Description of the Textural Appearance of Bread Crumb by Video Image Analysis

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ABSTRACT

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A method for the characterization of the appearance of bread crumb from digital images is proposed. Experimental breads were prepared by varying the nature of the surfactants added to the flour to change the textural appearance of the crumbs. Seven treatments were tested. The trials were repeated several times (three loaves for each treatment, four slices for each loaf, two images for each slice), giving 142 digital images. The textural features were extracted from images by an original mathematical procedure based on two-dimensional Haar transform. This procedure made it possible to characterize each digital image of crumb by a vector that included 66 numbers called texture characteristics. The relevance of the method was tested by applying discriminant analysis on the matrix of texture characteristics to identify the bread treatment from the digital image of its crumb. About 80% of the images were correctly identified by discriminant analysis, both in the training and in the verification set. However, the effect of loaf-to-loaf variation in breadmaking was important. The method can be applied without modification to any collection of textured samples.

Many baked cereal products such as bread, cakes, and cookies are prepared with dough in which natural or chemical leavens are added. One of the preparation steps is to get the dough rising. During this step, numerous bubbles of carbon dioxide appear in the dough. The textural appearance of the crumb depends on the preparation method of the dough and on other factors such as baking. The visual characteristics of the crumb are elements of the quality of the final product. Even if the proximate composition of industrial bread is correct, consumers are deeply influenced by the appearance of the crumb in their appreciation of the product. Moreover, technological studies of industrial processes need to have a method for an objective classification of crumb in baked cereal products. The surfactants added to flour play an important role in the baking characteristics of the final product. Pomeranz et al (1970) studied the effect of various additives in bread. They showed that the addition of phosphatidyl choline (lecithin) increased substantially the loaf volume of germ-enriched bread. Chung et al (1976) replaced wheat-flour lipids with several commercial sucro-esters and showed their beneficial effect on the loaf volume of experimental breads.

Numerous investigators have studied cereal products by video image analysis. Several studies have dealt with whole grains to identify the cultivars (Zayas et al 1986, Sapirstein et al 1987, Chen et al 1989) or to describe the histological characteristics

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of seed section. However, only a few have studied the texture of foods. Bertrand et al (1991) applied video image analysis to the description of the texture of pea ground with various mills. Zayas et al (1989) discriminated hard wheat brans from soft wheat brans by studying the grey level dependence. Smolarz et al (1989) characterized the texture of extruded biscuits. In their work, video images of tranverse cuts of biscuits were recorded. The computerized operations of image analysis included several steps: image digitizing, extraction of the sample contour, measurement of structural parameters, and statistical studies of these parameters. Considerable work has been done on the texture analysis of video images in fields other than the food industry (Weszka et al 1976, Haralick 1979). Basically, three types of approaches—structural, spatial, and spectral—can be applied for texture analysis. The first one assumes that textures can be modeled by the semirandom positioning of a few characteristic shapes (primitives) such as segments, polygons, and ellipses. In the spatial approach, the texture is locally characterized by a particular disposition of neighboring points of the images. The spectral method consists of the application of mathematical methods that emphasize the repetitive nature of grey level variations.

In this paper, we describe the extraction of crumb features from video images by a mathematical method based on a two-dimensional Haar transform, which is both spatial and spectral. The developed method was applied to an illustrative collection of bread samples prepared under various conditions to vary the crumb characteristics.

MATERIALS AND METHODS

Preparation of Breads and Sample Collection

The experimental breads were prepared following a standard procedure. The basic recipe was as follows: wheat flour, 300 g; distilled water, 186 ml; compressed yeast, 7.5 g; pure NaCl, 6.6 g. Flour and yeast, dispersed in water, were mixed in a thermostated Chopin mixer (Chopin, Tripette et Renaud, Villeneuve La Garenne, France) for 2 min at low speed, then for 11 min at high speed. Pure NaCl was added 7 min before the end of mixing. The final dough temperature was about 25°C. The dough was fermented in a chamber for 45 min at 29°C and 85% rh. The dough then was cut in three 150-g pieces, molded round by hand, placed in a greased cylindrical mold, and fermented for 90 min. The loaves were baked in a Chopin oven for 30 min at 240°C. When emulsifiers were used, they first were hydrated and then added to the aqueous phase of yeast and distilled water, except for the sucro-ester F10, which was too hydrophobic.

