Application of fuzzy-rule-based postprocessing to correlation methods in pattern recognition

T. Wolf, B. Gutmann, H. Weber, J. Ferré-Borrull, S. Bosch, and S. Vallmitjana

The use of fuzzy-logic techniques on the correlation output plane is analyzed as a method to improve the discrimination capabilities of pattern-recognition procedures. The study is divided into two parts: one recounts a computer-simulated example corresponding to pattern recognition by the use of input images that may be defocused, tilted, or corrupted by additive Gaussian noise, and the second part describes an experimental setup in which the deformation of foam material is studied. © 1996 Optical Society of America

Key words: Fuzzy logic, pattern recognition, optical correlation, postprocessing methods.

1. Introduction

Fuzzy set theory and fuzzy logic, introduced by Zadeh[1] in 1965 as a way of handling imprecise data, now have many fields of application in information-processing schemes. The study of fuzzy control[2] has found several applications, such as decision making,[3] process control,[4] and pattern recognition.[5]

Since the development of the classical matched filter,[6] pattern recognition by the use of optical correlation techniques has been widely studied. Some of the important problems encountered when different filters are used are their sensitivity to noise or to deformations of the objects in the scene that hinder discrimination and limit the recognition capability; besides, the presence of sidelobes in the correlation plane, caused by nonuniformities in the scene or to a composite-filter design, may lead to the occurrence of false alarms.

Several approaches have been used to overcome these problems. One of them is designing filters to minimize the effects of input-scene noise or deformations, which are constrained to yield narrow correlation peaks.[7] Another approach is based on the combination of the results of different filters, thus reducing the probability of false alarms.[8,9] Another possibility would be to process the output by a method that combines the information obtained with other known features of the object to be detected, which fuzzy logic achieves.

In this paper we present the use of fuzzy logic as a postprocessing method to improve the results in correlation applications. Our aim is to add more information, such as the shape or the expected position of the correlation peak, to the measurement of similarity between the object and the scene. In particular, we apply fuzzy logic because it is a suitable tool to carry out this processing.

The remaining sections of this paper are now described briefly. Section 2 gives a general background on fuzzy logic and its application. Section 3 deals with the application of fuzzy-logic postprocessing in the correlation output plane in a case of pattern recognition: the detection of an object affected by different kinds of degradation, such as defocusing, tilting, and additive Gaussian noise, by the use of a matched filter and a synthetic discriminant filter.[10] Section 4 describes a real application of the digital speckle-correlation method[11] to the study of deformations of foam materials under strain, as used in the automotive industries. Finally, in Section 5 a summary is presented.

2. Fuzzy-Logic and Fuzzy-Control Theory: Summary of Important Elements

There is a wealth of technical literature (see Ref. 2, for instance) introducing the subject of fuzzy logic, so

T. Wolf, B. Gutmann, and H. Weber are with the Institut für Mechanische, Bereich Angewandte Mechanik, Universität Karlsruhe, Am Fasanengarten, Postfach 6980, D-76128, Karlsruhe, Germany. J. Ferré-Borrull, S. Bosch, and S. Vallmitjana are with the Department de Física Aplicada i Electrònica, Laboratori d'Optica, Universitat de Barcelona, Diagonal 647, E08028 Barcelona, Spain.

Received 3 August 1995; revised manuscript received 14 June 1996.

0003-6935/96/356955-09$10.00/0

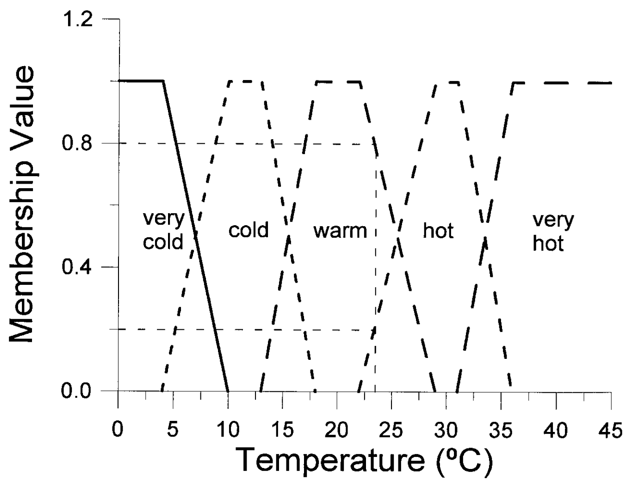


Fig. 1. Examples of fuzzy-logic linguistic values for the linguistic variable temperature.

only the definitions of the most important terms will be given here. In fuzzy logic the normalized truth value of a proposition does not have two discrete values, 0 and 1, like in Boolean logic, but lies in the interval [0, 1]. Thus a proposition need not be exactly true or false.

Quantities in fuzzy logic are operated as linguistic variables (e.g., temperature) that can take several linguistic values (e.g., high, low). The relation between real values and linguistic values is defined by the membership functions of fuzzy sets. The numerical values of an input variable can belong to one or more fuzzy sets to different degrees between 0 and 1. Figure 1 shows the linguistic variable temperature with five linguistic values ranging from very cold to very hot. Each numerical value of the temperature is assigned to at least one fuzzy set. The membership function of each set determines the degree to which a certain temperature belongs to the set. Thus, 23.5° C is hot to a degree of 0.18 and warm to a degree of 0.79. The process of assigning linguistic values to a variable is known as fuzzification.

Linguistic rules describe actions that are to be performed in certain input situations (e.g., IF temperature is high THEN set cooling to high). Several input situations referring to different linguistic variables (e.g., temperature and pressure) can be linked by generalized operators of Boolean logic (e.g., AND, OR). A common definition of the fuzzy AND operator is the minimum method: the grade of membership resulting from an AND operation between two grades of membership is the minimum of the two (e.g., 0.3 AND 0.5 = 0.3). Similarly the OR operator is commonly defined by the maximum method (e.g., 0.3 OR 0.5 = 0.5).

