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RESEARCH ARTICLE

Image analysis as non-destructive approach in characterization of Indian sweet meat spongy *Rosogulla*

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ABSTRACT

Quality characterization and sustenance of food quality is of major concern in food industry. The variability in the food texture is another concerning parameter affecting the acceptance of food products. The reliability and acceptability of the processed finished food products in the market depends on its overall quality characteristics. Most of the quality assessing approaches are destructive in nature and require more materials to analyze various parameters to judge its overall characteristics. Further, this approach requires several high-end equipment with trained technical man powers for handling such equipment and interpreting the complicated results. On the other hand, the Image analysis approach being non-destructive technique does not require the material to waste and not complicated even. The approach requires daily use equipment such as camera, laptop and software skills. Under the present investigation various characteristics of Indian made spongy rosogulla was performed using non-destructive offline approach. Multiple images of the samples were taken. In order to analyze and extract Gray-Level Co-occurrence (GLCM) matrix properties of the image a software program was developed using MATLAB software. The mean and standard deviation values were determined and compared for all the four offsets. The significant values were taken and compared for the selected properties among twenty-two properties.

Keywords: Non-destructive, image processing, texture, *Rosogulla*, GLCM

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INTRODUCTION

Food perception has multisensory dimension involving sight, taste, smell, hearing, and touch. Shape, size, texture, color, gloss and variety are various visual acceptability attributes (Paakki et al., 2019). Texture is the complex visual patterns, composed of spatially organized entities that have characteristic brightness, color, shape and size. Food texture involves the perceived physical features describing the spatial arrangement of color or intensities in an image or a selected region of an image. Work in area is multidisciplinary in nature, considering the food fracture and deformation, sound produced and its acceptability during biting and chewing and the internal micro and macro structure of food. Food texture encompasses mechanical, technical, physical, chemical, physiological and psychological facets of food (Tunick, 2011).

Awareness of textured properties is essential for all the stakeholders in food supply chain including farmers, food processors, marketing personal and the consumers. To achieve the desired qualities of the finished food products, the knowledge of the

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changes in the textural characteristics affected at involved unit operations. Determination of textural properties is one of the most common quality evaluation procedures. As non-destructive approach quality characterization of various food materials are illustrated (Prasad, 2015a, b; Prasad et al., 2010). The most widely used approaches to texture analysis are objective tests using a texture analyzer. Texture measurement devices include the selection of simple hand-held equipment and Instron system texture analyzer, which provide deformation time series data allowing for the estimation of a wide range of texture characteristics using force–time or force–displacement data (Chen and Opara, 2013). Conventionally, measurement of food texture is done using a texture analyzer like TA.XT2 texture analyzer, Stable Microsystems (Janve et al., 2013; Kumar and Prasad, 2017, 2018), Brookfield CT3 texture Analyzer Brookfield Engineering (Wang et al., 2018) and EZ-SX texture Analyzer Shimadzu (Sodhi et al., 2019). There is a growing interest to develop novel method for texture measurement which would be rapid than the texture analyzer. Number of in-direct type devices have been developed for food texture measurement as an alternative to conventional food texture measurement instrument. These tests can be categorized as destructive tests which involve force/deformation techniques for measuring the texture.

Non-destructive test enables determination of various quality parameters and has been found effective for many of the food products. Non-destructive approaches are very useful for rapid and accurate estimation of quality parameters. The recent interest is to develop and implement modern portable and handheld devices for quality evaluation (Abasi et al., 2018; Prasad, 2015a, b). Recent innovations in the field of food texture is in development of non–destructive techniques for assessment of food texture. Non-destructive texture detection method was investigated for pear using establishing relationship between different texture indices and vibration parameters (Zhang et al., 2014). Low intensity ultrasound has been used to assess the quality of various horticulture produce according to texture and firmness. This was achieved by determining ultrasonic velocity in relation to the physical characteristics like texture, firmness, total soluble solids, and acidity (Chandrapala et al., 2012; Prasad et al., 2000).

On the other hand, the optical approach in determining visible food texture are found effective, quick, non-destructive, noninvasive and can provide much information. When a light beam impinges on a product, most of the light will penetrate the porous structure, part of light will be reflected, some will scatter from the area close to the incident beam. Physical structure of surface and interior part as well as the chemical constituents, its distribution in the food matrix will affect the way light is absorbed and scattered (Huang and Lu, 2010). This opens the opportunity to measure food texture in terms of visual parameters.

The Indian subcontinent is famous for variety of dessert, especially the traditional spongy *rosogulla* and *gulab jamun*. For most of the Indians, a major meal without a dessert is of no attraction. There is a wide spectrum of milk-based sweets in different regions of India. Indian cousins vary from one region to other. However, *rosogulla* which is a traditional sweet of West Bengal is widely accepted in all corners of the Indian subcontinent (Pal and Roy, 2019). In the present study, image analysis technique was used to evaluate the in-direct characterization of Indian sweet meat spongy *rosogulla* on basis of visual textural parameters.

