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Developing novel 3D measurement techniques and prediction method for food density determination

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Abstract

Density is a physical characteristic which depends on the experimental technique used and structural properties of food. True, apparent, and bulk are different types of densities based on the way volume is measured. For porous foods such as grain food products, accurate measurement of density is challenging. Current measurement techniques for food density are inconsistent and nutrient databases do not have sufficient density data. Computed tomography (CT) and magnetic resonance imaging (MRI), laser scanners are non-destructive diagnostic tools for characterizing food microstructure. The objectives of this study were to 1) optimize the parameters of CT, MRI, and laser scanner to determine food density and compare the corresponding values with other traditional techniques, and 2) to develop neural networks as a prediction method for apparent and bulk densities. MicroCT 40 (Scano Medical Inc.), Lightspeed QX/i clinical CT (GE Healthcare), and 3 Tesla Signa HDx MRI (GE Healthcare) were used to acquire 3D images of foods for true density. A 3D laser scanner (NextEngine, Inc) was used to scan the foods items for apparent density. Neural networks were used in conjunction with the data collected from laser scanner and using food composition and processing conditions to generate a black-box prediction scheme. The results of CT, MRI, and laser scanner showed great potential to estimate density in comparison to traditional techniques. Porosity was estimated from the CT and MRI scanned image data. Laser scanner was successful in acquiring 3D images and calculating apparent density. Neural networks provided reliable density prediction power and were comparable to the other empirical equations in terms of accuracy. The ability to predict food density based on composition and processing conditions is necessary to fill gaps in nutrient databases and account for new foods.

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Keywords: Density; computed tomography (CT); magnetic resonance imaging (MRI); laser scanners; neural networks

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1. Introduction

Accurate measurement of dietary intake has always been a concern for researchers and is of particular importance recently, in the wake of obesity epidemic. To determine the weight of food consumed, the density of that food needs to be known. Density is a volume dependent property which can be easily determined if the volume was correctly measured or estimated [8]. Density defined as *density = [mass (g)/volume (cc)],* is measurable via a number of different methods and can be categorized into three distinct measurement regimes. 'True density' is the density of the pure substance or material determined from its component densities considering conservation of mass and volume. 'Apparent density' is the density of a particle including all pores (porosity) remaining in the material. 'Bulk density' is density when particles are packed or stacked in bulk including void spaces (void fraction) (Fig.1). For foods of a porous nature (e.g., sugar cookie) a difference in the apparent density and the true density is observed.

True density   Apparent density   Bulk density

Fig. 1. Example of true, apparent and bulk density of puffed cornflour pellets

Food materials are naturally irregular in shape, so accurate prediction of volume is challenging. The use of traditional displacement techniques is laborious and a large possibility of inaccuracy exists. The true density of food has been measured using a gas comparison pycnometer by measuring the volume of only the solid portion of the food [14, 25]. Mercury porosimeters can also be used specifically to measure the true density. However, there is no assurance that mercury has intruded into all the pores even at high pressures [18].

The solid displacement method using rapeseed has been commonly used for determination of volume of baked products such as bread [2, 18]. Non-homogeneity of the seed, seed-sample interaction (sticking), as well as crude and subjective levelling off of the seed in the sample vessel can contribute to large standard deviations. Various other methods such as the dimension measurement, though simple and effective cannot be used for soft, irregular foods and liquid foods. Apparent density can also be calculated by the buoyant force method and has been used on a large scale for fruits and vegetables. Errors arise due to the possibility of mass transfer from the sample to the liquid or partial floating of the sample. Samples have been enclosed in cellophane, polythene, or coated with a thin layer of varnish, wax or silicon grease to make them impervious to water [11, 12]. To avoid floating of sample, a liquid of lower density or a sinker rod has been used [15, 21].

Methods for determining bulk density generally determining the weight of the volume of the food using household measures (e.g., 1 cup, 1 tablespoon). These tools are commonly used and reported in the food composition databases. However, this type of density measurement poses the greatest challenge due to the variety of ways the pieces of solid food in cup may be arranged.

A large number of empirical equations and models also exist to determine density of foods. However, factors such as the formation of air phase or pores, swelling or anti-swelling of the solid phases, loss of volatiles, and interaction of constituent phases are not taken into consideration while developing these models [20].

