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ULTRASONIC INSPECTION OF CARBON FIBER REINFORCED PLASTIC BY MEANS OF SAMPLE-RECOGNITION METHODS. (Ultraschallpruefung von CFK Mittels Methoden der Mustererkennung). R. Bilgram. Aug.1985. 29p. (Eng. trans.)

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MINS: / ANALOG TO DIGITAL CONVERTERS/ COMPUTER GRAPHICS/ COMPUTERS/ ECHO SOUNDING/ QUALITY CONTROL

ABA: G.R.

ABS: In the case of carbon fiber reinforced plastic (CFRP), it has not yet been possible to detect nonlocal defects and material degradation related to

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ULTRASONIC INSPECTION OF CARBON FIBER REINFORCED PLASTIC BY MEANS OF SAMPLE — RECOGNITION METHODS

R. Bilgram

Translation of "Ultraschallprüfung von CFK mittels Methoden der Mustererkennung," Internationales Wehrtechnisches Symposium über CKF Eigenschaften, Prüfung und Bewertung von Kohlefaserverstärkten Kunststoffen, Erding, West Germany, May 8-10, 1984. Paper. pp. 1-27.

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16. Abstract

In the case of carbon fiber reinforced plastic (CFRP), it has not yet been possible to detect nonlocal defects and material degradation related to aging with the aid of a nondestructive inspection method. An approach for overcoming the difficulties regarding such an inspection involves an extension of the ultrasonic inspection procedure on the basis of a use of signal processing and sample recognition methods. The basic concept involved in this approach is related to the realization that the ultrasonic signal contains information regarding the medium which is not utilized in conventional ultrasonic inspection. However, the analytical study of the physical processes involved is very complex. For this reason, an empirical approach is employed to make use of the information which has not been utilized before. This approach uses reference signals which can be obtained with material specimins of different quality. The implementation of these concepts for the supersonic inspection of CFRP laminates is discussed.

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ULTRASONIC INSPECTION OF CARBON FIBER REINFORCED PLASTIC BY MEANS OF SAMPLE RECOGNITION METHODS

R. Bilgram
Messerschmitt-Bölkow-Blohm GmbH

1. Introduction /1.

Non-local defects such as manufacturing defects (e.g. process irregularities, material flaws) and aging defects (e.g. chemical, physical, mechanical degradation) in carbon fiber reinforced plastics (CFRPs) have previously been impossible to detect by nondestructive inspection methods. A set of solutions is seen in expanding in improving extensively proven ultrasound inspection (US inspection) with methods of signal processing and pattern recognition so that such defects can also be detected and moreover a detailed defect type analysis and classification can be performed during US inspection of a component.

The fundamental idea is that the US signal contains information about the nature of the medium through which the sound wave has passed, or the kind of reflector from which it was reflected, which information (Fig. 1) is not used in conventional US inspection.

Since an analytical treatment of physical processes during sound propagation in components is extremely complex, and hence practical inspection of the component is hardly helpful, an empirical route is taken to make this information useful: A measurement system is provided with reference signals such as are measured on material samples of various qualities, with a signal class assigned to each quality class. Suitably "trained," the measurement system checks while measuring the component whether it recognizes certain reference signal patterns in the signal,

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*Numbers in the margin indicate pagination in the foreign text.

and assigns the pattern to the corresponding signal or quality class.

Below we discuss briefly how such a procedure can be constructed, and what experience has been gained with it on various CFRP laminates.

The method is founded on work by Rose et al. [1-7] and on general literature on pattern recognition [8]. /2

2. Method

2.1. General

The US wave train transmitted by the testing head into the test specimen at the respective measurement point is reflected from the interfaces in the specimen according to the laws of sound propagation, is absorbed in the material and scattered by microscopic interfaces so that after a certain time the wave train can be received with a correspondingly reduced sound pressure as an echo or transmission signal (Fig. 2). In conventional US inspection, the time and amplitude of the electronically smoothed and rectified received signal are evaluated, i.e., they are usually applied for "good/bad" judgments via a threshold value discriminator within a time window. Interpretation is thus limited to whether a sufficiently high echo signal is received within the selected time window.

But precisely with media such as CFRPs, which strongly damp sound, how the received signal is constituted after passing through the material is a question of great interest -- i.e., what is the influence of various material quality features upon the signal features. The consistent utilization of this connection requires application of known signal shape analysis and pattern recognition techniques, and finally leads to an automatic classification of US signals or qualities. The prerequisite is that one must be able to verify (empirically) an interdependence between signal features and material quality.

2.2. Measurement System

A measurement system for such a pattern recognition method in US inspection (Fig. 3) consists of the US transmitter/receiver with the test head, coupled to the specimen manually via a contact medium or in an immersion bath via a water separation space, and the analog/digital converter, which accepts the received signals at a suitable scanning rate (up to 100 MHz) and transmits them to the computer for further processing. The results can be graphed or tabulated out via suitable peripherals. Via a monitor the US signal can be observed directly for supervision. /3

The procedure for applying pattern recognition can roughly be divided into three phases:

2.3. "Learning" Phase

Reference signals for the various quality classes are recorded from suitably prepared CFRP patterns ("good" signals and various "defect" signals). From the signals, suitable signal features are calculated, e.g., rise time, pulse duration, decay time of the envelope signal, various shape factors of the envelope signal, the HF output spectrum, the so-called analytical spectrum and/or the phase spectrum. Here "suitable" means: physically meaningful and useful for a class differentiation. At the end of the experiments, a data base is available containing a suitable selection of signal feature values for each class to be differentiated (e.g., 5), in a sufficient number for statistical purposes (e.g., 10-20 or more measurement points for each class).

Using this data base, a computation rule (algorithm) is then developed which using as few signal features as possible assigns the measurement points of the data base to the right classes. In principle this classification rule can be based on considerations of tabulated values and establishment of limit values, but preferably it uses graphic/visual examination of population diagrams and evaluation of probability density functions of the signal features of the classes being sought. Examples of this /4 are discussed further below. But since generally several classes must be distinguished and up to 5 signal features must be considered, human visual capacity or abstraction capability is exceeded and one lets a computer develop algorithms according to preset blueprints (i.e., calculate the coefficients for so-called discriminant functions), and then check the suitability of the algorithm by inserting the values from the data base.

Here it must be noted that in this learning phase it is possible to take account of the scattering of various parameters from the areas of material characteristics and testing data, which of course are reproducible only within limits, by fully including the corresponding scattering ranges in the base data.

2.4. Test Phase

As patterns of known error classes or quality features, by measuring as many US signals as possible, deriving the feature values and inserting these values in the algorithm from the learning phase, one checks how well the algorithm works at arbitrary points of the known defect samples -- i.e., how high the "hit rate" is. If it is not high enough, the learning phase must be repeated, either expanding the data base with further measurements, using other definitions for the signal features, or if necessary altering the testing boundary conditions (testing frequency, scanning window, amplification, etc.).

2.5. Inspection Phase

Given sufficiently high accuracy in the testing phase, testing can now be performed with the developed algorithm on unknown laminates. The result of each testing process is the classification of the respective measurement point, with a /5 certain probability < 100% (as with any non-destructive test result), which can be determined from the test phase.