Inference is the process of evaluation of the linguistic rules and integration of the resulting actions, thus leading to a linguistic conclusion. For fixed values of input variables several rules are often valid to a certain degree. The results of all these rules are combined by the OR operation, producing a fuzzy set for the output variable. The defuzzification process calculates a crisp value from this fuzzy set (e.g., the speed of a cooling fan). This is often done by the center-of-gravity method, which consists of a mean of the output numerical values weighted by their grades of membership.

A fuzzy processor can be incorporated into any program by the insertion of its characteristic diagram (membership functions and rules) into the code by means of sentences such as

(i) IF (input1 $<$ 0.5) AND (input2 $<$ 1) THEN output = $f1$(input1, input2).

(ii) IF (input1 $>$ 0.5) AND (input2 $<$ 1) THEN output = $f2$(input1, input2).

We implemented this procedure by building up the fuzzy system using a program that produces C-CODE to represent the characteristic diagram of the fuzzy controller. This C-CODE can easily be interfaced with the user programs. Fuzzy logic is not the only way to build up an appropriate controller, but an essential advantage of fuzzy logic is the ease of the transfer of expert knowledge into variables and rules.

3. Use of Fuzzy Logic as a Postprocessing Method for Pattern Recognition by Correlation

In this section we show how fuzzy logic can be applied to the classification of output intensity peaks from a correlation process. To carry out this process digitally we first use a classical matched filter because of its simplicity and because it retains some information about the shape of the objects in the input scene. In a further step, we generalize our results to the case of a composite filter, as it is a linear combination of the classical matched filters of each image in the training set. We use this composite filter as a synthetic discriminant function (SDF) adapted to detect two different classes and to reject a third.

A. Postprocessing of Classical-Matched-Filter Output

To show the methodology to build the fuzzy processor and its performance, we use a generated scene composed of a matrix of images belonging to three classes (columns), see Fig. 2, obtained from the application of different degradations to the top row of objects. Therefore, the first row has the original images; in the second row the images are defocused by convolution with a circle that has a 5-pixel radius; in the third row the images are rotated by 5°; in the last row the images have zero-mean Gaussian noise added (with a variance of 90, in 8-bit gray-scale images). The energy of the images is not normalized in order to consider a more realistic problem. The correlation of the overall scene and the fish at the top left-hand corner is shown in Fig. 3(a). The height of the correlation maxima is not a determining measure to assess detection because a simple threshold in this image retains peaks other than those belonging to the first class (left-hand column).

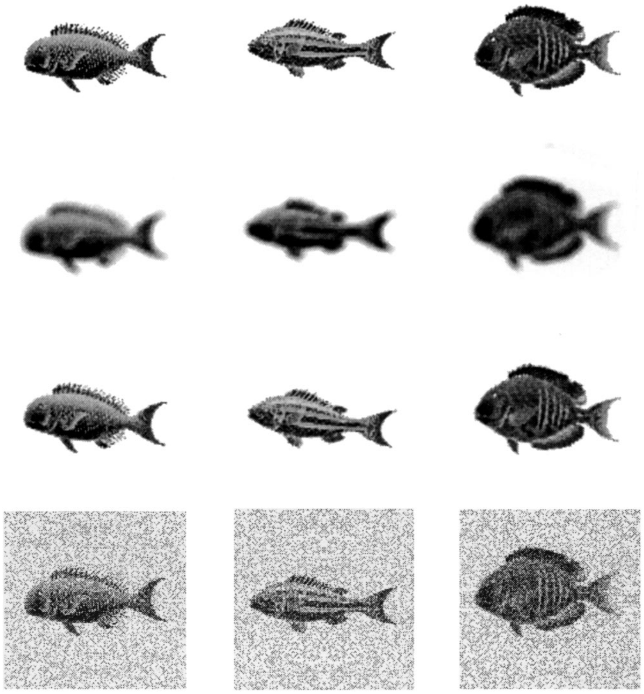


Fig. 2. Scenes used in the simulations. The top row contains the nondegraded objects.

To apply fuzzy logic, we have chosen two parameters (designated as z and r) to characterize a peak. First, z is related to the height of the peak. With the peak's height denoted by Z and the autocorrelation peak's height by Z_0, the value of the z parameter is calculated as

$$z = \left|1 - \frac{Z}{Z_0}\right|. \tag{1}$$

This is a measure of the deviation of Z from the ideal value Z_0, so that the best value for z is 0. The second parameter, which models the peak's shape, allows us to introduce this imprecise measure into fuzzy-logic-based processing. It is also related to the shape of the autocorrelation peak. If Δx and Δy are the full width at half-maximum (FWHM) of the peak in two orthogonal directions and Δx_0 and Δy_0 are the corresponding width values for the autocorrelation peak, then

$$r = \min\left(\left|1 - \frac{\Delta x}{\Delta x_0}\right|, \left|1 - \frac{\Delta y}{\Delta y_0}\right|\right). \tag{2}$$

To analyze the correlation intensity plane, we first localize digitally the local maxima in the plane, and we consider these maxima as possible peaks. Then we compute the values of Z, Δx, and Δy for each peak and combine these values with the previously computed values of Z_0, Δx_0, and Δy_0 to obtain the parameters z and r. We define the parameters as relative to the expected ones to permit the use of the same fuzzy-logic processor for any other target.

The definitions of the fuzzy sets are shown in Fig.