The bread loaves obtained were vertically cut into 12-mm-thick slices.

Four emulsifiers were tested: commercial soya lecithin, which is the only emulsifier allowed for french bread baking; phosphatidylcholine purified from soya lecithin; and two commercial sucro-esters commonly used in the food industry, namely F110 and F10, which differ in their hydrophobicity (F10 is much more hydrophobic than F110).

In the present experiment, seven treatments (coded 1 to 7) were studied: 1, normal flour with no additive (control); 2, flour defatted with pentane; 3, normal flour with 2% commercial soya lecithin; 4, defatted flour with 2% soya lecithin; 5, normal flour with 1.5% commercial sucro-ester F10; 6, normal flour with 1.5% commercial sucro-ester F110; 7, normal flour with 1.5% pure soya phosphatidylcholine.

Without changing the breadmaking conditions, three loaves were obtained for each treatment. In general, the four inner slices (Fig. 1) of each bread loaf were used for video image analysis.

Image Acquisition

The slices of bread were placed on a copy stand with a black background, illuminated by four 100-W lamps placed at each side of the sample 17 cm from the working plan. The CCD matrix camera IAC500 (I2S, Bordeaux, France) was fitted with a 55-mm objective lens (Nikon) and positioned at about 70 cm from the sample. The acquired monochrome images represented sample surfaces with a size of 5 × 5 cm. They were digitized in the form of matrices having 512 lines and 512 columns with a Trydin digitizing board (Visilog, Jouy-En-Josas, France). Each element of this matrix is an integer number describing the grey level of a point of the studied object and ranging from 0 (black) to 255 (white). The images of the two sides of each slice were separately recorded. For a given treatment, 24 images (three loaves × four slices × two sides) were acquired. However, some slices were not correctly cut and some samples were missing for treatments 5–7. One hundred forty-two images were actually studied. This collection was stored on a 300-megabyte hard disk for further mathematical processing.

Mathematical Procedure for the Characterization of Crumb

Images were processed on a Sun 3/150 workstation (Sun Microsystems, Mountain View, CA) (four megabytes of RAM) using programs written in C language by the authors.

Two-dimensional Haar transform. The Haar transform method (HT) is based on a class of orthogonal matrices whose elements are either 1, −1, or 0, multiplied by a power of $\sqrt{2}$. HT is computationally very efficient. The transform of an N-point vector requires only $2(N - 1)$ additions and N multiplications. The complete mathematical description of HT is out of the scope of this article. The theory is given by Lifermann (1980) and Hall (1979). Only those aspects related to texture characterization are presented here.

HT can be considered a method for the creation of a set of rectangular masks, which can be combined with the grey level value of pixels of square digital images, to obtain numerical values called Haar coefficients. These coefficients can locally characterize the texture of the studied image.

Haar masks are mathematically represented by rectangular basis matrices $\boldsymbol{M}$ including i lines and j columns. i and j can take only values that are an integer power of 2 and are smaller or equal to the number of rows and columns of the studied image. For example, in our case, with images of 512 × 512 pixels, there are nine allowed values of i and j: 2, 4, 8, 16, 32, 64, 128, 256, and 512. All of the possible combinations of these values are allowed for dimensioning the Haar basis matrices. For example, 2 × 128, 16 × 32, and 128 × 2 are possible dimensions. All