3. Sample Applications

3.1. Delamination Test

To illustrate the above description, a simple practical example can be used, in which an algorithm was developed to detect delaminations in a CFRP plate (5 mm thick, resin system 914 C, fiber T 300). Figure 4 shows two US signals from this example, as well as the HF spectrum, analytical spectrum, and envelope of these signals. In the example only 2 classes, namely the "good" range (Class 1) and "delamination" (Class 2) were to be distinguished. Hence is was sufficient to consider the relatively apparent features of the envelope, which are defined as shown in Fig. 5.

In the example in Fig. 6, one can see that feature No. 4 has almost identical probability density functions for both classes, i.e., the same values are measured with high probability for the "good" range and delamination. Consequently the feature cannot be valuable for classification. Feature No. 7 (upper half of Fig. 6) on the other hand, separates the two classes better. But as with the other features there is a relatively large range of overlap, meaning that a limit value that separates bc' classes 100% does not exist for any feature. Consequently 2 features must be used.

Here it is useful to consider the population graphs in question, i.e., the values are graphed in a coordinate network as in Fig. 7, formed by the feature axes. In the upper half, /6 features 5 and 6 were selected, and one sees that here it is still impossible to separate Classes 1 and 2 100% by a line. From the 45 possible pairings of the 10 features, the pairing 6/7 was found best. It is reproduced at the bottom of Fig. 7, and rather than the centroid normal (solid line) drawn by the computer, a line similar to the dotted line separates the two classes best.

The "blueprint" for the algorithm embodied in this separation line is a linear discriminant function with the general form:

$$f = c_0 + c_1 \cdot x_1 + c_2 \cdot x_2 + \cdots c_n \cdot x_n \qquad (1)$$

where x_i are the feature values of the current measurement point, and c are the coefficients to be determined by the computer program.

The determined algorithm reads:

$$f = -0.0262 - 3.9163 \cdot x_6 + 1.8879 \cdot x_7 \qquad (2)$$

The measurement values 6 and 7 determined at any given measurement point (i.e., according to Fig. 10 these are the position of the centroid of the envelope and the standard deviation of the curve points) are inserted in Eq. (2) and the result f is compared with a threshold value s = 0.782 and classified:

if $f \geq 0.782$ Class 1 = "good"

if $f < 0.782$ Class 2 = "delamination"

A correspondingly structured test program supplies the classification within ca. 4 sec., with an accuracy of nearly 100%. /7

3.2. Manufacturing Defects in Multidirectional Laminates

The actual domain of pattern recognition is US signals that do not contain such obvious information as (e.g.) a delamination echo, but due to deviating material properties present only certain signal alterations compared to a "good" standard. These alterations may be due to deviations in process parameters (pressure, temperature, time, etc.), contamination of the laminates (moisture, mold lubricants, separation films, etc.) and aging effects (chemical, mechanical, physical).

To give an example, plates of a 17-layer laminate type made of unidirectional carbon fiber prepreg 914 C-/T300 were hardened with various process defects. Figure 8 summarizes the 8 classes. 1 measurement point each was set on the 16 "good" samples, and 10 measurement points each on the other samples, so that in this case a data base of 86 measurement points is available for the learning phase. The 10 features were defined as in Fig. 5.

Here different studies were performed, i.e. linear discriminant functions per Eq. (1) were determined for 2 classes each. At this point we introduce another type of discriminant function, the hyperquadratic, with the general form:

$$g_i(\vec{x}) = \vec{x}^t \cdot [W_i] \cdot \vec{x} + \vec{w}_i \cdot \vec{x} + w_{oi} \qquad (3)$$

with x = feature vector
x^t = transposed feature vector
$[W_i]$ = weight matrix
w_i = weight vector
w_{oi} = weight scalar /8

For each class i, the value $g_i(x)$ is calculated; for the class in question, $g_i(x)$ is the maximum.

Computer programs were developed which automatically determine the best feature combinations for a given training data set, i.e., the selection of signal features that supplies a required minimum quota of correct class assignments for this data set. In the first step, an algorithm per Eq. (3) is developed for each signal feature and each class, and the accuracy is determined by inserting the training values. If the minimum quota (90%) is reached, it is reported and the computer recommends using this algorithm to solve the inspection problem. Otherwise, in a second step all combinations of two are tested, then all combinations of three and so on, until a satisfactory accuracy is reached. Experience shows that it is enough to include 2 or 3 features, but for 8 classes sometimes 4 or more features may be necessary.

An important question is the quality of a classification algorithm, i.e., what criterion should be used to evaluate which of the possible algorithms or error finding allows the best accuracy.

For this one considers the so-called "performance matrix" in Fig. 9 as a way of showing classification results in which the number of correct class assignments for each class, the total accuracy (= performance), detection quota (= detectability) and "good" quota (= specificity) or Class 1 quota, are graphed.

It is reasonable to expect such an algorithm primarily to detect "good" points and "bad" points with optimum certainty, and only secondarily to name the kind of defect correctly. Therefore the mean of the quota for Class 1 (= "good") and /9
the error detection quota (mean of quotas for error classes) is used as the evaluation criterion. Only when several possibilities yield the same total is the total accuracy used as a second criterion.

In the present case, for example, the situation shown in Fig. 10 developed. Using only one feature, features 5 and 8 each yielded 87.8% as a mean criterion; the total accuracy of 37.7% here favors feature 5. With 2 features, the pairing of Nos. 12 and 19 with a mean criterion of 96.2% was the best, and here up to 60.5% of all measured points could be assigned correctly.

The more features are considered, the higher the number of right assignments, and the main question is how much computer time per measurement point can be spent on classification.

The classification mechanism will be explained in more detail with this example. As noted above, for each class a discriminant function is defined. In Fig. 11, 4 such functions are graphed as an example for 4 classes, vs. the feature value. Each measurement process yields a certain feature value and the task of classification is to determine which of the functions at this point has the highest value.

Even with 2 features, this classification is still manageable (Fig. 12). Here the discriminant functions can be seen as areas (with hills and valleys) intersecting at the classification boundaries. Such intersecting lines are graphed in Fig. 12; the numbers mean that at this point of the "feature" plane the respective function has the greatest value of all 8 functions./10

3.3. Fabric Laminate Specimens

While the sample plate studied in the above section had a uniform wall thickness, in another test series, 27 specimens of 2 laminate types with 3 wall thicknesses were used, in a further step towards close-to-practice testing problems. Laminate type A is made purely of fabric prepregs (6, 12 and 18 layers). Type B is made of alternating fabric layers and unidirectional tapes (7, 13 and 19 layers). For each of the laminates, the corresponding classification algorithms were determined in which 10 very simple signal features (involving simple software) were used:

The first 5 features are defined like features 5-9 in Fig. 5, applied to the rectified HF signal (software: f(t) = /f(t)/). A further 5 features with the same definition were drawn from the HF output spectrum.

Although here we worked with greatly simplified signal features compared to the previous example, the defects were distinguished very clearly (close to 100%) using only 2 or 3 features (Fig. 13).

There are two possible causes for the good classification performance: First, the smaller number of classes (4 or 5), and second the defects seem more severe than in the example with multidirectional laminates (Sec. 3.3). /11

4. Summary and Prospects

The application of signal shape analysis and pattern recognition methods opens new prospects for US inspection, particularly of complex structures such as CFRPs. As was shown with some simple laminate forms, signal features can be defined and associated classification algorithms can be developed, with which US signals can be assigned to certain reference signal classes. Since these reference signals come from laminates with certain quality classes ("good" class and various defect classes), it is possible to assign US signals to a defect class.

