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A-C. Roudot

F. Duprat

M.-G. Grotte

G. O'Lidha

Utah State University
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A-C. Roudot, F. Duprat, M.-G. Grotte, G. O'Lidha[1]

Institut National de la Recherche Agronomique Laboratoire de Méthodes Physiques d'Etude Domaine St Paul,
BP 91, F- 84143 Montfavet Cedex, FRANCE
[1]St. Patrick College, Department of Biology, Maynooth, Kildare, IRELAND

Abstract

The visual aspect of food is a problem very often neglected for different reasons; one being the difficulty of modelling vision. However, it has been shown that, on simple synthetic images, automatic sorting in the same manner as human vision is possible.

Distribution heterogeneity of spots within an image is one important parameter for its characterization. A new algorithm was tested over simple numerical pictures that gave good agreement with visual appreciation. Images of twenty dry sausage slices were analyzed and different factors corresponding to aspect structure were calculated. Principal component analyses based on these factors allowed discrimination between the different types of sausage. The results obtained when studying the meat part of the slices were well correlated with the visual aspect.

Key words: Image analysis, visual appreciation, visual structure, dry sausage.

Introduction

Vision is the first sense that is used when choosing a food. The visual aspect is an important parameter that can involve acceptance or rejection by the consumer before any other organoleptic test. However, objective analysis of appearance seems to be difficult, or even impossible, because of the psychophysical elements involved.

Numerous groups have attempted to automatically detect features (Sarkar and Wolfe, 1985; Funt and Bryant, 1987; Roudot et al., 1988; Smolarz et al., 1989), or visual texture (Roudot, 1989; McDonald and Chen, 1992) that can be used to characterize the sample. But in food area, no investigation has been found that links visual perception and automatic classification. Some trials by computer scientists (Haralick et al., 1973; Ahuja and Tuceryan, 1989; Reed and Wechsler, 1990), show the feasibility of the method applied on synthetic images; these emphasize the necessity of describing new algorithms appropriate to this type of work.

Thus, some interest exists to look into the possibility of objectively evaluating the visual aspect, at least in some specific cases. To test the hypothesis, we have chosen to work on dry sausage slices, which is the type of food where external appearance is important in making a selection. Some work has already been done on this kind of food by Hildebrandt and Hirst (1985), but they only take into account the meat components' relative importance within slices. So, we have tried to automatically sort sausage slices in the same manner as an individual would do, according to his visual perception.

Synthetic Slices

Visual test

Different tests were undertaken on "synthetic sausage slices" created using numerical imaging techniques. Nine slices were prepared as explained below: A white disc was chosen as background ("meat"), on which several little dark discs ("fat") were positioned. To change the type of slice, the dark spots were rearranged upon the background, so that their number and relative area always remained constant; the only

Figure 1 (at right). The nine synthetic slices used to test the pasqualization algorithm. There is the same number of black spots in each image, so that the only difference between the different slices is the spot distribution. Automatic and visual sortings are noted below, with the number of pasqualization passages and the mean value, on an hedonic scale, given by 24 individuals.

Pasqualization sorting:

D(15),   I(16),   A(17),   H(17), F(18),   B(19),   G(23),   E(29), C(39).

Visual sorting (average value, hedonic scale):

D(5), I(10), F(19), A(20), H(24), B(28), G(37), E(38), C(42).

A   B   C

D   E   F

G   H   I
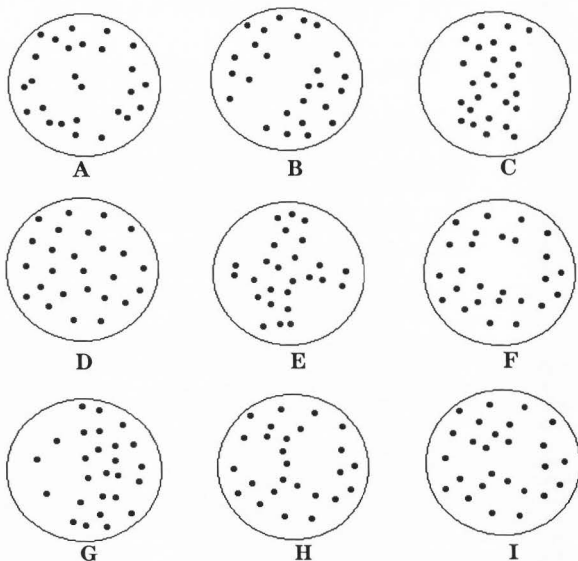
Algorithm 1

Pasqualization algorithm. On the basis of mathematical morphology, it allows the measurement of the homogeneity of the spots' distribution within a binary image.