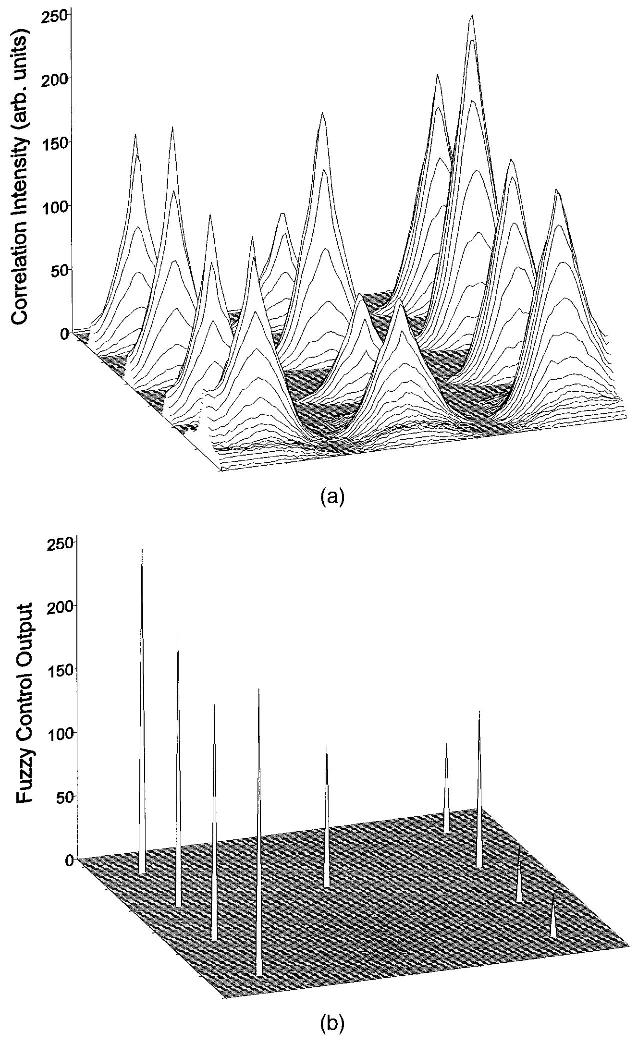


Fig. 3. (a) Correlation intensity plane corresponding to the scene and the filter matched to the top left-hand object. (b) Output image plane with the values of the fuzzy logic postprocessing.

4. For the parameter z we have defined four fuzzy sets, labeled very good (VG), good (G), medium (M), and bad (B); for the parameter r the fuzzy sets are only G, M, and B. The membership functions and their characteristic values are chosen by the study of a set of z and r values obtained from a database of images of the three fishes affected by a wide range of degradations. The rules are shown in Table 1. The defuzzification strategy chosen is the center-of-gravity method (see Ref. 2, page 385).

After the correlation plane has been scanned for local maxima and the values of z and r have been found for each, these values are passed to the fuzzy processor to obtain an output value ranging from 0 to 100. We consider as detection peaks the maxima with output values above 50 and reject those below this. This procedure has been tested with the scene shown in Fig. 2 with the filter matched to the top left-hand object and resulting in the correlation plane shown in Fig. 3(a). The results of fuzzy-logic postprocessing allow us to select the four

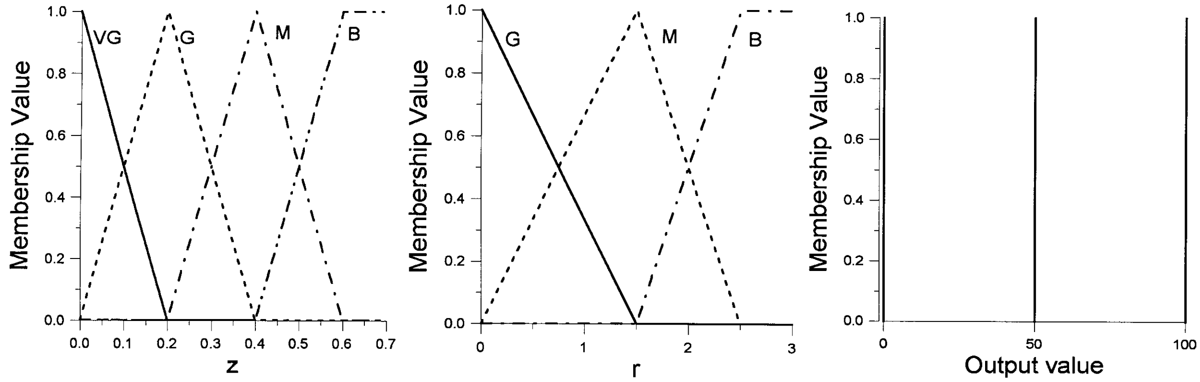


Fig. 4. Definition of fuzzy sets for matched filters.

Table 1. Rules for Fuzzy-Logic Postprocessing with Matched Filters

	z			
r	VG	G	M	B
G	G	G	G	M
M	G	M	M	B
B	M	B	B	B

left-side peaks, as can be seen from Fig. 3(b), in which the output value of the fuzzy processor has been written at the maximum position. If we use the same set of fuzzy rules with the filter matched to the top-central and right-hand targets, the results for both cases are also fully satisfactory.

B. Postprocessing a Composite-Filter Output

The second type of filter to which we have applied this postprocessing method is a composite filter used as a SDF designed to give a value of 1 for two classes (the true-class images corresponding to the left-hand and center columns in Fig. 2) and a value of 0 for the other (the false-class image in the right-hand column, Fig. 2). The filter is a linear combination of the training images, thus containing negative values. It is well known that the results of the correlation show sidelobes that can result in wrong identifications (see Ref. 8).

Our aim is to identify these sidelobes among the correctly located peaks. The definitions of the parameters to pass to the fuzzy-logic system are as follows: We correlate the first target of the true class with the composite filter to obtain the model parameters Z_1, Δx_1, and Δy_1, defined as in Section 3.A. Similarly, with the second target we obtain Z_2, Δx_2, and Δy_2. Then we scan for local maxima of the correlation plane resulting from the scene and the composite filter, computing Z, Δx, and Δy for each one.