The presented examples demonstrate that a measurement system (measurement technology and software) can be constructed to fulfil the posed task of detecting non-local production defects such as process irregularities, contaminations, pretreatment defects, etc., at detection rates of over 90%.

It can be assumed that certain aging defects can also be detected. Studies on this will begin this year.

At the moment, work is aimed at discovering by steps the requirements of a practical CFRP inspection, i.e. for detecting real defects with the necessary certainty in real components in an economically reasonable manner, even with more and more complex component geometries and laminate types.

The next steps are:

-- Search for a test that is independent of wall thickness and if possible of geometry. /12

-- Simplified operation and use of computer programs to master many-sided inspection problems quickly.

-- Increased computation speed using Assembler subprograms.

-- Collecting further experience from previous results concerning signal feature "quality," such as: Which ones respond especially sensitively to certain types of defects, or how can the "quality" of features best be evaluated.

-- Attempt at a physical explanation of the effect of certain defects upon the US signals.

-- Study of possibilities for automatic defect detection, without having reference specimens available.

-- Producing self-adapting changes in the classification algorithms in the test phase, so that these can be improved and refined continuously with the number of tests.

Precisely concerning the last aspect it should be emphasized that our developmental work in pattern recognition processes for US inspection will not terminate in an independent system that has a possibly incomprehensible or even controlled existence separate from physical considerations and practical inspection experience, but rather a system that is technically highly developed, capable and versatile, yet as simple to use as a conventional US device, a system to serve US inspectors as a tool for evaluating CFRP materials with all requirements according to the best knowledge and state of the art. This also includes detection of manufacturing defects previously undetectable without destruction, for which in our opinion pattern recognition offers a solution.

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Key to figures [pp. 15-27]

Fig. 1. US signals, top: example of "good" signal, bottom: example of "defect" signal.
a. smoothed and rectified b. time

Fig. 2. Diagram of ultrasound testing

a. workpiece
b. defect
c. coupling agent
d. testing head
e. (receiver only)
f. (transmitter and receiver)
g. screen image
h. back wall echo
i. defect echo
j. surface echo

Fig. 3. Measurement system

a. ultrasound testing device
b. testing head
c. analog/digital converter
d. computer
e. printer
f. graphics terminal

Fig. 4. Examples of 2 ultrasound signals from delamination example.

a. "good range"

Fig. 5. Definition of signal features of envelope signal

a. envelope signal
b. time
c. rise time
d. pulse width at ___%
e. decay time
f. area ratio
g. centroid position of area
h. asymmetry
i. standard deviation of curve points
j. deviation from Gauss bell curve
k. position of maximum

Fig. 6. Probability density for feature values Nos. 4 and 5 in delamination examples

Fig. 7. Grouping of both classes for two different feature pairings. The pairing 6/7 (below) is suitable to separate all measurements of both classes with a line; the upper one is not.

Fig. 8. Compilation of values of 8 sample classes with hardening defects. [Commas in numbers = decimal points]

a. sample No.
b. class
c. mean ILS value
d. [expansion unknown]
e. quota
f. finding rate
g. hardening pressure
h. defective vacuum sack
i. hardening temperature
j. tempered
k. untempered
l. cooled too quickly
m. separating film between ____ layers
n. silicone lubricant between ____ layers
o. good
p. (for moisture aging)
q. (for weathering)
r. (for adhesion defects ...
s. total
t. manufacturing/defect

Fig. 9. "Performance matrix" as means of representing results of classification. [Commas in numbers = decimal points]

a. actual defect class
b. found class
c. total
d. quota
e. detection
f. mean
g. employed features

Fig. 10. Compilation of best features/feature combinations for multidirectional laminates (8 classes) [Commas in numbers = decimal points]

a. number of features
b. employed features
c. mean criterion
d. total rate (accuracy)

Fig. 11. Example of 4 hyperquadratic discriminant functions for 1 feature. For $x_4 = 1.01$, e.g., class 4 is right.

Fig. 12. Decision plane for features 12/19 for multidirectional laminates (8 classes)

Fig. 13. Compilation of "hit quotas" for optimum feature combinations for the 6 types of fabric laminates. [Commas in numbers = decimal points]

a. laminate type
b. number of layers
c. of employed features
d. classes
e. total criterion
f. total rate (accuracy)

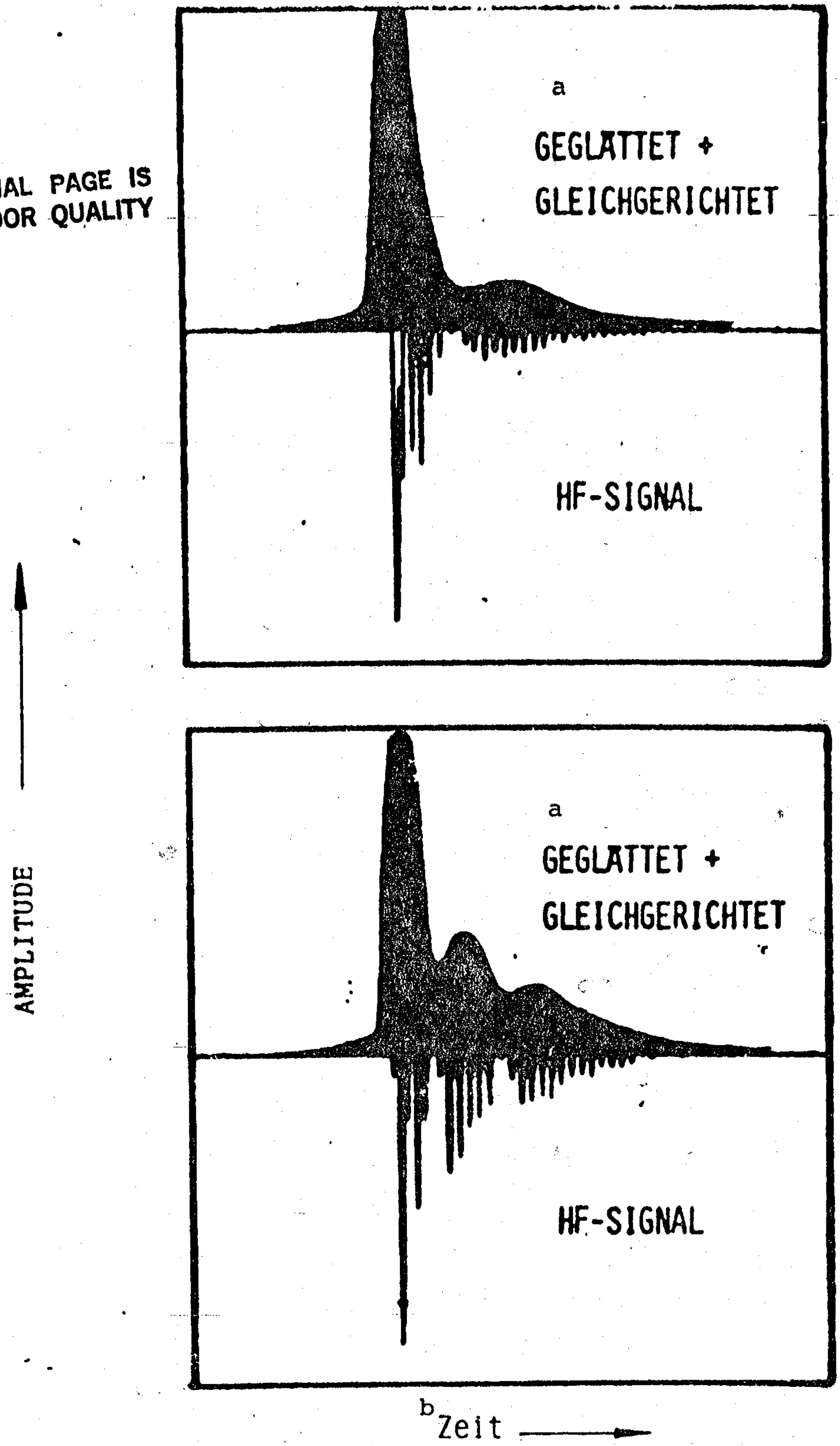


Bild 1: US-Signale, oben Beispiel für "Gut"-Signal
Fig. 1 unten Beispiel fur "Fehler"-Signal

