of \$0.57 L^{-1}.

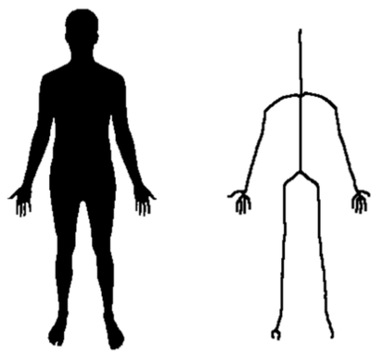
Moisture content impacts process performance. High moisture content in storage promotes biological degradation of fermentable sugars, which represents a loss of valuable biomass components after harvesting. Moisture content determination at the biorefinery can be an indication of the efficacy if the off-site storage conditions. Higher moisture content bales (> 25%) during the grinding reduces throughput which increases the overall production cost, which in turn affects the price of the final product.

Biorefineries' economic sustainability relies mainly on the available biomass cost and quality, which should meet the cellulosic biofuel cost and also get some profits. A cost-effective conversion process to produce biofuels from lignocellulosic biomass material relies not just on the material quality, but also on the biorefinery's ability to measure and adapt their process to the biomass's feedstock quality. For that, the biomass-to-energy conversion cycle at the biorefinery should include some sensing systems. These sensing technologies need to provide accurate, repeatable, and timely biomass indices through the biomass-to-energy chain. The application of appropriate sensing technology will be critical to developing a successfully integrated biomass management system [5]. The goal of this research is to extract the fundamental knowledge of the volumetric content of the material composition, ash content and moisture content early in the conversion process, which can help to optimize the conversion process. This work mainly lays a foundation to such work.

2 Background

2.1 Skeletonization

Skeletons are shape descriptors with a broad spectrum of applications in shape matching, recognition, animation, retrieval, and compression [6]. Skeletons provide medial axis representation of an object. Blum laid a foundation for the skeletonization algorithms [7]. Figure 1a, b shows an example image and its skeleton representation.



(a) (b)

Figure 1: (a) Example image (b) Skeleton

2.2 Graph theory

A graph represents a set of elements and a set of pairwise relationships between those elements. Here the elements are called nodes or vertices and the relationships are called edges. $G = (V, E)$ represents the graph of an object with vertices or nodes V and edge links E. Figure 2 shows an example of a simple graph. Any set of data points can be represented as a graph. In this work, skeletons are represented as graphs, in order to extract the shape information.

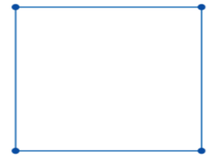


Figure 2: Example of a simple graph with four vertices represented by dots, and its four-edge links connecting them.

3 Materials and Methods

3.1 Image Acquisition

The CT scans used in this research for the corn stover bales are taken using the North Star Imaging (NSI) industrial CT 3D x-ray system at the Idaho National Laboratory. Figure 3 shows the setup we used to extract the radiographs for the corn stover bales. Figure 3a shows the detector and 3c shows the x-ray source. Here corn stover materials are set upon a 2.54 cm foam block in the form of a mini-round bale with a 12.7 cm diameter and 15.24 cm height (see figure 3b). In this experiment, scanning was performed with an x-ray tube voltage of 150 kV and corresponding tube current-time settings at 60 μA.

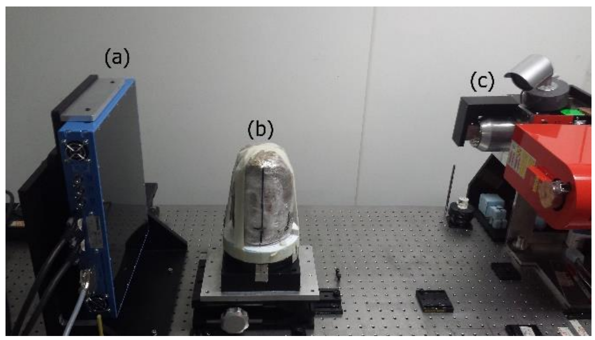


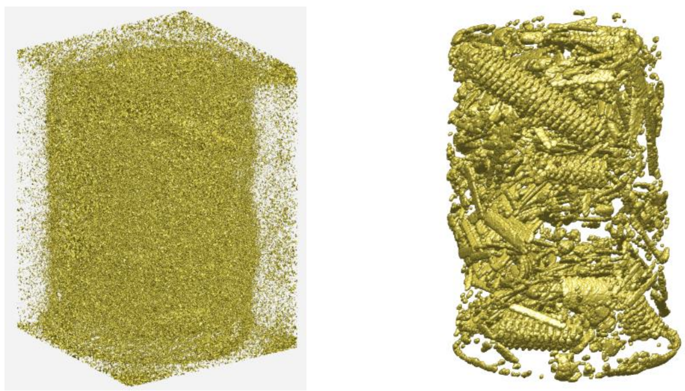
Figure 3: CT setup used to extract the radiographs of corn stover bale with (a) detector (b) mini-round corn stover bale (c) x-ray source.

