A PARALLEL NET OF (1-NN, K-NN) CLASSIFIERS FOR OPTICAL INSPECTION OF SURFACE DEFECTS IN FERRITES*

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Abstract The challenging task of optical inspection of surface defects in ferrite cores has been successfully approached with a set of methods. In this paper the attention is paid to the k Nearest Neighbours classifier developed for the system. A parallel net of two-decision classifiers is presented. The combination of the 1-NN and k-NN rules reduces the training time. A great part of computations is restricted to the class overlap area. The classification quality is significantly improved if a separate feature selection for each of the component classifiers is done. A dramatic improvement of classification speed obtained by reference patterns sets reduction for component classifiers is vital, as in the considered task the classifier is used for recognition of pixels. The proposed modifications of the classifier are of general usefulness for pattern recognition. The presented quality inspection system can be applied to various defect detection tasks.

Key words: statistical pattern recognition, nonparametric methods, k-NN rules, parallel classifiers, quality inspection, ferrite cores.

1. Motivation

Industrial inspection tasks require maximum reliability at minimum operation time. The present paper describes our attempt to meet these contradictive requirements. The challenge is made even more severe by the kind of the tested products, that is, the ferrite cores. Ferrite cores are manufactured by compacting and sintering the magnetic oxide powders, and by grinding some surfaces to required dimensions. During these processes a

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number of defects (called also irregularities) can appear. Defects on the mating surfaces of the core halves are of the greatest importance. The main difficulties encountered in their detection are: dark colour of ferrite, large variety of possible shapes and locations of defects, and variability of their appearance, also in typical light conditions [5]. The above circumstances have effectively prevented even the leading manufacturers of ferrites from automating the surface quality inspection.

One of the crucial parts of the applied inspection methodology is the k Nearest Neighbours (k-NN) classification. The quality of the classifier has significant influence on the general performance of the whole system. The positive overall results of inspection are due to significant improvements made in the k-NN classification method presented here.

Other parts of the system will only be mentioned here. For more details see [2, 5, 12, 15]. In the described application, the classified patterns are pixels of the image of a ferrite core surface. Besides that the classified region of an image is initially reduced in the first phase of processing (defect detection), the number of pixels classified in each run is large. The number of possible features can also be significant, so feature selection is indispensable. The k-NN classification method successfully meets all these requirements.

A parallel net of 1-NN and k-NN classifiers has been developed. The combination of these two decision rules has improved the training speed and has made it possible to constrain the most computation-intensive part of the algorithm to the class overlap area. Application of the net of parallel classifiers, one for each pair of classes (each of them is a two-decision classifier) significantly improves the classification quality if a separate feature selection for each of the component classifiers is done. Otherwise the classification quality remains the same or is only slightly improved with respect to the standard k-NN. The usefulness of the proposed network has been fully confirmed in our demanding application. A crucial acceleration of the classification phase was obtained by the reduction of the reference sets for each of the components classifiers. A slightly modified version of the Hart's algorithm was used for this aim.

The parallel net of (1-NN, k-NN) classifiers presented here is a general-purpose classification tool. The concept of parallel two-decision classifications for class pairs can be used also for other classifiers than the k-NN one. The whole described defect classification methodology can be used to investigate defects on flat surfaces of various materials, not only ferrites.

2. Overview of the applied methods

The monochromatic image of the ferrite core surface, possibly containing the defects of interest, is acquired by the system consisting of a highly specialised lighting set-up, a standard digital camera, and a computer.

The classification algorithm consists of the following three phases:

- **Detection phase:** Regions which might be a defect are detected. This phase is hierarchical: the morphological pyramid technique has been used. In detecting the defects of different sizes the structuring elements are kept the same, but the image is scaled down, to reduce the time of computations (see [2, 5, 12, 13] for details).
- **Classification phase:** Pixels of the regions selected in the detection phase are classified with the parallel net of (1-NN, k-NN) classifiers. The features used were selected from a large number of possible deterministic, statistical and textural measures.
- **Postprocessing:** Nearby blobs are linked and convex hulls of the results are found. Defects are counted and measured (see [2, 5] for details). Finally, the defects are compared with quality standards to get the final classification of the product as belonging to a respective quality class [5].

As mentioned above, this paper will be devoted mainly to classification. The well known classification method of *k nearest neighbours* (k-NN) has been used [1, 3]. The basic version of this method is the following.