Because the filter is designed to give the same Z value for each target, it is equivalent to using Z_1 or Z_2 (instead of Z_0) to calculate z in Eq. (1). For the widths, we compute r as follows:

$$r = \min\left(\left|1 - \frac{\Delta y/\Delta x}{\Delta y_1/\Delta x_1}\right|, \left|1 - \frac{\Delta y/\Delta x}{\Delta y_2/\Delta x_2}\right|\right). \qquad (3)$$

After these parameters have been computed, we pass them to the fuzzy-logic processor. The fuzzy sets are shown in Fig. 5 and the rules in Table 2. The results are shown in Fig. 6. The correlation values [Fig. 6(a)] at the center of the false-class object peaks are actually zero, but the remaining energy is high enough to make the sidelobes as high as those corresponding to the true-class objects. However, the fuzzy-logic postprocessing described is able to select the true detection peaks [Fig. 6(b)].

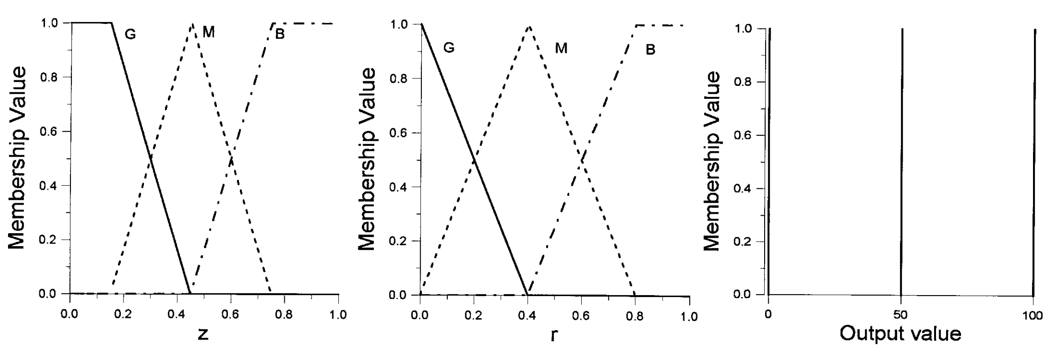


Fig. 5. Definition of fuzzy sets for composite filters.

Table 2. Rules for Fuzzy-Logic Postprocessing with Composite Filters

	z		
r	G	M	B
G	G	G	B
M	G	M	B
B	M	B	B

4. Fuzzy Logic and Correlation Techniques in the Analysis of Structural Deformation on Foam-Based Materials under Strain

A. Description of the Experiment

Soft polymer foams are generally used for vibration and shock absorption in packaging.[12,13] For characterizing these foams mechanically, their deformation behavior is studied in compression tests. The whole three-dimensional displacement-vector field (i.e., the in-plane and out-of-plane components of the surface displacements) has to be determined.

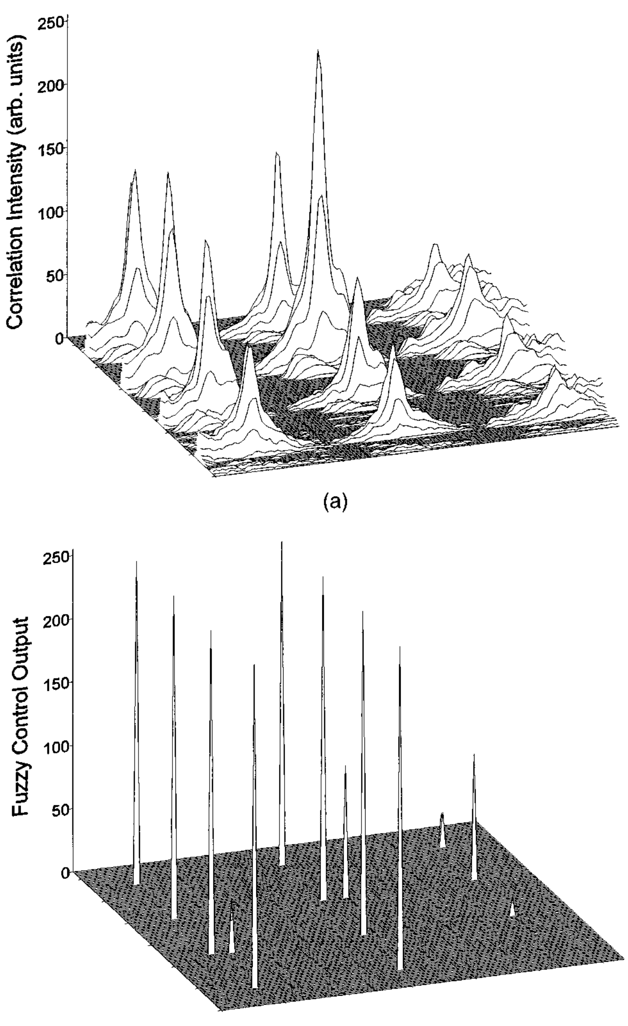


Fig. 6. (a) Correlation intensity plane corresponding to the scene and the composite filter designed for the left-hand and top-central objects. (b) Output image plane with the values of the fuzzy-logic postprocessing.

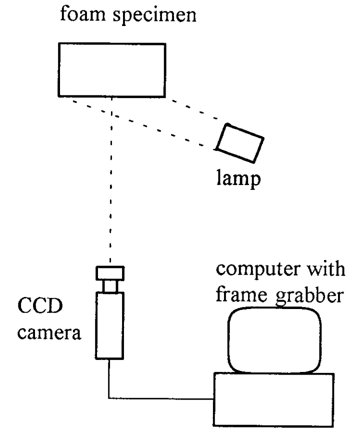


Fig. 7. Image-acquisition configuration.