3.2 Pre-processing

Once the higher density materials like rocks, and soil are removed, the next step involves detecting the corn stover material composition. The raw reconstructed images have background noise which do not contribute significantly to ethanol yield. Figure 4a shows a slice of the bale with background noise. We see in figure 4a that background and contents of corn stover bale have similar voxel intensity levels. In this work a few image preprocessing steps are incorporated to reduce the background noise and highlight the contents of the bale. In the preprocessing stage we thresholded and applied a morphological operation to remove background noise. Then the connected components are used to remove the small isolated voxels in the background noise. Connected components are extracted using the built-in function "bwlabeln" in MATLAB. The connected component labeling approach scans the given data and groups its voxels into components based on voxel connectivity. The isolated voxels are represented with small connected components that are defined to be noise and are removed by resetting their voxel values to zero. Figure 5 shows the 3D reconstructed data before and after removing the isolated voxels. The processed volume can now be analyzed for volumetric content of corn stover fractions.

(a) (b) (c)

Figure 4: A cross-sectional slice of mini-round bale at various stages of preprocessing (a) RAW reconstructed slice (b) Thresholded (c) After Morphological Processing.



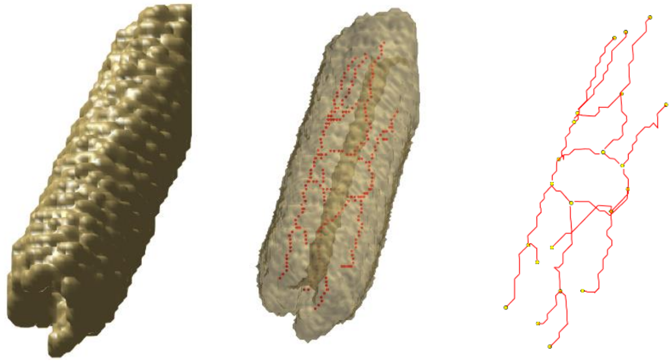
(a) (b)

Figure 5: Bale CT (a) Before pre-processing (b) After pre-processing

3.3 Automatic detection and volume estimation of corn cob fraction

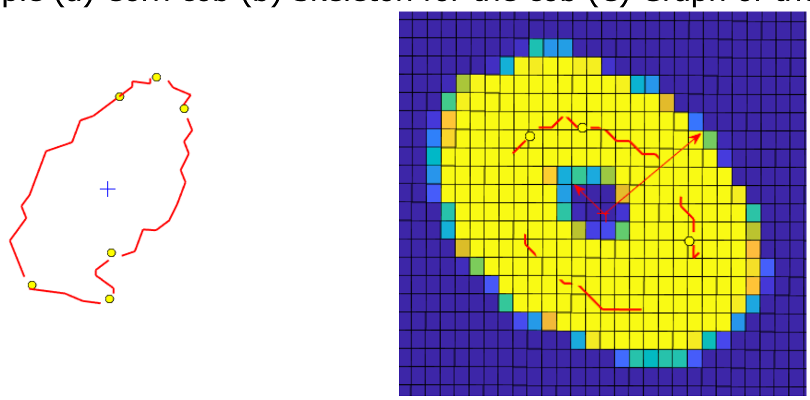
We applied a combination of image processing techniques to extract corn cob volume content in a given corn stover bale. Firstly, to simplify the detection problem, skeletonization is applied to extract the shape information while preserving its topology. Subsequently, graphs are used to represent the skeletons with nodes and edge information, which provides a pairwise relationship between each node. Figure 6a, b, c shows an example corn cob, the skeleton for the corn cob, and the skeleton's graph structure. X-ray reconstruction showed the corn cobs are hollow in the center, which forms a cyclic loop in the skeleton (see figure 6b). With this, the corn cob detection problem is simplified to loop detection. The cyclic loop is detected by removing all the branches (see figure 7a).