11/277

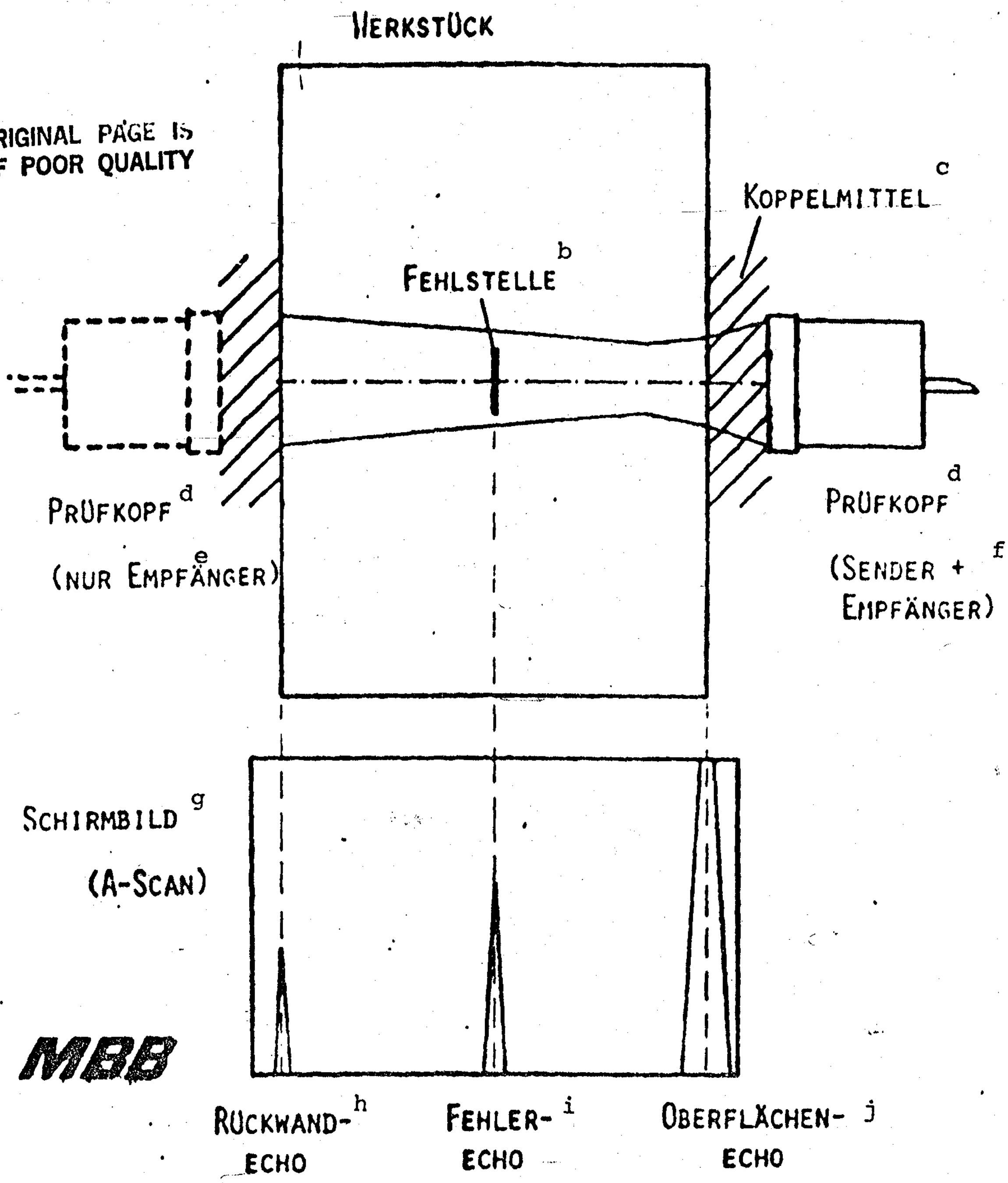


Bild 2: Prinzipdarstellung der Ultraschallprüfung.
Fig. 2

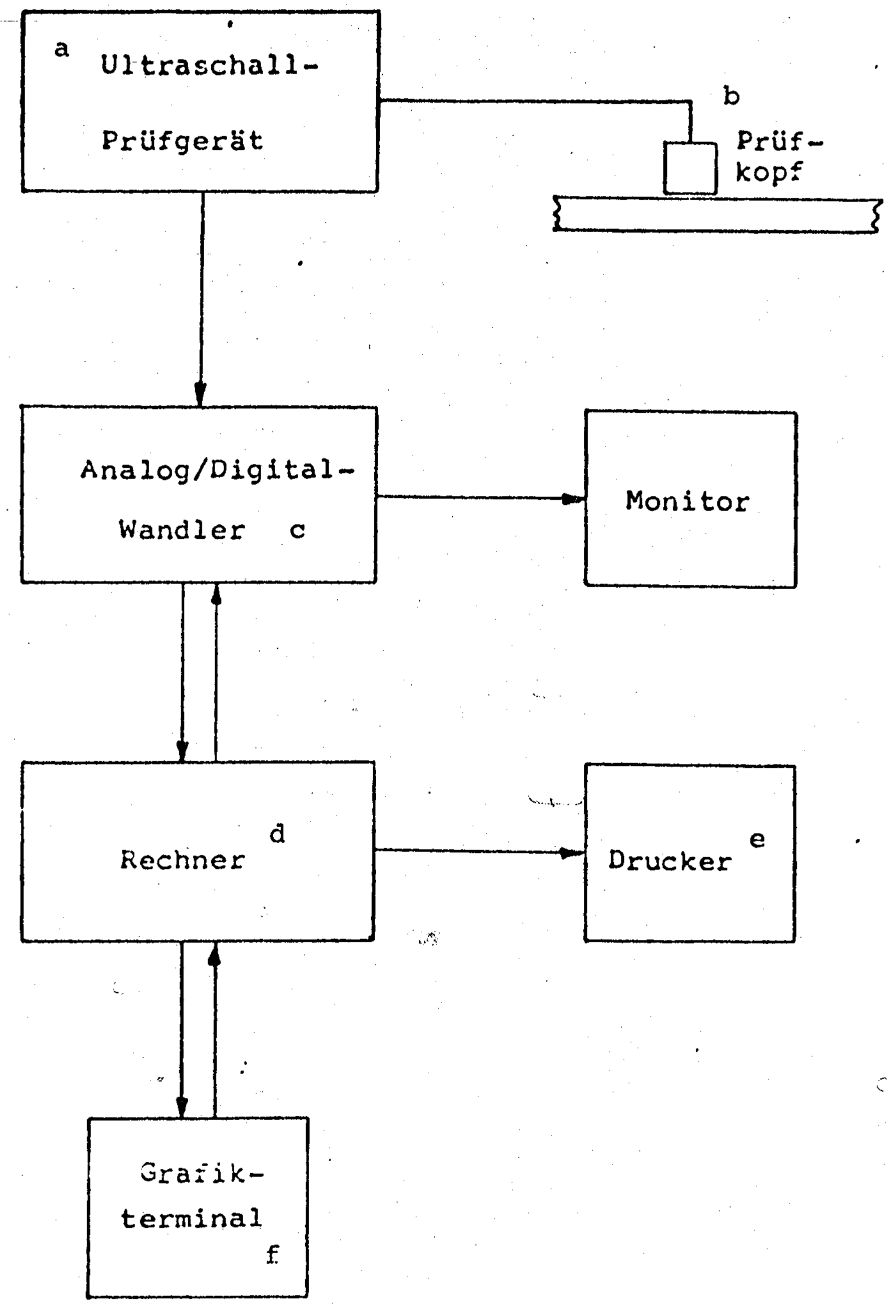