Optical methods have recently been used to study food microstructure. Image analysis of the microstructure, including the size, shape, networking, connectivity and distribution of various phases is possible. Computed tomography (CT), magnetic resonance imaging (MRI) and 3-dimensional (3D) scanners are currently being used on a wide-scale to understand complex food systems. CT, a medical imaging method, uses ionizing radiation in the form of x-rays to generate cross-sections of 3D image of an object from a large series of 2D images taken around a single axis of rotation. Micro CT has been used to study the 3D structure of cellular foods such as aerated chocolate, mousse, marshmallow, muffins [10], apple tissue [13] and the rise of dough [3]. MRI uses non-ionizing radiation frequency to provide image contrast on the basis of the molecular ability and physicochemical properties of water to acquire images. By variation of scanning parameters of MRI, contrast can be altered and enhanced in various ways to detect different features of a food item. Several studies such as the determination of structural properties of cereal products [22], study of bread baking [28] and grain structure of baked bread [26] have reported the use of MRI. However, most of these studies utilized CT and MRI for qualitative evaluation of foods for a better understanding of the physical food structure.

Few studies involving CT and MRI have been used for quantification. Porous structure of bread was evaluated using a micro CT by quantification of porosity using iterative cluster analysis based on k-means algorithm [6] whereas Wagner et al., [28] quantified porosity using paraffin microcapsules during proofing of dough in MRI. Porosity quantification from digital images involves segmentation and thresholding steps. Thresholding is the process of selecting pixels on the basis of brightness or color range. It basically converts a gray-scale image into a binary image [23]. Manual setting of threshold levels is possible by adjusting sliders on the image histogram while visually observing the image in a preview window. Hence, thresholding image is the step where most image measurement errors arise, due to inconsistent human judgment. A large number of automatic thresholding algorithms are present which can be used to separate the light and the dark regions using ImageJ software (*http://rsbweb.nih.gov/ij/*).

Geometrical characterization of food products was successfully shown using 3D scanners for food process modelling [27]. Laborious efforts were saved and errors decreased using a 3D laser scanner for volume estimation from the acquired 3D digital images of irregular foods.

In addition to accurate measurement, predictive methods are needed to accommodate new porous food entries which are homemade recipes. Very little work has been done to generalize the prediction of density of foods under a variety of conditions. Chengliu et al., [4] approached the density estimation problem using fuzzy logic using machine learning techniques applied to a specific food to predict French fry bulk density from different processing time and temperature as fuzzy sets. But a generalized methodology to predict the density of a mixture of foods does not exist.

Artificial neural networks (ANN) could be used for physical property prediction which consists of a multilayer feed forward model with a back propagation leaning rule [9, 17]. To obtain a final density of food, neural networks could be used to build a hierarchy system in which an identified food is passed through a series of categories depending on the required density regime.

The objectives of this study were to 1) optimize the parameters of CT, MRI, and laser scanner to determine food density and compare the corresponding values with other traditional techniques, and 2) develop neural networks as a prediction method for apparent and bulk densities.

2. Materials and Methods

The test samples used for these analyses represented foods typically eaten by adolescents [24]. The methods used required no sample preparation. Densities of the selected foods were measured using the following established techniques.

2.1. Gas Pycnometer

Stereopycnometer (Quantachrome Instruments, FL) connected to a nitrogen gas cylinder, was used to measure true volume of the selected food items. Food samples were weighed and volume was determined using the pycnometer in triplicate.

2.2. Solid Displacement Method-Rapeseed

A loaf-volumeter (National Mgf. Co., Lincoln, NE) was used to measure the apparent density of foods using rapeseeds. The volume of food items was measured in triplicate by the non-destructive, solid displacement method [2].

2.3. Computed Tomography (CT)

MicroCT 40 (Scano Medical Inc.) and Lightspeed QX/i clinical CT (GE Healthcare) were used to determine the porosity of the foods. The parameters of microCT were optimized for x-rays at 45 kVp and 177µA intensity. Medium resolution and 35.6mm sample cell was selected for scanning.

2.4. Magnetic Resonance Imaging (MRI)

A 3D fast spin echo proton density-weighted pulse sequence was used to acquire 0.5mm isotropic resolution images of foods using a 3 Tesla Signa HDx MRI (GE Healthcare). The MRI is equipped with proton spectroscopy for MRS and a real-time acquisition system for use with echo-planar fMRI.

2.5. Laser Scanner

A NextEngine 3D scanner (NextEngine Inc, Santa Monica, CA) was used, and the 3D surface images were converted into solid volumes using SolidWorks 2007, (SolidWorks Inc, Concord, MA). The volumes and densities estimated by scanning were compared using experimental measurements.