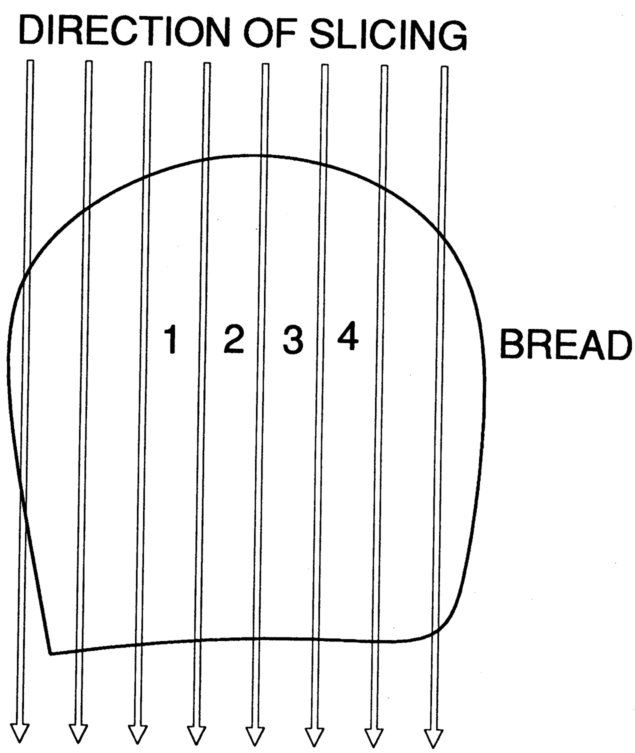

Fig. 1. Method of slicing bread. Inner slices 1–4 were used for video image analysis.

of the elements of each Haar basis matrix take the same absolute value, which is an integer power of $\sqrt{2}$. This numerical value is not important for our purpose. The sign of each element (+ or −) is determined by its position in the Haar basis matrix. The matrix is divided into four rectangular submatrices of equal size (Fig. 2). According to the position, all of the elements of each submatrix are positive or negative.

For the calculation of Haar coefficients, each kind of Haar mask is positioned on the digitized image studied (Fig. 3). Each mask can take every possible nonoverlapping position. For example, in our case, the 16 × 64 Haar mask (covering 1,024 pixels) can take 256 positions (512 × 512/1,024). At each position, a Haar coefficient is calculated. The grey level value of each pixel overlapped by the current mask is multiplied by the numerical value of the corresponding element of the Haar basis matrix. All of the obtained values at a given location and with a given mask are then algebraically added up to obtain a Haar coefficient. This mathematical procedure is equivalent to isolating a rectangular surface of appropriate shape on the image, dividing this surface into four rectangles, adding up the grey level values of the pixels that are placed in the upper left and lower right rectangles, separately summing the grey level values of the upper right and lower left rectangles, and subtracting one sum from the other to obtain a number proportional to the Haar coefficient. Each Haar coefficient is therefore associated with a shape and a location of Haar mask in the studied image.

+	+	−	−
+	+	−	−
+	+	−	−
+	+	−	−
−	−	+	+
−	−	+	+
−	−	+	+
−	−	+	+

Fig. 2. Example of a Haar basis matrix with a 8 × 4 mask. The same absolute value is given to each element with a positive (+) or a negative (−) sign.

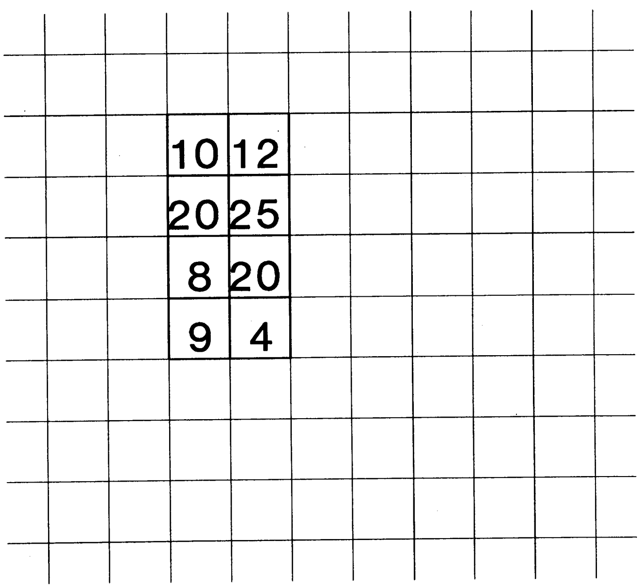

Fig. 3. Example of a calculation of the Haar coefficient. The numbers represent the grey level values in one portion of the digital image. The Haar coefficient associated with mask 4 × 2 is equal to $K|10 + 20 + 20 + 4 - 12 - 25 - 8 - 9|$, where K is a constant value.