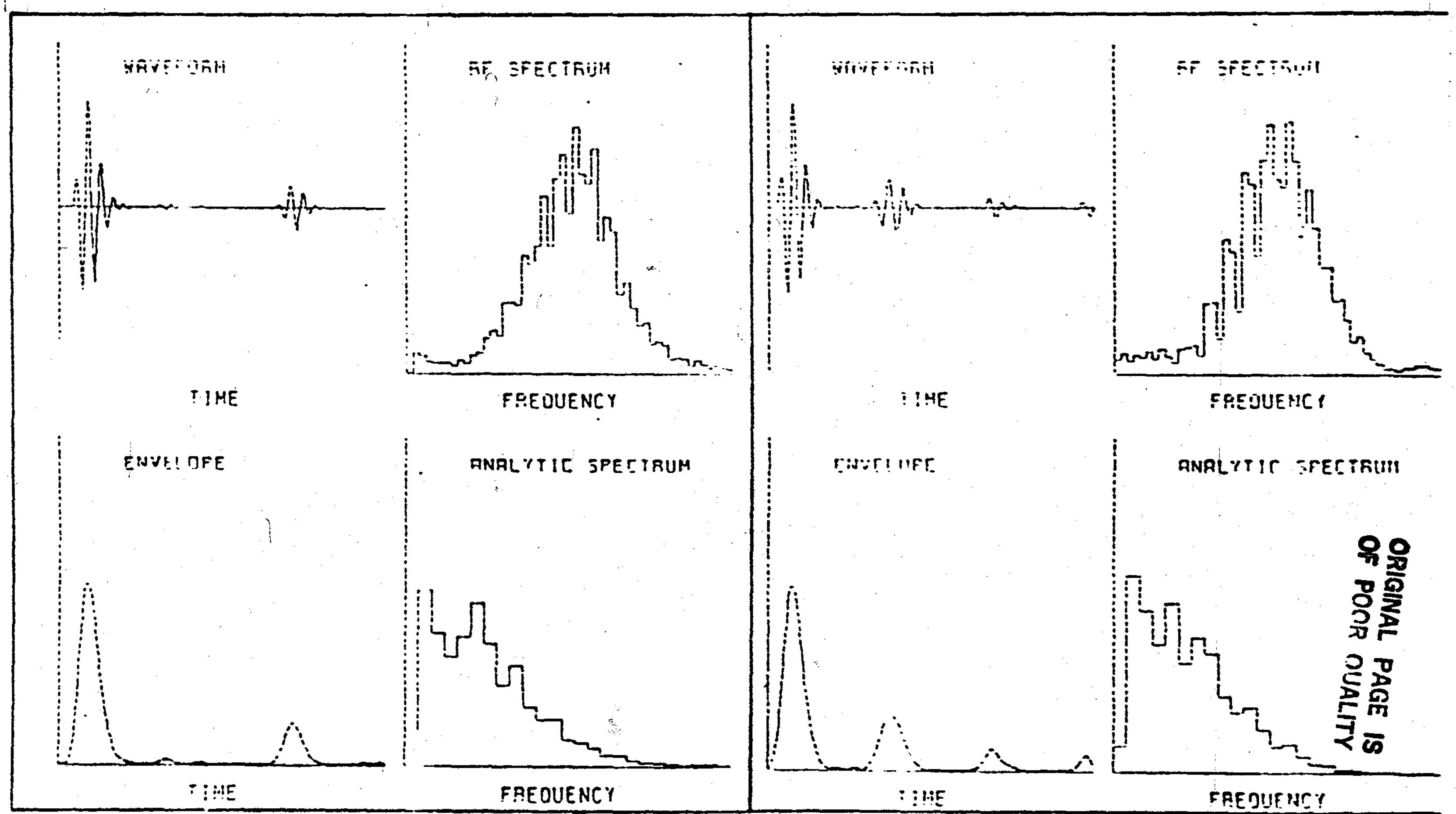


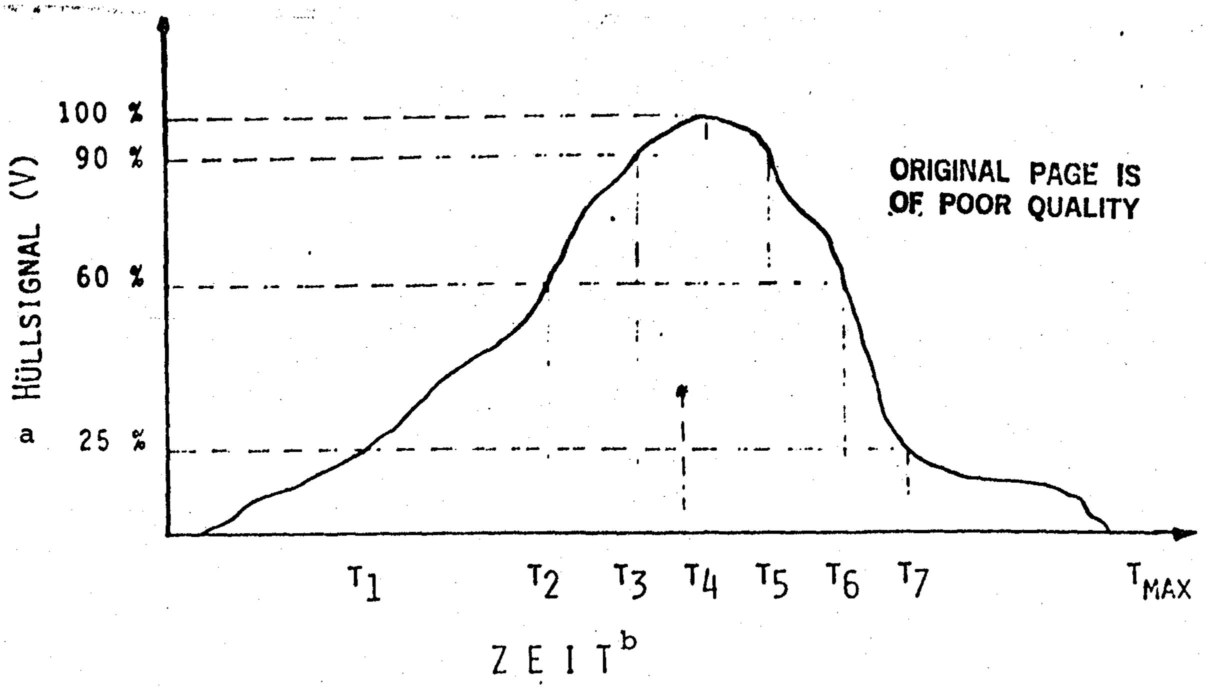
Bild 3: Meßsystem
Fig. 3



"Gut-Bereich" "Delamination"