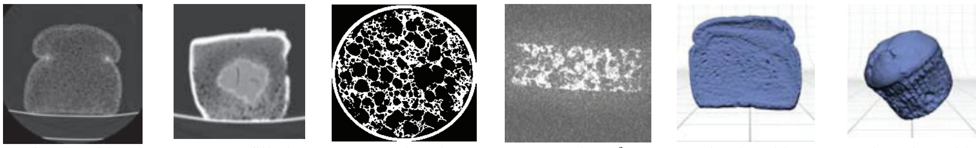
2.6. Artificial Neural Network (ANN)

Foods were categorized into true, apparent, or bulk density. True density was predicted [5], which served as an initial step in identifying the correct density. For apparent density, information about processing conditions was considered in addition to the food's components. Once the apparent density has been resolved in this hierarchy system it then passes, if needed, to the bulk density.

A simple model was generated using existing data in Food & Nutrient Database for Dietary Studies (FNDDS) (*http://www.ars.usda.gov/Services/docs.htm?docid=17031*), for apparent density predictions of a variety of chemically leavened cakes. In this neural network there were nine inputs including six compositions, processing temperature, processing time, and percent of leavening agent in the whole recipe. There were four hidden layers each with five neurons containing tangent sigmoid transfer functions. The output layer consisted of a single neuron containing a pure linear transfer function.

3. Results and Discussion

The CT, MRI and laser scanner were successful in capturing the features and geometric shape of the food products. The results of few of the foods scanned using CT, MRI and laser scanner are shown in Figure 2.



Classic white bread[a] | Cream-filled cupcake[a] | Sourdough English muffin[b] | Cereal Bar[c] | Classic white bread[d] | Chocolate chip muffin[d]

Fig. 2. Examples of scans using clinical x-ray CT (a), x-ray micro CT (b), MRI (c) and laser scanner (d)

The apparent density of a few select foods measured by the solid displacement method using rapeseed and the laser scanner is shown in Table 1. The density values from both methods was comparable and within range for all the foods. However, laser scanner technique was quick, easy while solid displacement was laborious and required multiple repetitions to avoid large variability. Further, true density of the same foods was measured using the gas pycnometer. Using this information porosity was calculated, porosity = *[1 – (apparent density/ true density)]*.

Table 1. Porosity measurement using laser scanner and other traditional techniques

Food Item	**Using Solid displacement Apparent density**	**Using Laser scanner Apparent density**	**Using Gas pycnometer True density**	**Porosity**
	g/cc	g/cc	g/cc	(%)
Sliced white bread	0.1937	0.2170	1.0541	79.41
Sourdough english muffin	0.3417	0.3049	1.2948	76.45
Cinnamon raisin bagels	0.3022	0.2682	1.2929	79.26
Chocolate chip muffin	0.4696	0.4889	1.2406	60.59
Cupcake	0.4576	0.5059	1.3264	61.86

In order to determine porosity from CT and MRI data, the most favourable threshold value is necessary. For this purpose, the scanned images from CT were segmented and for different threshold values porosity was estimated. Algorithms were developed in MATLAB® to count proportion of both classes of pixels in the binary images and obtain percentage porosity. The figure 3 shows the varying porosity when the threshold on the microCT is manually increased.

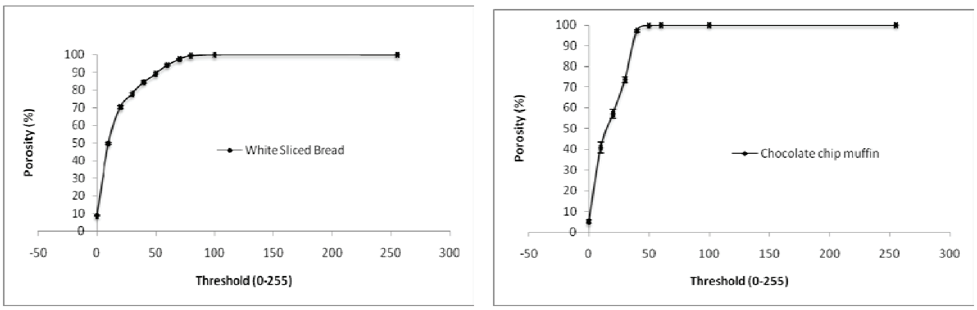


Fig. 3. Plots for White sliced bread and chocolate chip muffin scanned using microCT showing varying estimated porosity when threshold is manually adjusted

Using the porosity calculated from the experimental measurements conducted earlier (Table 1); the optimum threshold for white sliced bread and chocolate chip muffin is estimated to be 35 and 22 respectively. Due to complex nature of food systems, the threshold value is unique for every food. It would not be possible to generalize this value for rest of the foods. Hence, amongst various thresholding algorithms, Ostu's clustering algorithm was selected to perform automated thresholding. It is a histogram-shape based image thresholding method that minimizes the intra-class variance, defined as a weighted sum of variances of the two classes of pixels (foreground and background). The algorithm calculates the optimum threshold separating the two classes of pixels so that their combined spread (intra-class variance) is minimal [16]. Ostu's algorithm has been previously used in image analysis for understanding the role of sugar and fat in cookies [6], and during characterization of microstructural properties of breaded chicken nuggets [1].