The in-plane displacements are measured with the digital speckle-correlation method.[11] The surface of the foams is illuminated with white light from a high angle relative to the viewing direction of a CCD camera (Fig. 7). The camera and a frame grabber provide digitized 8-bit gray-level pictures of the foam surface. The rough surface of the foams generates a gray-level pattern with high contrast.

To obtain the in-plane displacement field, the algorithm compares the images of the foam surface in the deformed and undeformed states. This is done by the division of these images into a number of equidistant rectangular subsets of defined size, which we call correlation windows. Each correlation window has its characteristic pattern.

There are methods[14] that interpolate the data of the deformed and undeformed specimen to give a continuous intensity pattern. The pattern of the deformed state is varied numerically to map the real data of the undeformed state of the specimen. The success of the variation is monitored by the calculation of the correlation coefficient of the numerically varied data and the measured data. For little strain this method converges quickly. However, measuring the in-plane deformations of our foams with this variation method failed because the decorrelation effects were too strong. We therefore used a more efficient method based on the cross correlation of the windows in the undeformed and deformed state. The software then attempts to locate these characteristic patterns in both pictures to obtain the displacement between them.

If the displacement of a surface pattern between the two states of the specimen exceeds half the window size, there is no correlation between the windows. Thus large deformations would need correlation windows of 256×256 pixels or more, resulting in a long calculation time. As the calculated displacement of a window is just an average over the local displacements inside the window, local differences cannot be seen if the window size is too

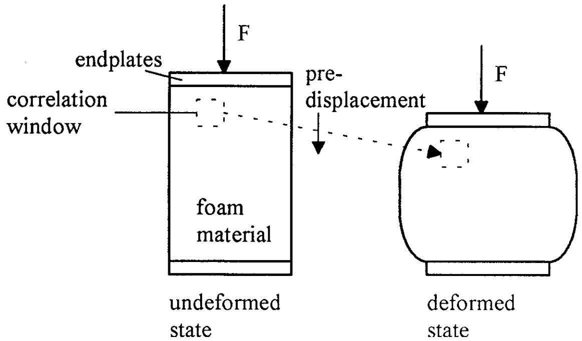


Fig. 8. Schematic diagram of the deformation process and the evolution of one compared window.

big. Therefore, it is necessary to use small correlation windows of 32 × 32 pixels or less.

A priori knowledge has to be used with this technique to obtain a correlation between the two states in the case of a smaller window size. With some materials [i.e., poly(ethylene)] the in-plane displacement of the specimen is almost proportional to the distance to the fixed end of the specimen. Thus, the approximate location of the window's pattern in the deformed state is known as predisplacement (D_x, D_y), and it can be cross correlated with the window in the deformed state (Fig. 8). The position of the correlation peak now gives only the deviation (d_x, d_y) of the position of the pattern from the estimated position. The full displacement now is given by

$$V_x = D_x + d_x,$$
$$V_y = D_y + d_y, \tag{4}$$

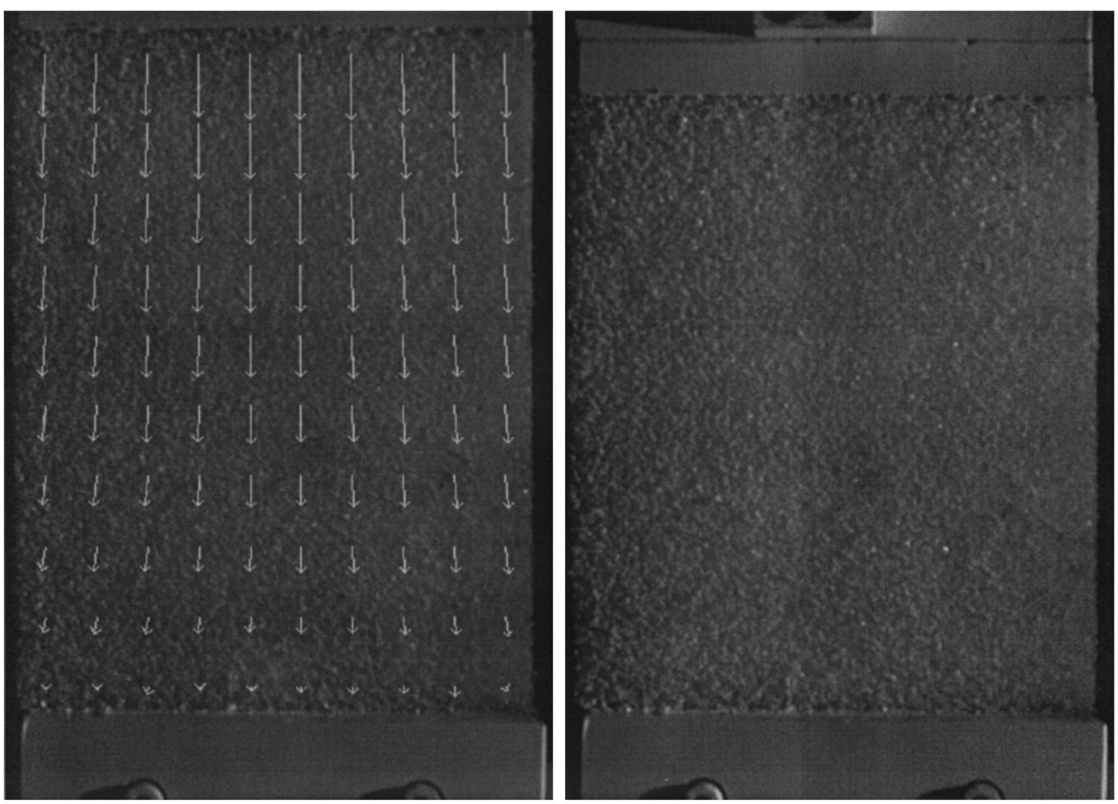
If the predisplacement is well known, the distance of the correlation peak to the center of the window should be very small or even zero ($d_x = d_y = 0$).