Pasqualization

S = {points P | P belongs to a spot}

$N(P)$ = neighborhood of the point P, P belonging to S
       = {points T | distance between T and P equals 1 pixel}

pasqualization = 0

while ratio less than 0.95
   {
   for each point T of the slice
      {
      if (T does not belong to S and T belongs to $N(P)$)
        then T belongs to S
      }
   ratio = (sum of points P belonging to S)/(sum of all the points of the slice)
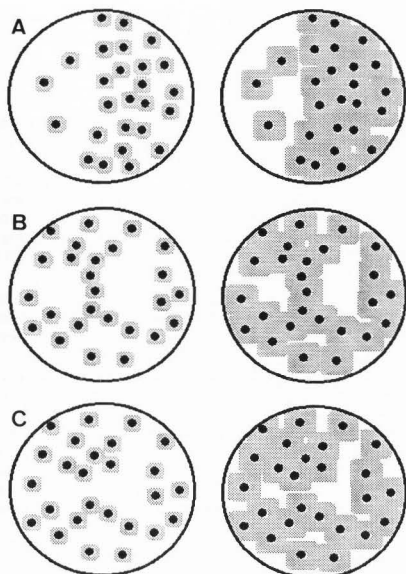   pasqualization = pasqualization + 1
   }

difference was their spatial distribution. The image was binary, to suppress the influence of color, edge detection, etc. (Fig. 1).

These nine images were drawn on paper and shown, in a random arrangement, to 24 laboratory personal who were asked to sort these images according to spatial distribution homogeneity of the dark spots among the white ones. A final visual sorting was made by averaging the results obtained.

The pasqualization algorithm

To model the evaluation of the visual aspect, a new algorithm called pasqualization was defined (algorithm 1). The basis of this method is the dilatation defined in mathematical morphology (Serra, 1986). The principle consists of covering all the "slices" by successive dilatation of the nuclei represented by the black spots. Each dilatation step consists of increasing each spot radius by one pixel. The program calculates the number of steps necessary to cover 95 percent of the whole "slice" area. A very inhomogeneous repartition of the spots needs a lot of dilatation steps and the pasqualization value is high (Fig. 2A). The image is more rapidly covered if the distribution is more homogeneous (Fig. 2B), and with a very homogeneous distribution of spots, few steps are needed to cover the image and pasqualization value is low (Fig. 2C).

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Figure 2. Results of pasqualization after respectively five and ten passages on three samples, from the sample with the more inhomogeneous spot repartition (**A**) to the more homogeneous one (**C**) with an intermediate (**B**). The grey part is the result of the spots smudging. Pasqualization stops when the sum of the grey and black parts covers more than 95 percent of the slice area.

When this algorithm was applied on our "synthetic slices", the results were very similar to visual ones. So, we have an automatic method of evaluation of image homogeneity where the only difference occurring between images is the spatial distribution of spots. However, the limits are quite clear: **a**) The images are binary; **b**) The shape of the white spots are all circular; and **c**) Their relative area is constant.

Automatic sorting according to visual aspect is possible with this new algorithm, when the samples are quite simple. However, a verification is needed to see if this method can be used on real samples with different spot shapes, areas and colors.

Real Dry Sausage Slice

Twenty slices were analyzed corresponding to fifteen different types of dry sausages. In one case three slices were taken from the sausage and in another four slices. This choice was made to test variations in the same sausage and to compare with variations between
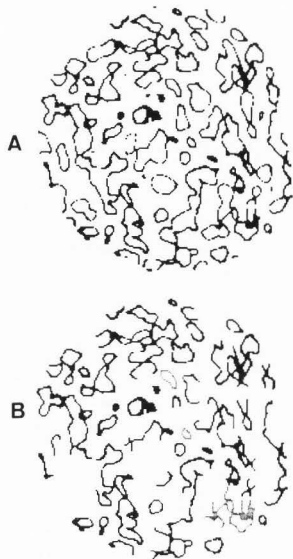
Figure 3. Result of the spots detection algorithm. **A**: Raw result, each spot is individually detected. **B**: Final image, some spots are rejected, because they are too small or because their shape are too different from the average. So, different parameters can be calculated on each one, before being averaged over the retained spots.