Table 2 shows the porosity calculated from the different 3D internal imaging techniques. The threshold was calculated using Ostu's algorithm and further algorithms were used to obtain percentage porosity. The advantage of MRI over CT is that MRI has the ability to change the contrast of the images. Small changes in the radio waves and the magnetic fields can completely change the contrast of the image. Hence, it is possible to get higher detail and highlight various parts of the sample. On the other hand, CT is cheaper and takes lesser time to acquire images. Hence, for simple foods CT could be utilized whereas MRI could be used for food mixtures containing multiple components.

Table 2. Porosity estimated using ostu's algorithm and 3D imaging CT techniques

Imaging Technique	**Food item**	**Porosity**	
		(%)	**SD***
Micro CT	Multigrain bread	68.412	1.353
	Cinnamon raisin bagels	75.745	3.142
Clinical CT	Bread roll	56.637	3.618
	Sourdough English muffin	45.519	7.195

*SD is the standard deviation between the 2D slices of each food item

Figure 4 shows the ANN model generated for chemically leavened products. It is possible to use this model for simulations of decomposed recipes of new or existing products. Each recipe is reduced to a mass percent ingredient list which is cross-referenced with FNDDS to obtain a total proximate analysis. Results are summarized in Table 3.

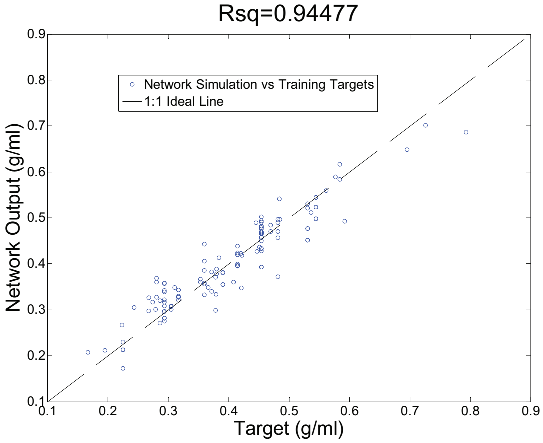


Fig. 4. ANN model for chemically leavened products

A pre-processor was added to the neural network which used the previously described inputs in a simplified mechanistic model [7] to reduce the dimensionality of the input vector to a feasible value. This was done via principal component processing. The outputs were then passed to the neural network and trained using the existing data from FNDDS. Instead of setting aside a portion of the training data for validation, kitchen experiments were done to test the network.

Table 3. Apparent density estimated using laser scanner and predicted by ANN

Food Item	Using Laser Scanner; Apparent Density		ANN prediction
	g/cc	SD	g/cc
Sugar cookie	0.827	0.052	0.7193
Spritz cookie	0.479	0.048	0.4983
White cake	0.577	0.061	0.6287
Pound cake	0.886	0.093	0.4907
Hostess Ding Dong	0.512	0.009	0.4969

4. Conclusions

Density measurement of porous foods (e.g. cake, bread) and food mixtures (e.g. breakfast cereal, salad) is challenging. The determination of the mass is straightforward, but volume is difficult. This study demonstrates successful acquisition and application of techniques to measure density of foods using image processing techniques. They require no sample preparation and can supply volume information. Procedures are currently being developed to build 3D geometrical models of these food products from CT and MRI scans. Advances in the above mentioned internal imaging techniques can now be used to measure volume and porosity of food samples. Owing to the complex nature of the wide variety of food items (apart from simple baked foods), the response of the CT and the MRI needs to be studied in further detail for different foods with varied oil and moisture content. The variability in results and tedious nature of the traditional measures shows that credible methods and precise analytical methods are needed to reduce variability and measure density. For foods, these measurements are not always possible using traditional techniques or by 2D image analysis using statistical techniques. With CT, MRI and laser, full 3D images can be obtained with good resolution. They can further be used to understand the design, analysis, and processing science of food products.

Neural networks can be used for existent composition data (from food label or recipe) and new data being collected from laser scans, MRI, and CT images for network training. Further work is in progress for the use of neural networks to determine void fraction to resolve bulk density. Our intention is to use this more globally to determine the density of any food given the processing conditions and its composition. Currently the model does not generalize well for higher moisture content products, but inclusion of processing parameters such as baking time, temperature, mixing time and rigor, may alleviate this.

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