Fig. 4

Bild 4: Beispiele für 2 Ultraschallsignale des Delaminationsbeispiels



$F_1 = T_3 - T_1$ = ANSTIEGSZEIT [c]

$F_2 = T_6 - T_2$ = PULSBREITE BEI 60 % [d]

$F_3 = T_7 - T_1$ = PULSBREITE BEI 25 % [d]

$F_4 = T_7 - T_5$ = ABKLINGZEIT [e]

F_5 = FLÄCHENVERHÄLTNIS [f] = $\int_0^{T_{max}/2} V dt \Big/ \int_{T_{max}/2}^{T_{max}} V dt$

F_6 = SCHWERPUNKTSLAGE DER FLÄCHE [g]

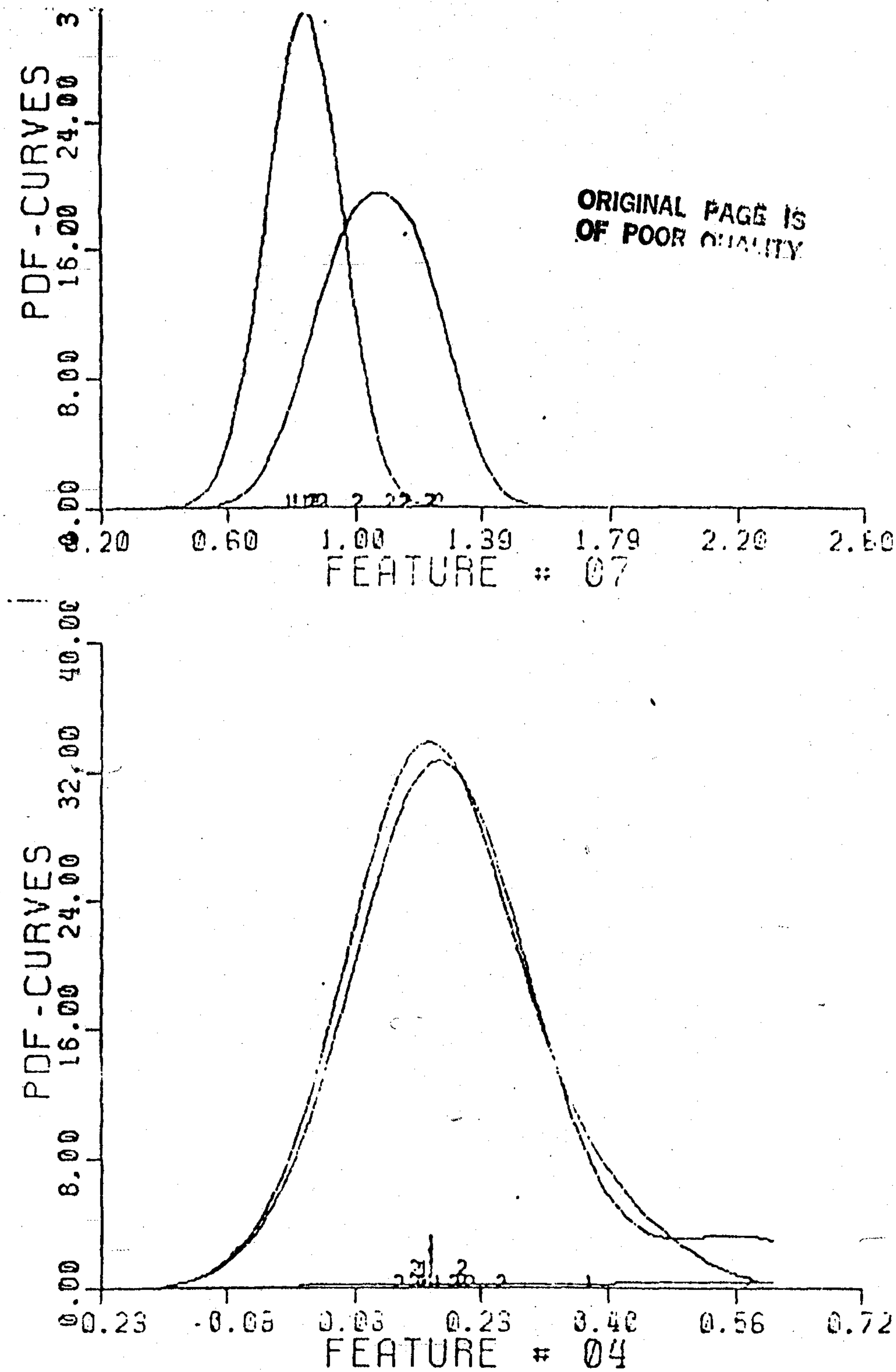
F_7 = STANDARDABWEICHUNG DER KURVENPUNKTE [i]

F_8 = SKEWNESS (ASYMMETRIE) [h]

F_9 = KURTOSIS (ABWEICHUNG VON GAUSS-GLOCKENKURVE) [j]

$F_{10} = T_4$ = LAGE DES MAXIMUMS [k]

~~Bild 5:~~ ~~Definition~~ von Signalmerkmalen des Hüllsignals
Fig. 5 (Video Envelope (V))



MBB

Bild 6: Wahrscheinlichkeitsdichte für Merkmalswerte
Fig. 6 Nr. 4 und Nr. 5 bei Delaminationsbeispiele