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different types. Different groups were sorted visually. To be validated, the same results had to be obtained in our tests.

Digitization

Immediately after being cut, the slices were placed on a black background under a video camera in a diffuse lighting chamber. Four white incandescent light bulbs were placed around the chamber in order to obtain a homogeneous illumination in the center field of view of the camera (Paulsen and McLure, 1986; Roudot and Duprat, 1989). The camera was linked to a computer (a PC compatible model) through a digitization card (an analog/digital electronic card, PC PICX from Synaps, Paris, France). Two options could be used: color, or black and white analysis. Preliminary tests had shown that our images were saturated with red tint. Red color had absolutely no significance, and all color variations came from green and blue components. As green correlates well with image brightness and with eye sensitivity, we decided to work with it.

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Algorithm 2

Spot detection algorithm. It detects the different spots within an image, and marks and sorts all the pixels belonging to each one. It is a highly recursive algorithm.

L   = {points P ¦ level1 < level(P) <= level2}
S(P) = {points T ¦ belongs to the same spot as P}

for (each point P belonging to L and P not belonging to a spot)
{
  (1) for (each point T belonging to N(P))
    {
      if (T belongs to L)
        then
        {
          T belongs to S(P)
          P=T
          goto (1)
        }
    }
}

The image has 256x256 pixels, corresponding to a camera field of view of about 10x10 cm. The brightness of each pixel is coded over 8 bits, i.e., can take 256 levels among 0 (black) and 255 (white). A smoothing pretreatment is made over all the raw images to reduce the consequences of the inhomogeneity of the sample lighting and the possible artifacts due to poor image resolution, excessive electronic noise, etc.

Method of analysis

The first idea to study differences between sausage slices is to compare their fat areas, the distribution of fat pieces and the shape of these pieces. A problem then is to detect the border of fat which often blends into the meat. With this method another question arises; is the visual discrepancy only due to fat and not due to meat structure or due to the relation between these two main structures? Gödel has shown that all information in an image cannot come from the structural parts nor from the background. A study of the whole image is necessary (mentioned in Hofstadter, 1985).

In this work, the range of brightness of the slice in the image is divided into sixteen parts, from the darkest corresponding to meat, to the brightest corresponding to fat. These sixteen parts (called levels) are partly superimposed to smooth the variations of the different parameters measured over the range of brightness.

Numerical analysis

All calculations are made independently on each of these sixteen levels. The program detects each spot and marks its corresponding pixels (Fig. 3 and algorithm 2). Different parameters are evaluated to obtain a characterization of each spot. These results are then averaged over the whole slice. The pasqualization algorithm is applied to measure the homogeneity of spots' spatial

distribution on the slice. All these calculations are performed on each of the sixteen levels of the image, to obtain a description of the slice's visual aspect.

Calculated parameters include:

- The number of spots.
- The total area defined as the percentage of the slice area covered with these spots.
- The average area of the spots.
- The shape factor S/P^2, with S being the area and P the perimeter of the spot: this is the most used measure of spots' shape in image analysis. A low value of this factor means that the spot is filamentous, a high one that it is more circular. Values obtained for each spot are then averaged over the whole slice.
- Following two parameters which evaluate the compacity of the spots (compacity is a measure of the percentage of void included in the smallest square containing the spot):
  - D^2/S, where D is the greatest distance between points in a spot and S is the spot area. The value of this factor measures the void quantity left by the spot in a square whose side has a length of D. When this parameter has a low value, the spot is very compact. It can be filamentous but it is included in a small-sided square. Alternatively, if the value is high, the spot is very extended in one direction, it can be included in an ellipse with a high eccentricity.
  - Dm^2/S, with Dm being the mean distance between points in a spot. The physical interpretation is the same as above, but the distance used is an average, and so, some compensation can occur between different elements in the same spot.
- Following two parameters evaluating the spatial distribution of the spots:
  - L/R in percent, with L being the distance between the gravity center of the spots and the geometrical center of the slice, and R the theoretical radius of a circle having the same area as the slice. This is a measure of the circular distribution of the spots around the center of the slice. When all the spots are concentrated on the same side of the slice, its value is high. But this factor does not give any information on radial distribution.
- The pasqualization, which is the number of dilatation steps necessary for the spots to cover 95% of the whole slice. This is a direct measurement of spot distribution when the spots' shapes and areas are identical in the different samples. Here, its value must be balanced, taking spot characteristics into consideration.