Since fully intact corn cobs resemble a cylinder, volume information of a corn cob can be roughly estimated by measuring the radius and height. Starting with the cyclic loop, the radius is estimated by determining the center of mass for the loop and calculating the distance to the outer boundary. To start tracing the height, a regression plane is fitted to the cyclic loop. We moved the plane along the normal direction, and tracing is continued until a change in the radius is observed.



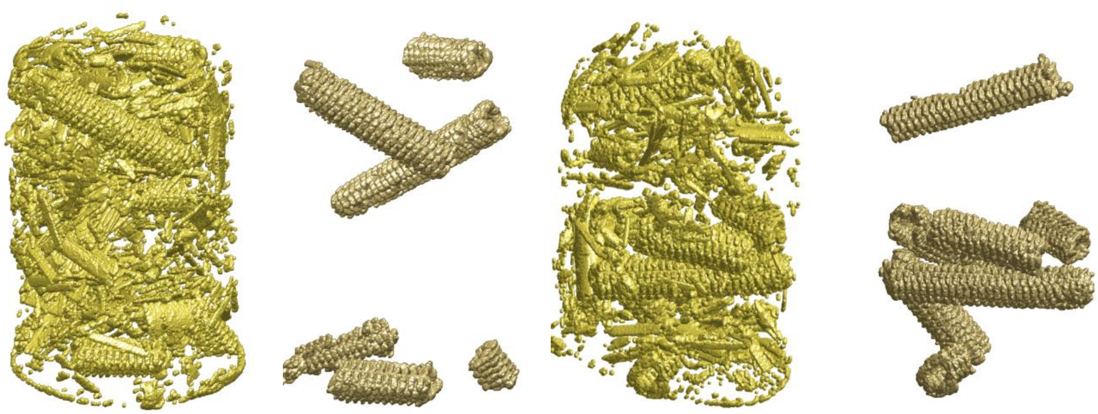
(a) (b) (c)

Figure 6: Example (a) Corn cob (b) Skeleton for the cob (C) Graph of the cob



(a) (b)

Figure 7: (a) Cyclic Loop with center of mass represented with blue cross (b) 2D cross-sectional image of cyclic loop with arrows pointing the two distances which we measure



(a) (b) (c) (d)

Figure 8: (a) Baleset # 1 (b) Cob Extracted for Baleset #1 (c) Baleset # 2 (d) Cob Extracted for Baleset #2

Table 1: Volume of cob extracted from the test bale sets

	Total Volume	Max deviation from true volume
Bale set # 1	18.07 cubic inch	2.50 cubic inch
Bale set # 2	20.07 cubic inch	1.33 cubic inch

3.4 Experimental results

We have tested this approach on two mini-round bale sets. Figure 8 shows the 3D view of the two bales and the corn cobs extracted from them using this procedure. Table 1 shows the estimated volume of the corn cobs extracted from the bale set.

4 Discussion & Future Work

We are able to detect, locate, and measure corn cobs in minibales. Further research is required to devise a more efficient and optimized detection model. There are several limitations with the proposed idea as it cannot be extended to a broken corn cobs (see figure 9). Using just cyclic loop detection may not be optimal in a real-world application. Our next research goals include optimizing the model to differentiate between a loop formed with a corn cob and fully intact corn stalk. We are also working on devising a model for detecting the broken corn cobs by incorporating corn cob texture information.

Long term goals include extracting the other plant anatomical fractions like stalks, leaves, and husks. We are already in the process of using the curvature information of the corn stalks and diameter to classify between upper stalks and lower stalks. We are also working on detecting the rocks and metals in the corn stover bale picked up by the baler. These rocks and metals are higher density materials compared to corn stover fractions. Since the density difference is significant, a high contrast can be observed between the rocks and metals to corn stover fractions in the radiographs. These rocks and metals could lead to a significant downtime at the biorefinery if they damaged the grinding equipment. They can also cause sparks, which

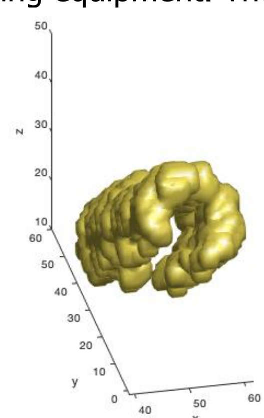


Figure 9: Example of an broken cob piece

can easily cause ignition and increase the chance for fire. It is essential to detect the shape, dimensions, and approximate location of these rocks and metals in the bale early in the screening process. Necessary measures can then be implemented to remove the contaminants of the bale before proceeding to the next steps. Our future plan includes adapting a similar analysis method to other lignocellulosic biomass materials such as forest residues and waste-derived feedstocks.

5 Acknowledgements

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