MATERIALS AND METHODS

Human vision can discriminate surfaces and objects based on textural aspects. In the similar way, computer vision system can take advantage of surface texture to distinguish and recognize objects. Computer vision in texture analysis may use other features to perform the task of object recognitions (Mirmehdi, 2008). Unlike with size, shape and colour condensing texture information into a few simple summary properties is not possible as the patterns of these spatial variations can be highly elaborate and convoluted (Jackman and Sun, 2013).

Rosogulla

Rosogulla, a soft, spongy and syrupy dessert famous in Indian subcontinent and South Asia is made from *chhana* by cooking and soaking in sugar syrup (Gurveer and Goswami, 2017). *Rasgulla* is common name in India and the dessert is known as *Rosogolla* or *Roshogolla* in Bengali. *Rospgulla* is made from *chhana*, an intermediate product obtained by heat acid coagulation of milk (Sengupta and Bhowal, 2017). Traditionally, manufacturing of *Rosogolla* involves preparation of *Chhana*, a co-precipitate obtained by thermal treatment in acidic condition, kneading of *chhana* into smooth paste, making the kneaded *chhana* into small balls of about 6 to 7 g each, cooking the balls in boiling sugar syrup (50 to 55° Brix) followed by its soaking in sugar syrup (35 to 40° Brix) for overnight (Chavan et al., 2009). *Rasogulla* a sweet meat comprises of two components as solid and liquid. Small balls of *chhana* cooked in sugar syrup form the solid part and syrup is the liquid part. In this study, market samples of *rosogulla* from a popular sweet shop in Karnal, India were procured. Samples were brought to the lab and sugar syrup was drained off. The *rosogulla* ball were cut into two half and the images were acquired towards the flat face of the cut *rosogulla* ball.

Image acquisition

Images of *rosogulla* samples were acquired by a computer vision system, which mainly consisted of a digital camera, a cabinet, controlled illumination unit and computer. Digital camera (Canon PowerShot A3400 IS, Canon, India) was interfaced with the computer (Lenovo, i7, 3.5 MHz, 4 GB RAM, 64 bit) using a USB cable for image transfer. The RGB image was obtained at 16 mega pixel resolution and saved in a.jpg format. To have controlled illumination 4 CFL light source were installed on the top of cabinet. To acquire an experiment image, *rosogulla* sample was placed on the product loading platform, which has a neutral grey background. The camera was set in Auto mode and was manually triggered to capture the images.

Image processing

Image processing algorithms are based on mathematical modeling. There are various types of image processing algorithms like image enhancement, noise removal, image inversion, segmentation and recognition. The image is complemented in image inversion to extract information stored in dark pixels. Algorithms are developed to improve image clarity, brightness and contrast and applied various filters for the image enhancement. The image segmentation algorithms are further developed for determining the region of interest (ROI) (Sharma, 2017). Edge detection of the image is one of the key segmentation methods and various types of operators are used for detecting edges include Sobel, Prewitt, Robert and canny operator (Ahmed, 2018).

Matrix laboratory (Matlab) is an important multi-paradigm numerical approach in soft computing environment and is a proprietary programming language protocol developed by MathWorks. It allows data manipulations available in form of matrix, development of functions, plotting the functions with the algorithm's implementation, creation of user-friendly interfaces, and interfacing with other programs developed using different programming languages. Thus, the image processing using Matlab is a powerful approach for effective data analysis. The results of applying image processing algorithms can further be analyzed for both qualitative and quantitative characterization (Sharma, 2017). Image processing technique was developed to characterize the visual textural properties of *rosogulla* (Fig. 1). Images were first converted into grayscale images, segregated in RGB color space, calculated the Lab values and then on gray scale image GLCM algorithm is applied. Statistical analysis was carried out in order to check the significant differences in GLCM parameters.

Fig 1: Acquired and processed image of *Rosogulla*

Visual texture measurement

The unique feature of Indian traditional dairy products is that they are obtained by a wide variety of methods involving a range of unit operations. This leads to a great range of product structures and textures. The chemical components of traditional dairy products including incorporation of food additives, and the specific processing conditions would determine the texture and microstructure of the products. Retaining the product's complex texture, while adopting modified or new processes, is a real challenge to the manufacturer. Hence, characterization of a product's texture is valuable not only in process development but also in monitoring the textural quality in routine production (Rangi et al., 2019). Both rheological and visual texture of *rosogulla* are the important characteristics for judging the quality and acceptability. The *rosogulla* should be soft and spongy texture according to consumer preference (Gurveer and Goswami, 2017). The surface uniformity in texture with evenly distributed porus internal structure of *rosogulla* further adds the desirable characteristics and that depends on the compositional and process variabilities. Appropriate quantity of moisture, fat, protein and calcium content of *channa* will result in production of soft spongy and uniformly textured *rasogulla*.