Successive scanning of the complete surface then yields the in-plane displacement field. The quantity and size of the correlation windows can be defined by the user. Figure 9 shows a specimen in the undeformed state and one under a compression of 10%. The surface has been divided into 10 × 10 correlation windows with sizes of 32 × 32 pixels. The resulting in-plane displacement field has been drawn into the picture of the undeformed state.

The underlying results obtained from each correlation window are shown in Fig. 10. The dark regions correspond to a high value of the correlation function, and the white regions to a low value.

B. Use of Fuzzy Logic to Determine the In-Plane Displacement Field

A large strain on the specimen, up to 40%, leads to decorrelation effects. This produces errors and false alarms when correlation techniques are applied.



(a) (b)

Fig. 9. (a) Gray-level pattern of the illuminated surface of a foam material in the undeformed state with the displacement field. (b) Foam material deformed under 10% compression.

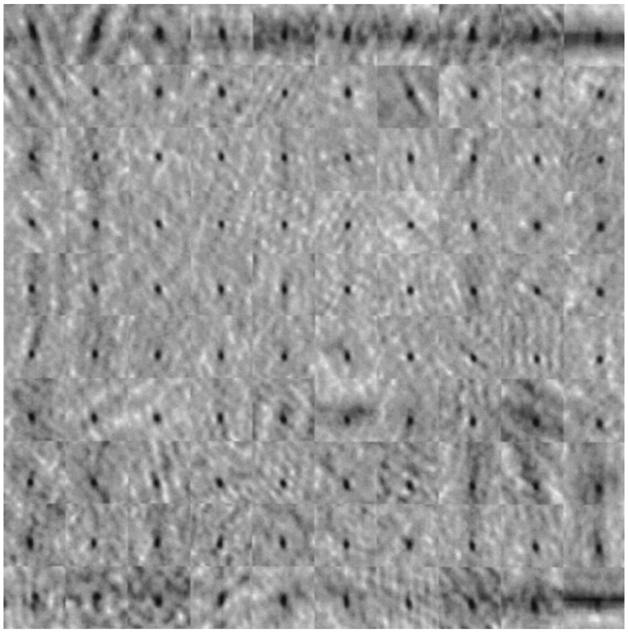


Fig. 10. Cross-correlation pattern of the windows defined for the images in Fig. 9.

The most important cause of this trouble is the deformation of the pattern inside a correlation window when the specimen is under strain. Figure 11 shows the calculated in-plane displacement field of a foam under a strain of 30%. The deformation of the foam is expected to be homogenous, thus errors in the displacement field are obvious to an experienced user. We have marked with black dots these errors in the displacement field.

Figure 12 shows two of the correlation windows that lead to incorrect displacement values if the correlation peak is identified only by the global maximum of the correlation function inside the range of the window. Also shown are the neighboring windows that lead to a correct evaluation of the displacements. Correlation peaks inside these windows are marked by a white dot. It is obvious that, in each of those windows in which an error occurred, the user would have identified the smaller local maximum in the center of the window as the correlation peak. This identification is based on the positions of the peaks in the neighboring windows and the knowledge that compression of the studied foam material should result in an almost homogenous deformation of the specimen's surface. So, even if there are several false alarms in the correlation plane that may even have the expected shape and higher correlation values than the correct peak, it is still possible to distinguish between these false alarms and the correct correlation peak by the distance of the peak from the center of the correlation window.

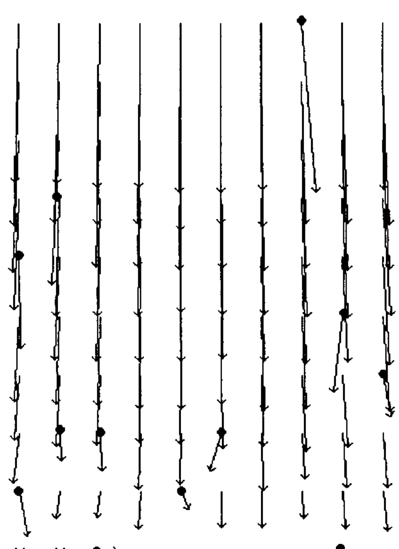


Fig. 11. Calculated displacement field under a 30% compression. The errors are marked with black dots.

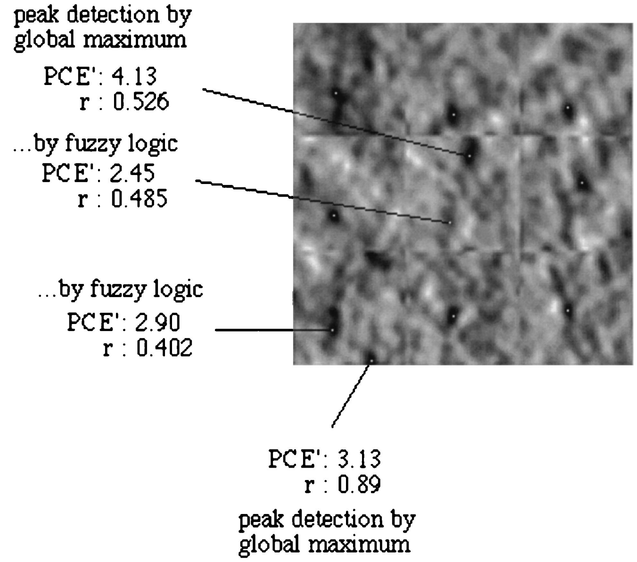


Fig. 12. Correlation windows illustrating the sources of the errors shown in Fig. 11.