Results

When looking at the different graphical representations of the slice, it can be seen that for almost all samples some levels appear with few large spots representing more than 80 percent of the whole area covered by spots, and some small spots. Thus the different parameters calculated and averaged over all the spots have
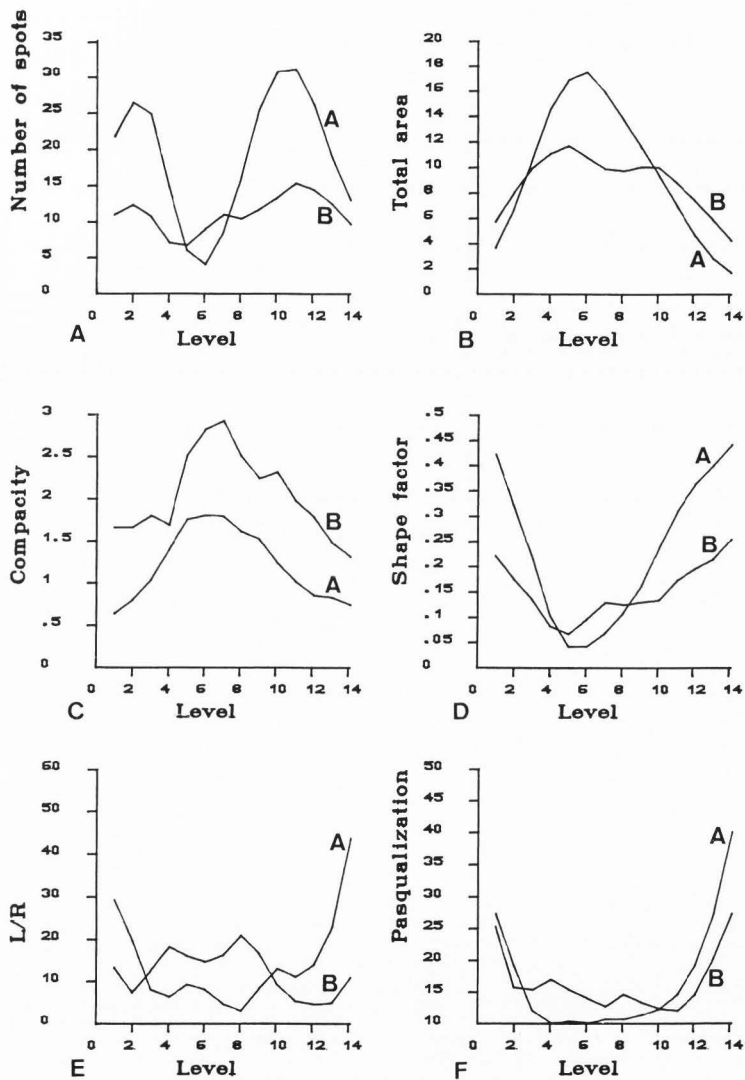
Figure 4. Examples of the variations of number of spots (**A**), total area (**B**), compacity (**C**), shape factor (**D**), L/R (**E**), and pasqualization (**F**) over the sixteen levels for two dry sausage slices A and B.

no real meaning. To correct this, before calculating final values, a sorting of significant spots is made. A histogram of the shape factors is generated and its median value is determined. The selected spots have their shape factor value nearest to the median value. The minimum area covered by the retained spots must be at least 80 percent of the area covered by all the spots. With this condition, all the curves obtained are relatively smooth (Figs. 4A-4F).

- Number of spots (Fig. 4A): When going from dark to bright levels, the value of the curve diminishes, reaches a minimum around one or two spots, and then increases.

- Total area (Fig. 4B): Its curve is almost exactly the opposite of the first one. This shows that at low and high levels of meat and fat, the slice is a conglomerate of many small independent parts. The intermediate levels with few spots with an important relative area can be interpreted as a binding zone between meat and fat.

- Compacity (Fig. 4C): The two parameters used to measure compacity give very similar results with a curve that grows, reaches a maximum, and then decreases. It can be seen that the maximum of these curves does not always correspond to the minimum in the number of spots. When few spots occur, they cannot be included in small-sided square, they show a direction in which their elongation can be large.