Assume that a set of patterns from each class is given. The sum of these sets is called the *training set*. Information contained in this set is used to construct the k-NN classifier. This set can be treated as a set of m points in a n-dimensional feature space. A class-membership of each of these m points is known. The training set can be written in the form of a matrix with m rows and $n+1$ columns, where the first column contains the class numbers. To define the k-NN classifier, the value of k and a certain set called the *reference set* must be established. A computational process called the *training* of the k-NN classifier must be carried out to determine k and the reference set. Probability of misclassification, estimated by the well known *leave-one-out method* (described also in [4]), is used as a main criterion to find the value of k and the reference set. *Feature selection* is included to achieve this aim. Additional computations are done to reduce the size of the obtained reference set. Finally, the reference set can be represented by the matrix with a smaller number of rows as well as a smaller number of columns than that for the training set. In a special case the reference set could be equal to the training set. Then, the training process would be constrained to finding the value of k. To recognise an unknown pattern it is necessary to find its k nearest neighbours in the reference set. The unknown pattern is assigned to the class to which the majority of these k neighbours belong. A (1-NN, k-NN) classifier has been described in the previous works [7, 9].

The decision in that classifier is based on two rules. The 1-NN rule detects whether the classified objects lie in the class overlap area, and if this is the case, it produces the final decision. In the opposite case the decision is based on the k-NN rule. The class overlap area and the number k of NN are determined by the leave one out method. There are two advantages of the (1-NN, k-NN) classifier in comparison with the standard one. It reduces the time required for finding the optimum number k of NN since these computations are constrained to the objects which belong to the class overlap area. Furthermore, it accelerates the classification phase. The k-NN rule is activated only for the objects which lie in the class overlap area. The remaining objects are recognised by the 1-NN rule which operates faster than a k-NN rule if k is greater than 1. The classification quality remains nearly the same.

A parallel network of k-NN classifiers was proposed in [10] and more precisely described and compared with a standard k-NN classifier in [8]. All the component classifiers decide between two classes only. The number of all possible pairs of classes equals the number of the component classifiers. The global decision is derived by voting of all the component classifiers.

Each of the component classifiers operates as follows. For each class i a certain area A_i is constructed such that it covers all the training patterns from the class i and a possibly small number of training patterns from other classes. In the classification phase, if a pattern lies outside of all areas A_i, then the classification is refused. When it belongs only to one of the areas A_i, then the classification is performed by the 1-NN rule. Patterns that lie in an overlapping area of some A_i are classified by the k-NN rule. Such a classification rule, called in this paper the (1-NN, k-NN) rule, is used by all component classifiers.

Rejection of the redundant features can significantly improve the performance. Feature selection requires a review of some feature combinations. Error rate must be calculated for each reviewed feature combination (with the leave-one-out method). For the k-NN rule and the training set with m patterns, just as many computations are required as for the test set method with $m-1$ patterns in the reference set and m patterns in the test set. In each of these two cases, we need to find the k nearest neighbours out of $m-1$ patterns and in both cases this task must be performed m times. In the feature selection for the k-NN rule the optimum number k for each reviewed feature combination needs to be determined. The determination of k for large training sets may be too expensive. Hence, if the reference set is large, we replace the full feature combination review by the well-known *forward* and *backward feature selection* strategies, described for instance in [4].

Large improvement in classification speed can be obtained by reducing the set of reference patterns. A slightly modified version of the Hart's algorithm [6] has been used. Simultaneously, the k-NN classification has been reduced to the 1-NN version in the classification phase, without any loss of accuracy.

3. Types of defects and the problem of their visibility

A pair of ferrite cores with their mating surfaces visible can be seen in Fig. 1. Two types of defects are of main importance on mating surfaces: chips and pull-outs.

A chip emerges where the material has been removed in the way of brittle cracking during grinding or as a result of another mechanical impact (Fig. 2).

A pull-out is a place from which the material has been taken away by a stamp during

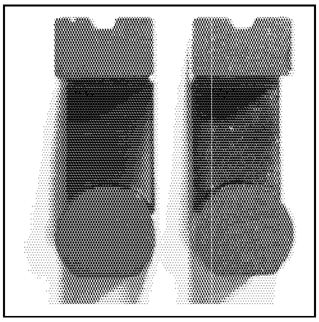

Fig. 1. Cores: mating surfaces.