To make use of this knowledge we created a fuzzy-logic processor. In the first step all local maxima in the correlation plane have to be found. For each of these maxima the following input variables have to be calculated and entered as inputs to the fuzzy-logic processor. First is the peak-to-correlation energy PCE′ (Ref. 15) as a normalized value of the peak's height:

$$\mathrm{PCE}' = K'(m_{p'} n_p) \Big/ \left\{ \frac{1}{W^2} \sum_{\substack{m,n \\ m \neq n_{p'} n \neq n_p}} [K'(m, n)]^2 \right\}^{1/2}, \quad (5)$$

with

$$K'(m, n) = K(m, n) - \frac{1}{w^2} \sum_{i,j=0}^{W-1} K(i, j), \quad (6)$$

where $K(i, j)$ is the correlation-value pixel (i, j), W is the pixel size of the rectangular correlation window, m and n are the x and y pixel positions, respectively, inside the correlation function, and mp and np are the x and y pixel positions, respectively, of the local maximum under observation.

Second is the distance of the peak to the center of the correlation window with respect to the size of the correlation window. This accounts for the fact that in larger correlation windows the user may allow a greater distance from the correlation peak to the center of the window.

$$d^2 = \frac{(x - x_{\text{center}})^2 + (y - y_{\text{center}})^2}{0.5\ \sqrt{2}\ W}. \tag{7}$$

Third is the shape of the local maximum obtained by the calculation of the ratio of the FWHM in the x and y directions. This quantity is compared with a user-given value.

$$r = \left(\frac{\Delta x}{\Delta y}\right) \Big/ \left(\frac{\Delta x_0}{\Delta y_0}\right). \tag{8}$$

For different basic foam materials and different strains there will be different values of the PCE′ and shapes of the peaks. There are two ways to handle this problem. One is to create different fuzzy processors for different materials and strains. An easier way is to determine default values of the PCE′ and the shape and then to scale the input values to the range of the linguistic variables.

To determine these default values, two steps are needed: First, the in-plane displacement field has to be determined without fuzzy logic. An average PCE′ of the global maxima of each correlation window has to be calculated. This value will contain the values of several false alarms (approximately 5–10%) but is good enough to serve as a default value for the first examination with the help of fuzzy logic because the PCE′ values of false alarms usually differ from the PCE′ of correlation peaks by only ~20%. Second, the in-plane displacement field is determined with only the PCE′ and the distance d as input variables. Most of the errors will now be removed. The PCE′ and the shape of the peaks detected by fuzzy logic now serve as default values for the determination of the in-plane displacement field with fuzzy logic and all three input variables. These default values can be used to test all specimens of the same material.

Figure 13 shows the fuzzy sets of the linguistic input variables and the output variable, which is referred to as the peak quality. Figure 13 contains six singletons (fuzzy sets with a Dirac delta as a membership function), each corresponding to a different peak quality (1 denotes bad, 6 denotes very good). Because of the high number of rules (27 altogether) many different output fuzzy sets are needed to distinguish between rules with close input values.

Table 3 lists, in three sections, the linguistic rules used in the fuzzy-logic processor. They contain the values of the peak quality for different combinations of the input values. After the first fuzzy processor was built and its decisions examined, only three modifications had to be applied to the processor to achieve overall satisfactory results.

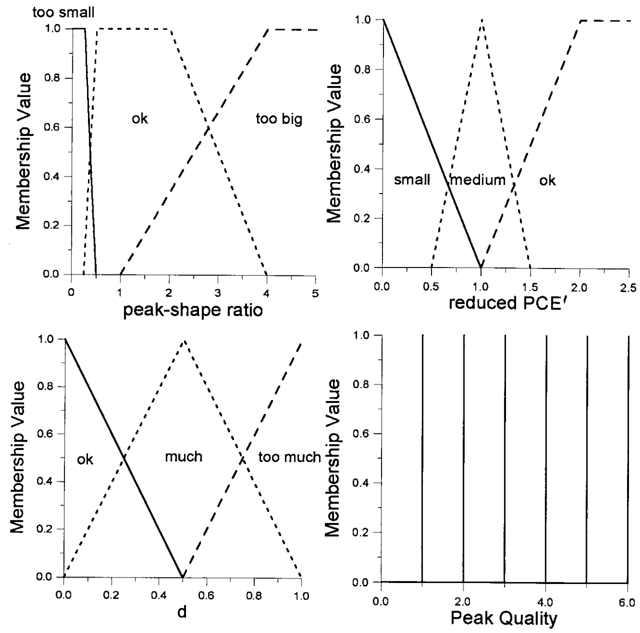


Fig. 13. Definition of the fuzzy sets for application to foam-based materials.

The fuzzy-logic system calculates a peak-quality value for all local maxima inside a correlation window. The local maximum with the highest peak quality is identified as the correlation peak.

Figure 14 shows the calculation of the displacement field shown in Fig. 11, with the help of fuzzy logic. The default values are PCE′ = 3.99 and $r_0 = 0.563$. Figure 15 shows how the number of errors increases with compression applied to the specimens made of poly(ethylene). With the help of fuzzy logic the number of remaining errors is substantially diminished when evaluating compression tests with a strain of greater than 20%.