- Shape factor (Fig. 4D): The shape factor reaches a minimum for the level that shows the minimum number of spots. This can be explained by the fact that these spots cover a wide area but are filamentous. Their perimeter is large and the ratio S/P^2 is low. When the cutting level corresponds to meat (dark part of the image) or fat (bright part), the spots are more compact and the shape factor is higher.

- L/R (Fig. 4E): This parameter shows the distribution of the spots within the slice. When its value is large, the spots are located away from the center of the slice. The result is very sensitive to the quality of the image: for instance, the presence of skin on the slice can change the calculated value considerably. This sensibility to artifacts explains the high values obtained for the lower and higher levels. In fact, whatever level is studied, the circular distribution of spots tends to be homogeneous.

- Pasqualization (Fig. 4F): This is preferred to L/R because it is less sensitive to artifacts, and gives a smoother curve, the variations of which are similar to the preceding parameter. Typically, this curve decreases to reach a minimum, remains constant for a while before increasing. But these variations are influenced by the great differences of the spots' total area between the different levels: if the nuclei total area is large, it needs fewer passages to cover the image, than if the nuclei area is small.
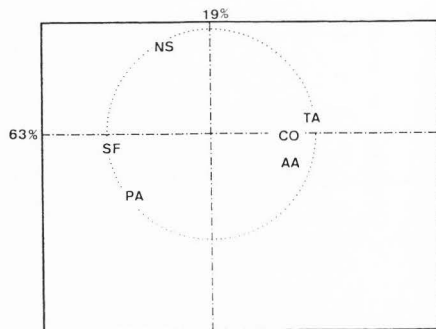

Figure 5. Correlation circle of the PCA shown on picture 6. The first axis with 63% of the variance takes into account the shape factor (SF), total area (TA), compacity (CO) and average area (AA) while the second axis with 19% of the variance is directed by the number of spots (NS) and Pasqualization (PA).

Studying each factor in turn, allows the determination of the differences between the dry sausage slice images. Each parameter corresponds to one particular physical aspect of the slice, when vision tends to give a global idea of the appearance. An approximation of this idea is reached by performing two principal component analyses (PCA), one slice by slice, and the other level by level. The purpose of the PCA method is to describe a population together with certain parameters supposed to discriminate among this population. The best linear combination of the different parameters is calculated in order to observe the experimental points in a plane constituted by two axes where the maximum of the total variance of the system is represented. Our PCA are performed on a PC computer using the algorithm from Foucart (1982).

Principal component analysis on each slice

All the different levels of all the slices are statistically analyzed together using a PCA. The parameters include: number of spots, total relative area of spots, average area of the spots, shape factor, one parameter of compacity, and pasqualization. L/R is not used because it correlates well with pasqualization and only one parameter of compacity is used because the two parameters calculated are very similar. The two main axes have 63 and 19 percent, respectively, of the total variance (Fig. 5). Globally the first axis corresponds to the shape of the spots (shape factor, compacity and areas) and the second axis to the homogeneity (number of spots and pasqualization).