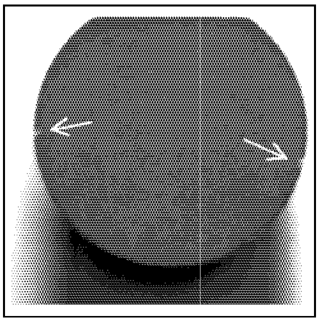

Fig. 2. Example of chips.

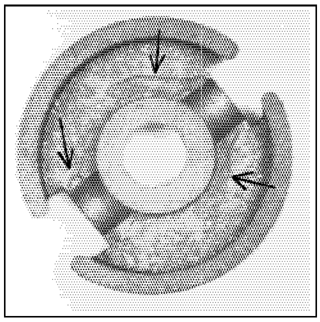

Fig. 3. Example of pull-outs.

the pressing process (the soft material has stuck to the stamp, Fig. 3).

As far as the mating surfaces are considered, the two types of defect can be indiscernible. Although they arise in different places of the production line, one can accompany another: a chip can appear where the material has been previously weakened by a partial pull-out in form of an undersurface defect. Moreover, the influence of the two types of defects on the quality of the final product is the same. Consequently, in this case the chips and the pull-outs can be treated together.

Because of the dark colour of the investigated objects, the problem of defect visibility becomes vital. The lighting system should provide for maximum insensitivity to position and direction, give possibly large contrast of defects, and large difference between irradiation of the tested surface and of other visible surfaces on the tested object and the base. Six circular lighting systems have been tested [15]. Finally, a specially designed Variable Light Beam Illuminator (VLBI) [2, 5] has been seleted for the presented experiment.

4. Features of the classified patterns

The pixels marked in the detection phase are treated as patterns to be classified. Each single pixel is a pattern. Its features are found as functions defined on its square neighbourhood, called the *simple neighbourhood.* To have direction-invariant features, besides a simple one, a *rotated neighbourhood* is used. The edges of the rotated neighbourhood are placed along the dominating direction of texture, calculated locally in the simple neighbourhood, according to the spectral method proposed in [16] (see [2, 5]).

From several groups of features tested the following 30 features have been preselected for use in the experiment presented in this paper: textural features according to [11] (described also in [14]), calculated in the rotated neighbourhood, and the *section of brightnesses function* along the line normal to the dominationg texture direction (in

feature	1	2	3	4	5	...
value	$I(0)$	$I(1)/I(0)$	$I(-1)/I(0)$	$I(2)/I(0)$	$I(-2)/I(0)$	...

Tab. 1. Calculation of features for the section of brightnesses function (see text).

other the experiments, up to 150 features were used at a time). The selected features made it possible to get very satisfactory results of final recognition.

The section of brightnesses function has been designed within the Project to reflect long-distance brightness relations, without having to consider a large number of features. A line section centred at the pixel of interest, directed according to the dominating texture direction – which coincides with the maximum gradient direction – is placed in the picture. It passes through other pixels located symmetrically on both sides of this central pixel. Let us index the central pixel with index 0, the pixels towards darker region of the image with positive indexes, and towards the opposite direction with negative indexes. Then, the subsequent features are calculated as indicated in Tab. 1.

5. K nearest neighbours classification

5.1. The modified version of the 1-NN rule

Let us assume that n_c is the number of classes and that the reference set consists of n_c subsets: $X_1, X_2, ..., X_{n_c}$, and each X_i contains patterns from the class i only. We associate these sets with the positive real numbers $e_1, e_2, ..., e_{n_c}$ defined as follows:

$$e_i = \max d(X_i \setminus x_j, x_j), x_j \in X_i \tag{1}$$

where $d(X, x)$ denotes a distance function between a pattern x and a set X. This means that e_i is the distance between x_j and the nearest pattern in $X_i \setminus x_j$.

We also define the areas $A_1, A_2, ..., A_{n_c}$:

$$A_i = x : d(X_i, x) \leq e_i. \tag{2}$$

Now, we can formulate a modified 1-NN rule. A pattern represented in the feature space by a point x is assigned to the class i if it belongs to the area A_i and does not belong to any other A_j, where j differs from i. If x lies outside of each $A_i, i = 1, 2, ..., n_c$, then the classification is refused. When x belongs simultaneously to more that one area A_i, then the classifier selects the class which is most heavily represented in the intersection of these A_i. Possible ties can be broken by choosing the largest class in the reference set.