Visual texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects. Though texture plays a significant role in image analysis and pattern recognition, only a few architectures implement onboard textural feature extraction. One of such extraction methods is based on GLCM (Mohanaiah et al., 2013).

GLCM parameters

Gray Level Co-occurrence Matrix (GLCM) is a statistical method for the detection of texture that takes into account pixel spatial relationships. GLCM functions characterize the image texture by determining the frequency of occurrence pairs of the pair with specific value occur in an image. The Co-occurrence probability is calculated by following mathematical formulation (Clausi, 2002; Luo et al., 2020):

$$pr(x) = \{p(i,j)|(d,\varphi^o)\}$$

$$p(i,j) = \frac{p_{ij}}{\sum_{i,j=1}^{G} p_{ij}}$$

In which, $pr(x)$—the probability; $p(i,j)$—the co-occurrence probability between grey levels *i* and *j* within the given a distance *d* and an orientation φ^o; p_{ij}—the number of the occurrence of the gray levels.

The GLCM features were originally proposed almost four decades ago (Haralick and Shanmugam, 1973). Since then, it has been used extensively in many texture analysis applications and continues to be an important feature extraction method in the domain of texture analysis. The GLCM is primarily a two-dimensional (2D) histogram that multiplies the possibility and the accuracy of image texture analysis. This technique employs the following steps. The probability of co-occurrence between two gray levels *Ix*,*y* and *Ix*′,*y*′, given a relative orientation and distance, can be computed for all possible co-occurring gray level pairs in an image window (Perez Alvarado et al., 2016).

GLCM technique is used to estimate image properties regarding with second order statistics texture feature. Third and higher order statistics includes relation of three or more pixels, so it is not implemented due to interpretation difficulty and processing time (Gade and Vyavahare, 2018). The creation of the GLCM matrix is based on the distance between pixels, the pixels angle 0°, 45°, 90° and 135° (Kaya et al., 2013).

The GLCM creates a square matrix of dimensions equal to the maximum intensity and composed by the frequency of the different intensities of grey within the stack. This processing is strongly influenced by the pixel pitch and the direction (Malegori et al., 2016).

Gray level co-occurrence matrix functions characterize the image texture by determining how often pairs of the pixel with specific value occur in an image. It will use this to create a GLCM and then extract statistical measure from this matrix. It can be explained as; thus, gray co-matrix function creates GLCM by determining how many times a pixel with a particular intensity (gray level) value i present in a specific spatial relationship between two pixels. Each element (i,j) in the resultant GLCM is the summation of occurrence of the pixel (i) in the specified spatial relationship to a pixel with value (j) in the input image. After the gray level co-occurrence matrixes have been created, several statistical textures can be derived (Olaniyi et al., 2017).

For visual texture analysis twenty-two different parameters were extracted from the *rosogulla* images (Table 1). The images were captured for four replicate sample. Statistical analysis (One-way ANOVA) was carried out to check the significant differences in GLCM parameters.

Table 1: List of GLCM properties extracted from image

Sl. No.	Parameter code	Parameter
1.	Pro1	Autocorrelation
2.	Pro2	Contrast
3.	Pro3	Correlation (Matlab GLCM function)
4.	Pro4	Correlation (User defined function)
5.	Pro5	Cluster Prominence
6.	Pro6	Cluster Shade
7.	Pro7	Dissimilarity
8.	Pro8	Energy
9.	Pro9	Entropy
10.	Pro10	Homogeneity (Matlab GLCM function)
11.	Pro11	Homogeneity (User defined function)
12.	Pro12	Maximum probability
13.	Pro13	Sum of squares
14.	Pro14	Sum average
15.	Pro15	Sum variance
16.	Pro16	Sum entropy
17.	Pro17	Difference variance
18.	Pro18	Difference entropy
19.	Pro19	Information measure of correlation 1
20.	Pro20	Information measure of correlation 2
21.	Pro21	Inverse difference normalized (INN)
22.	Pro22	Inverse difference moment normalized

RESULTS AND DISCUSSION

Textural properties of *rosogulla* derived from GLCM were plotted and compared (Fig.2). Based on the magnitude, the properties could be classified into different categories as major, intermediate, and minor. High magnitude major properties having values more than 5 were autocorrelation (Pro1), sum of squares (Pro13), sum average (Pro14) and Sum variance

(Pro15). Intermediate properties were in the range of1-5 like Cluster Prominence (Pro5), Entropy (Pro9) and Sum entropy (Pro16). Other properties were of lower value < 1 and were classified into minor magnitude category. To determine significant difference between the properties statistical analysis was applied separately for major, intermediate, and minor properties. Among major properties there was no significant difference ($p < 0.05$) between Pro1 and Pro13. In case of intermediate properties, no significant difference was observed between Pro9 and Pro16.