Graphical representations are made slice by slice, giving a "fingerprint". The curves can be divided into two parts: the first one corresponding to transition from dark meat to the binding zone and the second one from
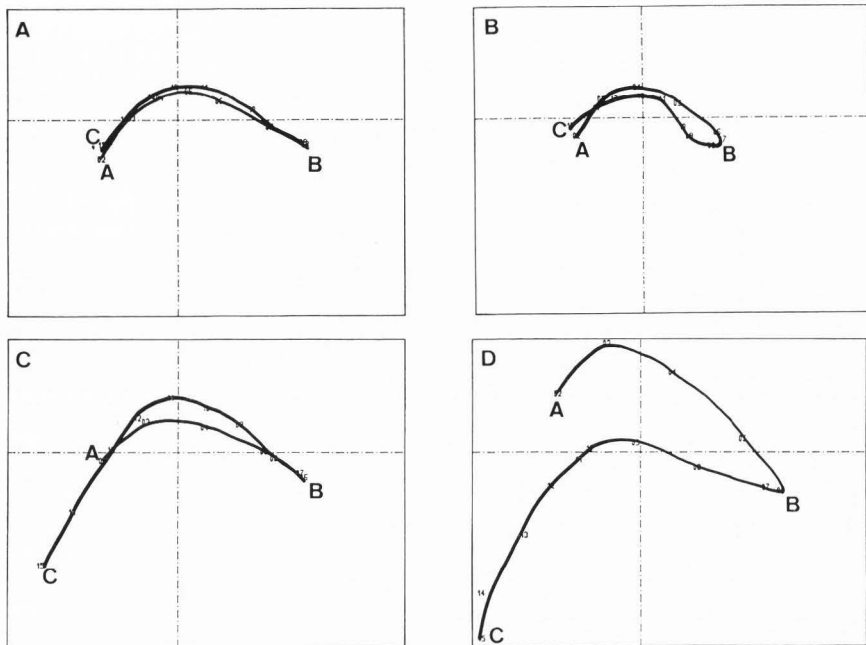
Figure 6. The four different types of the principal component analysis made level by level over each slice. Whatever type is analyzed, it can be seen that going from the black part of the image (meat; point A) to the medium level (point B), the spots become elongated (shape factor diminishes) but more compact (compacity increases). When going from medium to bright level (fat; point C), two cases can occur: the structure modifies with an exactly opposed transformation, or their heterogeneity increases (pasqualization increases) while the spots become more round (shape factor increases).

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the binding zone to bright fat. Different shapes can be distinguished (Figs. 6A-6D):

- The first and the second parts of the curve are superimposed: from an aspect point of view, the sausage variations of structure are the same in meat and in fat (Fig. 6A).

- The first and second parts are very short: the structure is almost the same whatever level is chosen (Fig. 6B).

- The lengths of the first and the second parts are very different but they are partly superimposed: the structures between fat and meat are partly the same, but variations are greater in one of these two parts (typically in fat) (Fig. 6C).

- The lengths and shapes are different: structures within fat and meat are different (Fig. 6D).

This PCA allows the creation of four classes. It can be noted that when the two parts of the curves are of different lengths, it is always the second one (corresponding to variations between fat and the binding zone) which shows the greater variations. Structure in fat is more complex than in meat.

Principal component analysis on each level

For each of the sixteen levels, a PCA is performed over the twenty slices of sausage. The different parameters used are the same as in the PCA above. It can be seen that for low levels (meat, Fig. 7A), the values for slices cut in the same sausage are similar. The two groups can be easily discriminated. When the levels correspond to fat (Fig. 7C), these groups are less different and slices within each one are more different from each other. Figure 7B shows intermediary results in the binding zone.

It can also be seen that some slices are very different from the meat detected in these PCA. These slices were already seen in the PCA slice by slice, by
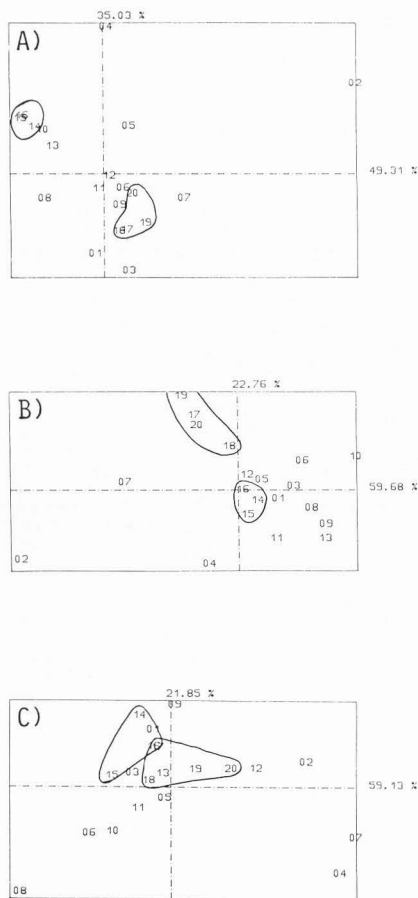
Figure 7. Principal component analysis made for three different levels over the twenty slices. **A** - dark level (meat); **B** - intermediate level; and **C** - bright level (fat). Each number corresponds to one sample. Areas marked in black show the distribution of the slices coming from the same sausage. It can be seen that the brighter the level studied, the more different the result is from visual classification.

having very unusual curves.