Measurement of the texture characteristics. Figure 4 indicates how the Haar coefficients can be representative of the texture characteristics. If the surface covered by a given mask is less than the surface of elementary objects in the image, the associated Haar coefficient will be close to zero. In contrast, if the surface of the mask is close to that of the elementary object, the coefficient will have a higher absolute value. According to the size of the Haar mask, a rough-to-fine sampling is performed. Moreover, masks having very elongated shapes can be representative of the fibrous appearance of the studied textures. In the present study, the absolute values of the Haar coefficients were taken as numerical measurements of the local texture characteristics. However, Haar transform gives a large number of Haar coefficients equal to the number of pixels in the studied image. This number was reduced by two methods. First, as the texture of crumb was considered to be the same at any location of the image, it was logical to add up all of the absolute values of Haar coefficients associated with a same shape of mask. For example, as mentioned above, the 16 × 64 Haar mask gave 1,024 Haar coefficients. A single number, which is the sum of these 1,024 absolute values, was kept to represent a feature of texture associated with this mask. Second, it was supposed that, according to the chosen magnification, the texture was described by masks covering rather small surfaces of images. The masks of large size seemed to be irrelevant for texture measurement; they covered surfaces much larger than those of observed alveoli. Moreover, masks of large size give only few Haar coefficients. For example, only four Haar coefficients are obtained with a mask having a surface of 256 × 256 pixels. With large masks, the sampling in each image was found to be insufficient. Among the 81 (9 × 9) possible masks, only those covering less than 1/64 of the surface of the image were kept for the study. This choice also meant that Haar mask sampling is reproduced at least 64 times for each image. There were only 66 such masks for images 512 × 512 pixels. The texture of an image was therefore described by a vector of 66 positive numbers called texture characteristics.

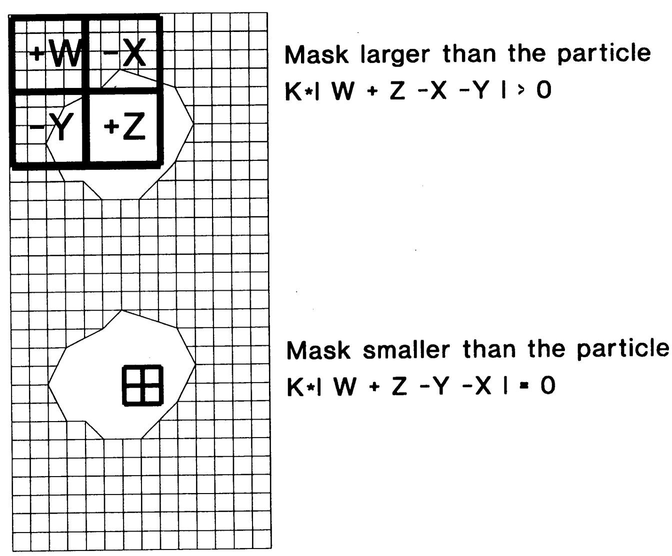

Fig. 4. Haar coefficients as measure of particle size.

Description of textures. From the 142 images, a matrix of texture characteristics, $\boldsymbol{T}$, with 142 rows and 66 columns was obtained. The relevance of the proposed method and the similarities between textures were evaluated by achieving discriminant analysis on $\boldsymbol{T}$. The first test investigated the possible common crumb textural features obtained by the same bread treatments. According to the treatments, seven qualitative groups were created. The matrix $\boldsymbol{T}$ was divided into a training set and a verification set, each including 71 observations. The image of one side of the slice was put in the training set, while that of the other side belonged to the verification set. A stepwise discriminant analysis (SDA) (Romeder 1973) was carried out with the training set to identify the nature of treatment from the texture characteristics. SDA makes it possible to introduce variables one after the other in the prediction while taking their discriminant ability into account. The results then were verified on the second set.

A second test was performed to study the effect of loaf-to-loaf variation in breadmaking (within treatment variation). The studied qualitative groups were defined by the loaf from which each slice was obtained. As 19 loaves were available, 19 qualitative groups were formed. The observations included in the training and verification sets were the same as mentioned above.

Graphical data representations then were obtained by canonical discriminant analysis (CDA) (Foucart 1982), including only the texture characteristics selected by SDA.

RESULTS AND DISCUSSION

Effect of Treatment on the Texture Characteristics of Crumb

SDA was performed to discriminate the crumb according to the bread treatment. The texture characteristics were introduced stepwise in the order of their predictive performance. Figure 5 shows the percentage of correctly classified samples as a function of the iteration step and the texture characteristics lastly introduced in the discrimination. Only a few variables were necessary to obtain a rather high percentage of correct classification. With only three texture variables, 73 and 77% of the samples were correctly attributed to their qualitative groups for the training and verification sets, respectively. A complete random attribution would have given about 15% correct identification. The best results were obtained by introducing six texture characteristics, giving about 81 and 82% correct classification for training and verification sets, respectively.