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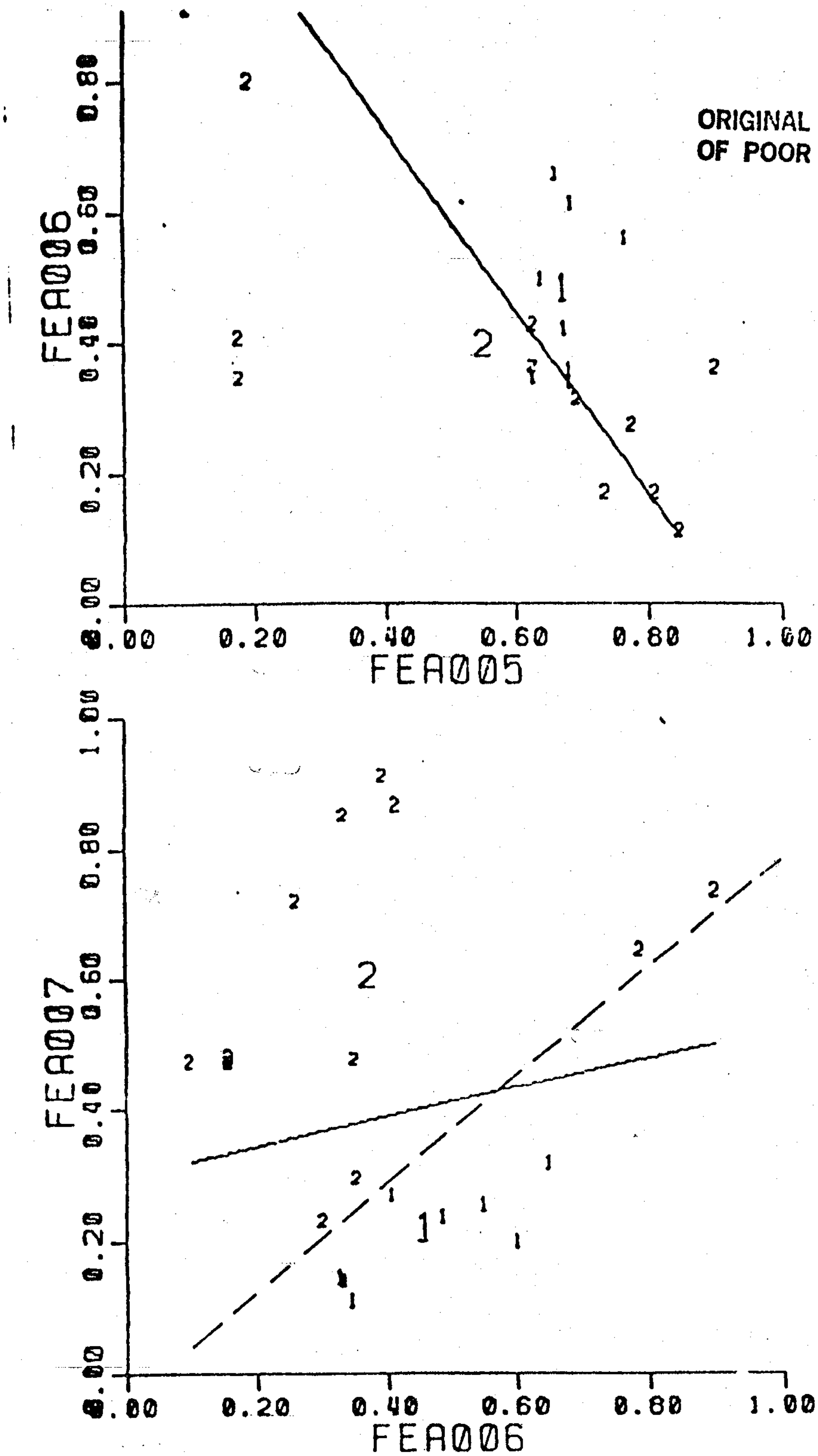

Bild 7: Gruppierung der beiden Klassen für zwei verschiedene Merkmals-Paarungen. Die Paarung 6/7 (unten) ist geeignet, alle Messungen der beiden Klassen mit einer Linie zu trennen, die obere nicht.

Fig. 7

Nr. a		b	ILS-Wert N/mm²	d	%	rate %
C21 I C21 II	50 % Aushärtedruck g	2 2	62,4 59,8		80,0	93,3
C22 I C22 II	defekter Vakuumsack h	3 3	48,2 48,5		90,0	100,0
C23 I C23 II	Härtetemperatur 150°, getempert i,j	4 4	67,2		100,0	100,0
C24 I C24 II	Härtetemperatur 150°, ungetempert i,k	5 5	66,1		80,0	90,0
C25 I C25 II	Abkühlung zu schnell l	6 6	50,8 50,3		70,0	100,0
C26 I C26 II	Trennfolie zw. 2./3. Lage 8./9. Lage m	7 7	66,6 53,9	del.	80,0	100,0
C27 I C27 II	Silikonfett zw. 2./3. Lage 8./9. Lage n	8 8	62,3 46,9	del.	90,0	100,0
C31 C32 C33 C34	gut (für Feuchtealterung) o,p	1	73,0			
C35 I C35 II C36 I C36 II	gut (für Klimaalterung) o,q	1	72,8		87,5	-
C41 I C41 II C41 III C41 IV	gut (für Klebfehler I) o,r	1	71,0			
C42 I C42 II C42 III C42 IV	gut (für Klebfehler II) o,r	1	71,3			
				Summe: s	84,7	97,6

Fig. 8

~~Bild 8:~~

Zusammenstellung der Werte der 8 Probenklassen mit Aushärtefehlern

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gefundende Klasse[b]	tatsächliche Fehlerklasse:[a] 1	2	3	4	5	6	7	8
1	15	1	0	0	0	0	0	0
2	1	9	0	3	1	3	1	0
3	0	0	9	0	0	1	1	1
4	0	0	0	5	4	1	0	0
5	0	0	0	1	3	5	2	0
6	0	0	0	0	0	0	0	1
7	0	0	0	0	0	0	6	1
8	0	0	1	1	2	0	0	7
Summe:[c]	16	10	10	10	10	10	10	10
Quote:[d] % 60,5	93,7	90,0	90,0	50,0	30,0	0,0	60,0	70,0
Detekt.[e]: % 98,6		90,0	100,0	100,0	100,0	100,0	100,0	100,0
Quote[d] 1: 93,7								
MW[f] : 96,2								

[g] verwendete Merkmale: # 12,19

Bild 9: "Performance-Matrix" als Darstellungsweise für
Fig. 9 Klassifikationsergebnisse

Zahl der Merkmale [a]	benutzte Merkmale [b]	Mittelwert-kriterium [c]	Gesamt-quote [d]
1	5	87,8 %	37,7 %
	8	87,8	32,7
	17	87,1	36,4
	6	86,3	35,2
	16	86,3	35,2
	.	.	.
	.	.	.
2	12 19	96,2	60.5
	5 14	92,3	52,2
	8 19	92,3	50,9
	.	.	.
	.	.	.
3	12 19 25	96.9	63,0
	5 8 14	96,2	60,5
	5 11 14	96,2	71,7
	6 19 24	96,2	63,0
	12 19 24	96,2	65,5
	.	.	.
	.	.	.

Bild 10: Zusammenstellung der besten Merkmale/Merkmalskombinationen
Fig. 10 für multidirektionale Laminate (8 Klassen)