When a textural analysis is carried out automatically in the meat portion of the samples, a good correlation can be found with visual analysis. Structure variations are important in the analysis of the fat portion, as may be seen on the other PCA, but they are less significant when compared with visual classification. Correlations between automatic analysis and visual inspection are better when using the meat zone rather than the fat zone in image analysis.

Conclusions

This work has shown that an objective characterization of the visual aspect of dry sausage slices is possible. A sorting of different types of slices can be made corresponding to a visual classification. However. the method is very hard to use because it requires the inclusion of many parameters, all of which have to be subjected to statistical analysis. From another point of view, sausage slices have a very clear visual structure; however, with less structured food this method may not be satisfactory.

Nevertheless, visual texture of a food maybe the most important factor involved in the consumer choice. Thus, in this work, taking into account visual parameters such as shape, relative area or homogeneity, we have, for the first time, presented an objective method of sorting food according to its appearance.

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Discussion with Reviewers

R.G. Cassens: What is the actual level of correlation between visual and automatic inspection?

P.B. Newman and M.F. Devaux: What are the grounds of comparability (or the criteria of acceptability) between computer and subjective assessment?

Authors: To test the pasqualization algorithm, we used 9 synthetic images which were presented to 24 people. The results of the two sorting procedures were exactly similar except for two images which were inversed between these two methods. In the case of real slices analysis, the only point of comparison we had was the authors' visual appreciation. Among the fifteen different types of sausage, there were visually different samples, for instance, with a lot of very small pieces or long parts of fat. These sausages, very different from each other, had to be well discriminated in an automatic analysis. On the other hand, slices coming from the same sample, had to be close together.

R.G. Cassens: Can an analysis for color be worked into the image analysis?

Authors: Color analysis can be worked, but it takes time and needs much more computer memory than a black and white analysis. Another reason of not using it here is that the red component of the color is saturated over all the images and so does not give any information, and the blue component has very little intensity and has almost no significance. The main part of the information contained in our images is within the green component. At least, the latter is well correlated with human eye sensitivity. An analysis of the green component gives a good approach of human visual appreciation.

T. Ishii: Why do you divide the range of brightness into sixteen parts?

Authors: Brightness is coded over 256 levels. Dividing brightness into two parts signifies that we decided that meat is under a given level, and fat above this level. It is not the aim of this work. On the other hand, if we divide that range into 256 parts, it is impossible to find structured spots, we only obtain isolated points without any intrinsic significance. The choice of sixteen parts was then made after different assays: it gives images with spots having a size and a shape sufficiently defined, and it is enough not to preimpose significant levels.

T. Ishii: Is it possible to reduce the number of levels to save time, during the level by level calculation?

R.G. Cassens: What is the time requirement for conducting the automatic analysis?

Authors: Dividing the range of brightness into sixteen parts is a good choice in this analysis. However, it is possible to modify this number, but if this one is small, we lose too much information to obtain interesting results. To perform this analysis we use a IBM PC compatible model (a 80386 model at 25 MHz). The analysis of one slice needs around three minutes. At present, the purpose of this work was not to introduce this kind of analysis on a factory processing line. Our aim was to be able to objectively appreciate visual differences between food samples (e.g., tasting panel), processing speed was not taken into account at this stage of our analysis.

H.W. Swatland: Might better results have been obtained by first eroding the spots to find their centers, then using algorithm 1? Thus, instead of curvilinear responses, we could have visualized a response surface which might have compensated for the irregularity of spot shape.

Authors: The spots are highly irregular and very filamentous. Thus there is a high probability that their centers are not included in the spots. In this case, erosion will make this spots disappear from the image. The suggested solution might have been used if in the spot detection algorithm we had defined L only as {points P | level(P) < = level2}. The consequence of this new definition would be that spots would become far more compact. But even in that case, our previous remark is pertinent for some spots with a low shape factor.

T. Ishii: How was the total variance derived?

Authors: We consider a mathematical space of n dimensions (here n = 6: number of parameters used for the PCA). This space represents the total variance of the cloud of experimental points (100%). If we project this cloud on the plane defined by the two main axes, this plane only represents 63 + 19% of the total variance. For more details, please see Foucart (1982).

S.H. Cohen: Please elaborate further about the "Total Area" and its significance?

Authors: As mentioned in the text, the total area is the percentage of the slice area covered with spots. This total area is very important at the medium levels, and since the number of spots is small at these levels, we interpret these two facts as if this medium zone is a binding zone between meat and fat.