Table 3. Rules of the Fuzzy-Logic System for Application on Foam-Based Materials for d = OK, d = Much, and d = Too Much

	Shape Ratio		
PCE′	Too Small	OK	Too Big
d = OK			
Small	0	2	0
Medium	1	4	1
OK	3	6	3
d = Much			
Small	0	1	0
Medium	0	2	0
OK	2	4	2
d = Too much			
Small	0	0	0
Medium	0	1	0
OK	1	2	1

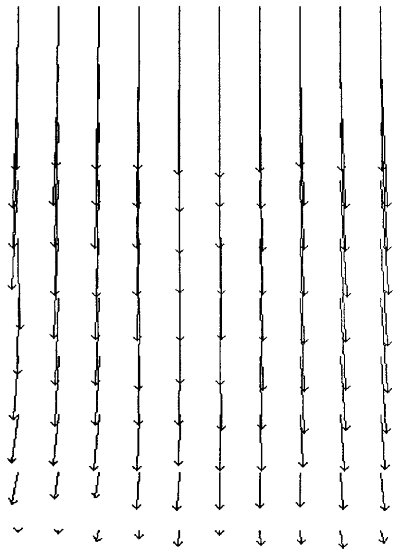


Fig. 14. Calculated displacement field after the application of the fuzzy-logic controller.

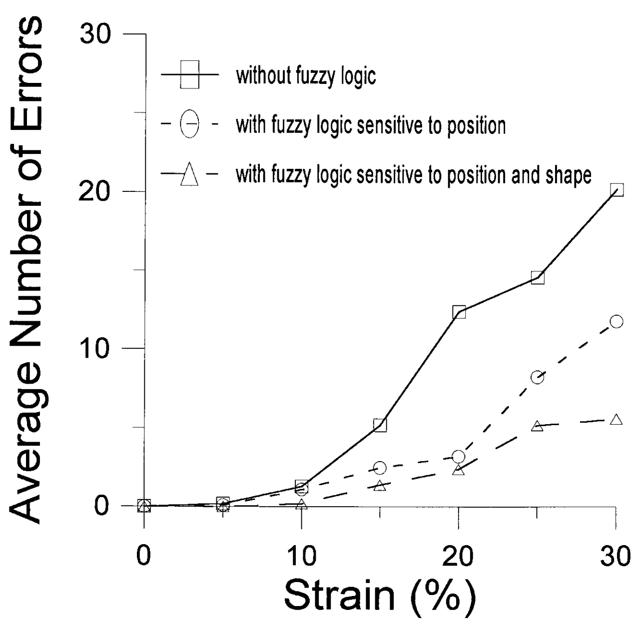


Fig. 15. Plot of the number of errors in the calculated displacement field versus the compression ratio for several calculation methods.

5. Summary

We have shown that the use of fuzzy logic for postprocessing the output of a correlation-based evaluation method is a valuable tool for selecting detection peaks. Our procedures have been tested for two cases. The first case was analyzed by computer simulation for input images that may be defocused, tilted, or corrupted by Gaussian noise and by the use of matched and SDF filters. In the second, and practical, case the analysis by digital speckle correlation of the deformations of foam materials under strain was studied. In all situations the fuzzy-logic method shows good behavior even when the inputs are not normalized in energy.

This paper was supported in part by the Comisión Interministerial de Ciencia y Tecnología (CICYT) under contract TAP94-0303. J. Ferré-Borrull gratefully acknowledges a grant from the Generalitat de Catalunya. Another part of this paper was supported by the government of Baden-Würtemberg (4-motor project), and this support is gratefully acknowledged by T. Wolf, B. Gutmann, and H. Weber.

The e-mail address for T. Wolf, B. Gutmann, and H. Weber is ig11@rz.uni-karlsruhe.de; that for J. Ferré-Borrull, S. Bosch, and S. Vallmitjana is santi@optica.fae.ub.es.

References

1. L. A. Zadeh, “Fuzzy sets,” Inf. Control **8,** 338–353 (1965).
2. J.-S. R. Jang and C.-T. Sun, “Neuro-fuzzy modelling and control,” Proc. IEEE **83,** 378–405 (1995).
3. W. G. Wee and S. K. Fu, “A formulation of fuzzy automata and its application as a model of learning systems,” IEEE Trans. Syst. Sci. Cybern. **SSC-5,** 215–223 (1969).
4. E. H. Mamdani and S. Assilian, “An experiment in linguistic synthesis with a fuzzy logic controller,” Int. J. Man–Mach. Stud. **7,** 1–13 (1975).
5. H. J. Caulfield, “Fuzzy syntactical pattern recognition,” Appl. Opt. **29,** 2600–2602 (1990).
6. A. VanderLugt, “Signal detection by complex spatial filtering,” IEEE Trans. Inf. Theory **IT-10,** 139–145 (1964).
7. Ph. Réfrégier, “Optimal trade-off filters for noise robustness, sharpness of the correlation peak, and Homer efficiency,” Opt. Lett. **16,** 829–831 (1991).
8. M. Montes-Usategui, J. Campos, I. Juvells, and S. Vallmitjana, “Sidelobe elimination for generalized synthetic discriminant functions by a two-filter correlation and subsequent postprocessing of the intensity distributions” Appl. Opt. **33,** 3050–3059 (1994).
9. D. P. Casasent, A. Ye, J. S. Smokelin, and R. H. Schaefer, “Optical correlation filter fusion for object detection,” Opt. Eng. 33 (6), 1757–1766 (1994).
10. Z. Bahri and B. V. K. Vijaya Kumar, “Generalized synthetic discriminant functions,” J. Opt. Soc. Am A **5,** 562–571 (1988).
11. D. J. Chen and F. P. Chiang, “Optimal sampling and range of measurement in displacement-only laser-speckle correlation,” Exp. Mechan. **32,** 145–153 (June 1992).
12. N. C. Hilyard, ed., *Mechanics of Cellular Plastics* (Macmillan, New York, 1982).
13. E. Geissler and H. Weber, “Computer-aided package design for sensitive products,” Packag. Technol. Sci. **4,** 311–314 (1991).
14. M. A. Sutton and W. J. Wolters, “Computer vision determination of displacement using an improved digital correlation method,” Image Vision Comput. **1,** 133–139 (1983).
15. J. L. Horner, “Metrics for assessing pattern-recognition performance,” Appl. Opt. **31,** 165–166 (1992).