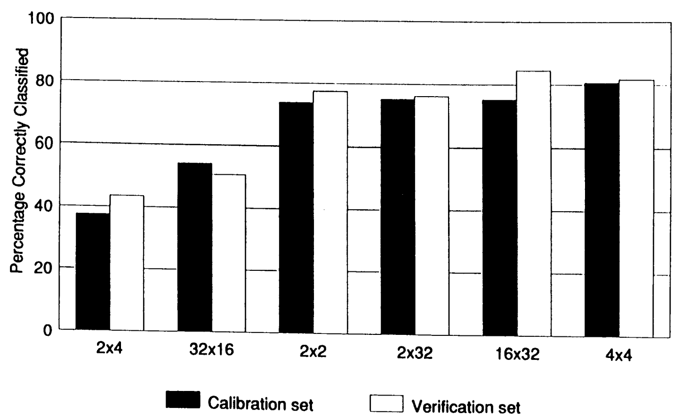

Fig. 5. Discrimination of crumbs according to the treatment. Percentage of images correctly classified as a function of the variable used, which are introduced stepwise.

TABLE I
Computerized Identification of the Treatments from Their Crumb Characteristics[a]

	Training Set[b]							Verification Set[c]						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1	12							11						1
2	1	11							12					
3			9	2	1					9	2			
4			4	8						3	9			
5					7		1					5	2	1
6	1					4	2		1				5	
7	1				1		7	1					1	7

[a]Treatments (1–7) used in the experiment are indicated in the horizontal row. Column numbers identify treatments by stepwise discriminant analysis. Each block contains the number of corresponding samples.
[b]Fifty-eight samples out of 71 correctly identified (82%).
[c]Fifty-seven out of 71 samples correctly identified (81%).

The results are summarized in Table I. In this table, the rows give the actual bread treatments and the columns the treatments that were identified by SDA, both for the training and the verification set. Each block contains the number of corresponding samples. For example, treatment 3 was represented by 12 images in the training set. The row labeled 3 in Table I shows that, in the training set, nine samples were correctly identified, and two others were wrongly classified in treatment 4 and one in treatment 5. The numbers on the diagonal line of the table therefore correspond to correctly identified samples.

Some treatments such as 1 (normal flour) and 2 (defatted flour) were very often correctly identified. In contrast, the treatments in which soya lecithin was added to normal or defatted flours, namely groups 3 and 4, were often mixed up with each other. It is well known that lecithin is able to improve the surfactant properties of dough and therefore reduces the effect of variations in lipid content. The confusions among groups 5, 6, and 7 seemed less significant and could not be interpreted. The six introduced variables corresponded to Haar masks of the sizes 2×4, 32×16, 2×2 , 2×32, 16×32, and 4×4 pixels, respectively. It is interesting to note that three masks presenting discriminant abilities had sides of 32 or two pixels. As 32 pixels represented about 3 mm of distance at the surface of the sample, it was possible that this length was in the order of magnitude of typical alveoli in some bread crumbs. Two pixels represented about 0.2 mm. It is doubtful that alveoli of this size could be identified. It is more likely that Haar masks having such dimensions acted as boundary extractors: these masks were actually very similar to well-known operators used in image analysis for extracting boundaries, such as Sobel or Prewitt operators (Gonzalez and Wintz 1987).

CDA was assessed on six texture characteristics selected by SDA. Figure 6 gives the factorial map of CDA, which emphasizes the similarities and the differences between the samples. The