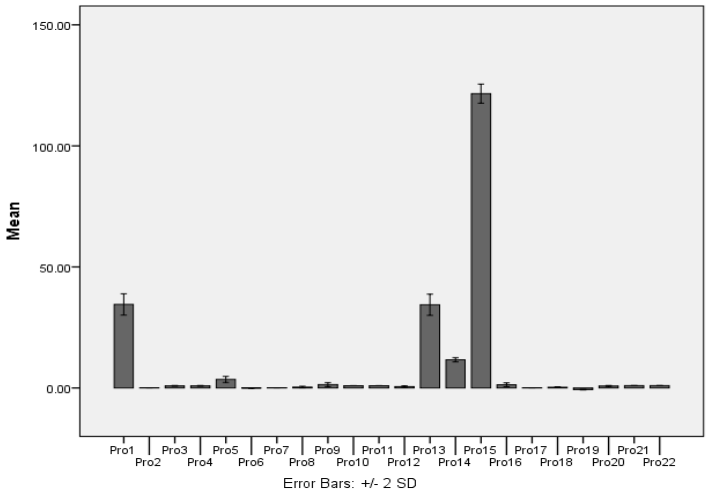

Fig 2: Mean values of different GLCM parameters

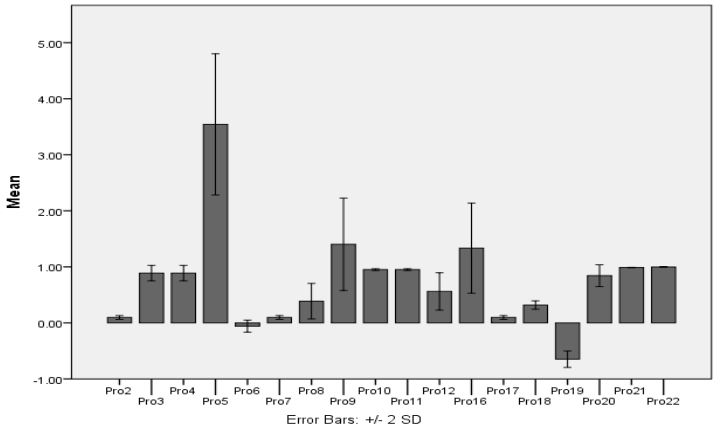

Fig 3: Plot for lower magnitude GLCM parameters

Among all the 22 textural parameters extracted from GLCM, it was observed that only cluster shade (Pro6) and information measure of correlation 1 (Pro19) resulted in negative values (Fig. 3).

Textural parameters classified as minor properties were again subjected to post doc test to determine homogenous subsets. It was observed that minor properties could be grouped into 5 subsets (Table 2). Analysis shows that for texture evaluation of *rosogulla*, all of the GLCM features must be initially extracted. For a particular variant of *rosogulla*, these parameters can be

reduced, and few may be selected which significantly represent the textural properties. Such an approach will help to reduce the redundant parameters.

Table 2: Homogenous subset of minor GLCM properties

GLCM Property	Subset				
	1	2	3	4	5
Pro19	-.64714				
Pro2		.09733			
Pro6		-.06931			
Pro7		.09717			
Pro17		.09733			
Pro18			.31802		
Pro8			.38787	.38787	
Pro12				.56137	
Pro3					.88826
Pro4					.88826
Pro10					.95144
Pro11					.95143
Pro20					.84327
Pro21					.98921
Pro22					.99850
Sig.	1.000	.122	.988	.090	.195

* Means for groups in homogeneous subsets are displayed.

The technique of texture imaging has proven to be a useful and effective tool for measurement of visual textural properties. The GLCM was able to express visual textural parameters in terms of numerical values It is important to emphasize the non-destructiveness of this method. The method, being also rapid and simple to apply, could be an effective way to quantify textural properties (Malegori et al., 2016). Gray level co-occurrence matrix functions characterize the image texture by determining how often pairs of the pixel with specific value occur in an image (Olaniyi et al., 2017).

CONCLUSION

The present study shows that it is possible to quantify visual texture parameters using Grey Level Co-occurrence Matrix (GLCM) properties. Twenty properties can be further classified into major, intermediate, and minor properties on the basis of magnitude. The results helped to propose a method to reduce the number of properties which can be effectively used to express visual textual aspect of an important Indian traditional food item *rosogulla*.

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