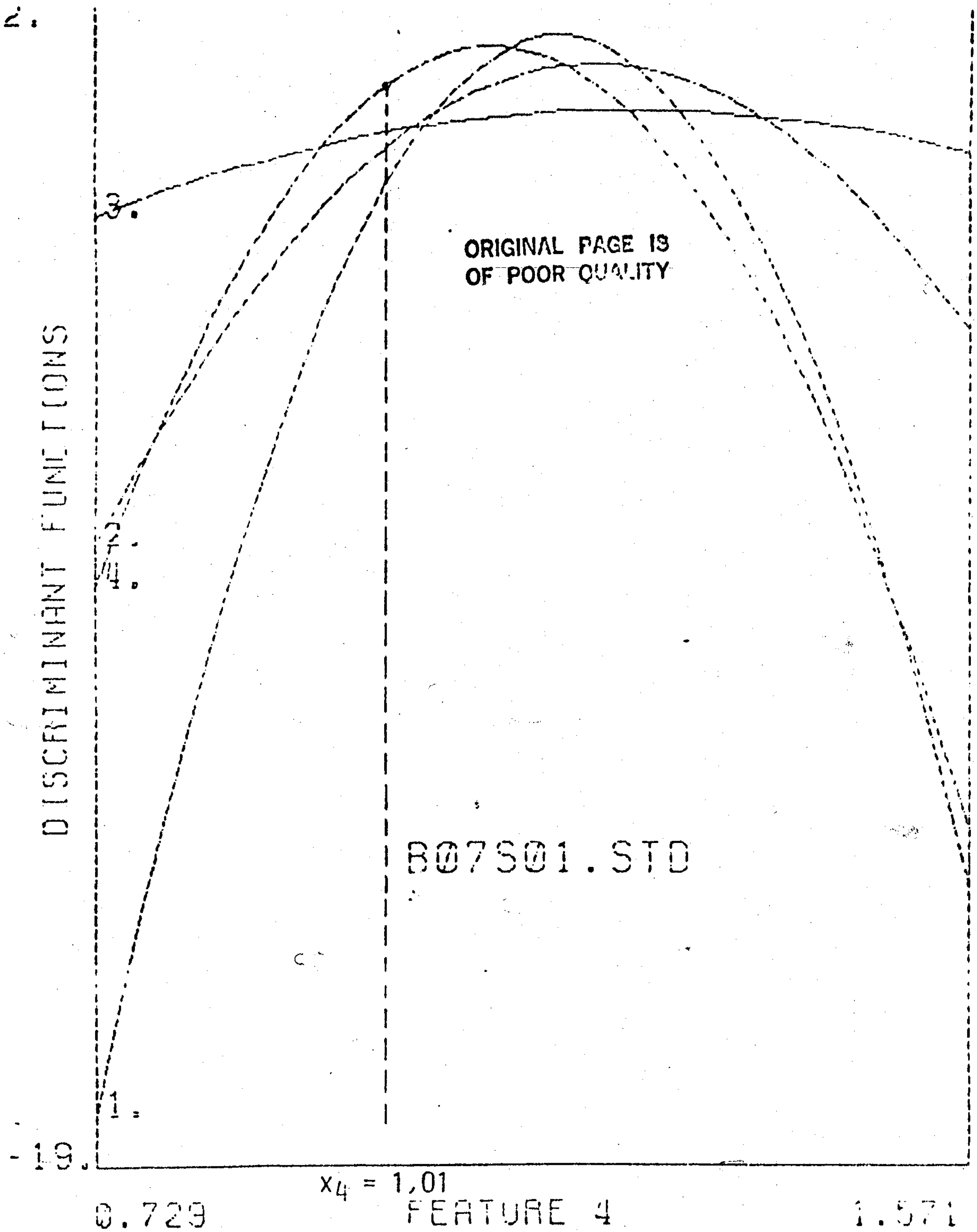

Bild 11: Beispiel für 4 hyperquadratische Diskriminanten-
Fig. 11 funktionen für 1 Merkmal
für x_4 = 1,01 ist z. B. Klasse 4 richtig

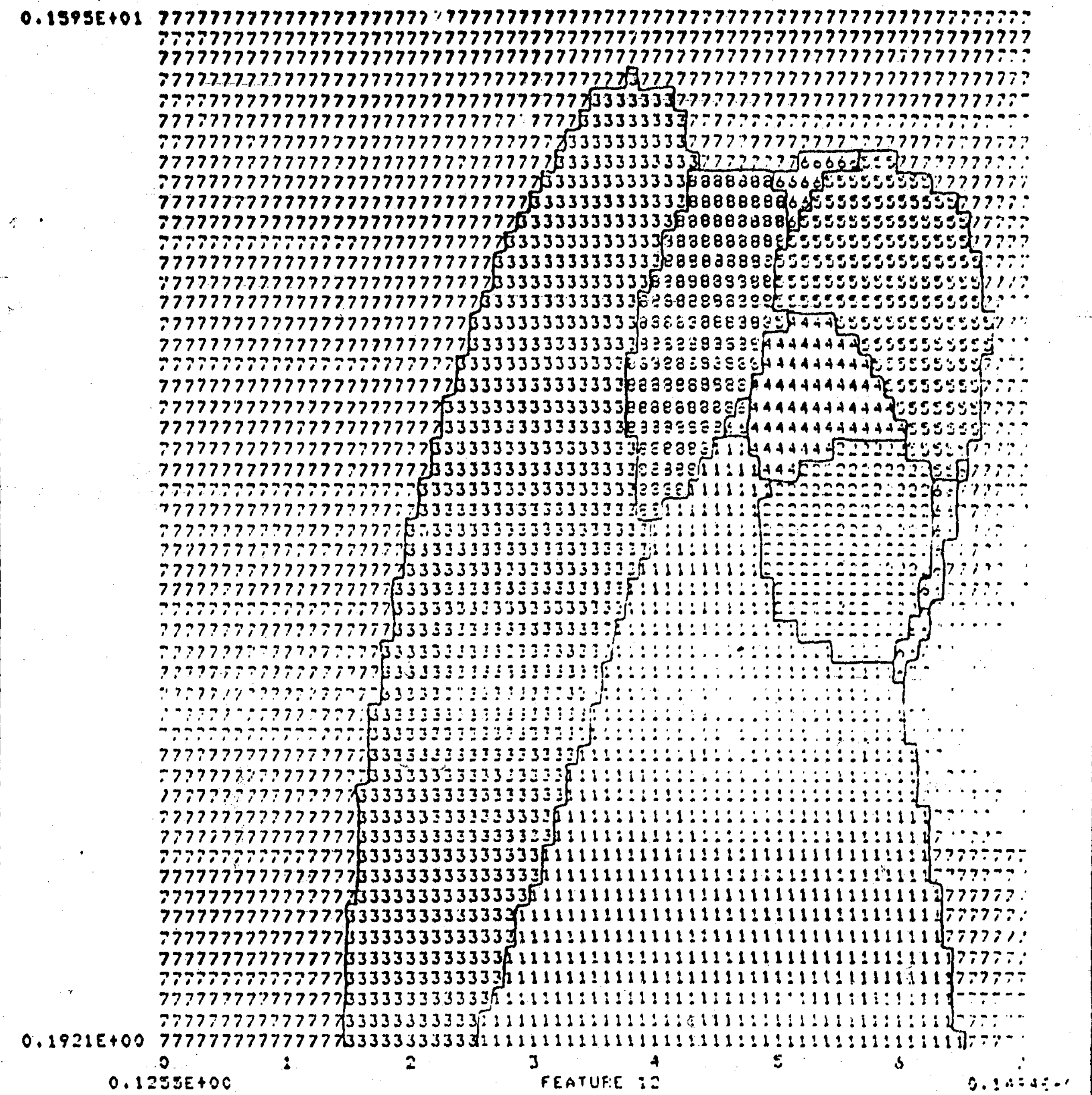

Bild 12: Entscheidungsebene für Merkmale 12/19 für multidirektionale Laminate (8 Klassen)

Fig. 12

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typ a	zahl b	der benutzten Merkmale c			
A d (5 Klassen)	6	76,3	86,3	86,3	97,5
	12	91,7	96,9	99,0	100,0
	18	78,8	92,5	98,8	100,0
B d (4 Klassen)	7	85,0	98,3	100,0	-
	13	91,7	100,0	100,0	-
	19	93,3	100,0	-	-

e Summenkriterium (%)

A d (5 Klassen)	6	62,0	74,0	88,0	94,0
	12	81,7	91,7	98,3	100,0
	18	74,0	86,0	96,0	100,0
B d (4 Klassen)	7	82,5	97,5	100,0	-
	13	67,5	95,0	100,0	-
	19	77,5	100,0	-	-

f Gesamtquote (%)

Bild 13: Zusammenstellung der Trefferquoten der optimalen Merkmals-
Fig. 13 kombinationen für die 6 Gewebelaminattypen

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