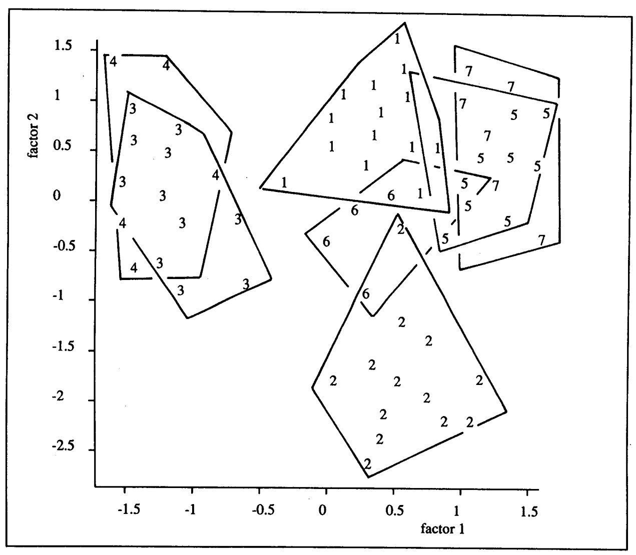

Fig. 6. Canonical discriminant analysis of crumbs according to the preparation mode. Representation of factors 1 and 2. The numbers indicate the treatment code (see Materials and Methods). For the sake of clarity, the overlapped points are not given here, but the boundaries take their position into account.

TABLE II
Correlation Coefficients Between the Haar Characteristics Used in Canonical Discriminant Analysis and Scores Associated with Factors 1 and 2

Haar Mask	Factor 1	Factor 2
2×4	0.98	0.03
32×16	0.25	0.96
2×2	0.48	0.45
2×32	0.86	−0.144
16×32	0.32	0.65
4×4	0.98	0.01

factor 2 can be easily interpreted as a size estimation of alveoli. The points that were placed opposite on factor 2 corresponded to very typical images of the crumb. Visual examinations of these images clearly showed that high values on factor 2 were associated with large alveoli of the crumb. The texture characteristic extracted from mask 32×16 had a correlation coefficient of 0.96 with scores of the second factor (Table II). It was therefore logical to assume that this mask played a role in the estimation of the average size of alveoli. Less obvious is factor 1, which seemed to be related to the thickness of the walls between alveoli. The texture characteristics extracted from masks 2×4 and 4×4 had correlation coefficients equal to 0.98 with scores of the first factor. Treatments 3 and 4 gave rather thick and regular walls in contrast to treatments 5 and 7. This interpretation is in agreement with the hypothesis that some masks act as boundary extractors.

The results could therefore be summarized in the following way. In comparison with the control, the effect of defatting flour (treatment 2) was to induce the formation of very small alveoli in the dough. This effect was suppressed by the addition of 2% soya lecithin (treatment 4). In contrast to other additives, lecithin seemed to give rather thick walls of the alveoli (treatments 3 and 4). The sucro-ester F10 (treatment 5) and the phosphatidylcholine (treatment 7) gave heterogeneous sizes of alveoles, with a delicate aspect. The breads of treatments 5 and 7 were actually more easily deformed than the others.

Effect of Loaf-to-Loaf Variation in Breadmaking

The matrix of texture characteristics was used with the same training set and verification set as mentioned above to evaluate the effect of variation within treatments. As 19 individual loaves were prepared, 19 qualitative groups were formed for SDA. If variability in breadmaking had no effect on the texture of the crumb, SDA would not be able to identify that one slice belonged to a particular loaf. SDA gave a percentage of loaves correctly identified equal to 68 and 56 for the training and the verification set, respectively. Three texture characteristics were selected by SDA, related to Haar masks 2×4, 32×2, and 2×2. Among these masks, two had been selected before for the discrimination of treatments. These results show that variation in breadmaking within treatment produced an artifact in the evaluation of the effect treatment. However, the breads were generally mixed up with one another within the same treatment. Eighty-three percent of the sample of the training set and 76% of the verification set were correctly attributed to one of the seven groups of treatments. The effect of variability in breadmaking was therefore weaker than the effect of treatment. It also is interesting to note that the associated map of CDA (not presented here) was very similar to that shown in Figure 6. This means that the features involved in individual loaf identification were the same as those selected for the identification of treatments.

CONCLUSION

Video image analysis can be an interesting method for the characterization of textures in food products. In the present study, we have shown that this method classified various textures of crumbs efficiently and seemed to be adaptable to industrial quality control. However, the presented results were obtained with a rather small collection of images (about 20 images for each treatment) and would need to be confirmed on larger collections. The classifications of texture can be used together with other measurements such as loaf volume to compare various methods of breadmaking. The two-dimensional Haar transform has shown to be a very fast method and can also be used for other textured products such as foams, fibers, or powders.

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