Let us denote by A the set of all points in the feature space, each of which belongs only to one of the areas $A_i, i = 1, 2, ..., n_c$. It is easy to notice that each pattern of the training set that does not belong simultaneously to two or more areas A_i is an element of A. Feature selection for the proposed 1-NN rule as modified above consists in finding a feature subset that maximises the number of patterns of the training set in the set A.

5.2. The (1-NN, k-NN) rule

The modified 1-NN rule can assign the class membership or refuse the classification. This rule can be improved if the patterns which lie in the intersections of some A_i are classified by the k-NN rule with k nearest neighbours found in the whole reference set. Thus, some of these k nearest neighbours can lie outside of the intersection of all A_i containing the classified pattern. In this manner we have created the combined (1-NN, k-NN) rule. So, if the classified pattern belongs exactly to one area A_i, then the decision is based on the 1-NN rule; if it lies in the intersection of some areas A_i, then the decision is made by the k-NN rule. When the classified pattern lies outside of each A_i, then the classification is refused. Thus, the "easy" patterns can be recognised by the simple 1-NN rule, while the "difficult" ones are recognised by the more sophisticated k-NN rule.

Two feature selection sessions are recommended. One for the modified 1-NN rule to maximise the number of patterns from the training set in the previously mentioned set A, and another one to minimise an error rate for the k-NN rule. The expected advantage of the proposed modification is a significant acceleration of the search for the optimum value of k as well as of the classification itself.

5.3. Parallel net of (1-NN, k-NN) classifiers

A multi-class problem can be reduced to some two-decision tasks. One of the possible solutions may be the construction of a parallel net of two-decision classifiers, a separate classifier for each pair of classes, and then forming the final decision by voting of these two-decision classifiers. We shall consider such a network with the component classifiers based on the combined two-decision (1-NN, k-NN) rules. The component classifiers which refuse the decision (this happens when the classified pattern lies outside of all areas A_i) do not take part in voting.

This parallel network of two-decision classifiers should offer better performances than the simple combined (1-NN, k-NN) classifier or the standard k-NN rule. This results from the geometrical interpretation of both discussed types of classifiers. In the case of the standard classifier, the boundary separating any pair of classes i and j depends also on the patterns from the remaining classes. They have an influence on the value of k and on the selected features. These patterns act as noise. The parallel net may reduce this noise effect. By using the error rate estimated by the leave-one-out method as a criterion, we can find an optimum number of k for the k-NN rules and perform the feature selection separately for each one of the component classifiers.

5.4. Problem of reduction of the reference set

Although the use of the (1-NN, k-NN) rule instead of the standard k-NN classifier makes the classification faster, this acceleration is not satisfactory. We shall apply that rule only in the training phase which comprises feature selection for all the component classifiers and determination of the optimum numbers k of NN for each of the reviewed feature combinations. Any classification rule, in our case the (1-NN, k-NN) rule, can be approximated by the simple 1-NN rule which is faster than the k-NN one. To do this it is enough to reclassify all the objects from the reference sets for all pairs of classes. The (1-NN, k-NN) component classifiers will then be replaced by 1-NN classifiers with new reference sets, obtained by reclassification. If $k > 1$ then the speed of classification will be improved.

The speed of the 1-NN classifier depends linearly on the reference set size. Hence, it is reasonable to use the reference sets of the small sizes. The reference sets for the 1-NN rule can be reduced. In the literature numerous procedures for this aim can be found. The fastest one is the Hart's algorithm.

5.5. Hart's algorithm and its modification

The Hart's algorithm [6] operates in the following manner. The first pattern from the original reference set is inserted into the reduced set, so it contains only one pattern in the beginning. Then all the remaining patterns from the original set are classified by the 1-NN rule with the current reduced set as a reference set. During this process, each misclassified pattern is joint to the reduced set. If all patterns have been presented then again all patterns from the original set are classified by a 1-NN classifier with the use of the current reduced set. This process is continued until all the patterns from the original reference set are correctly classified, i.e., till the reduced reference set is consistent with original one. The consistency guarantees that the classification based on the reduced set has similar performance as the one before reduction.

It can be noticed that mainly those patterns which are close to the class boundary are selected to the reduced set, except those chosen at the beginning. To remove this undesired phenomenon, in each step of reduction the reference set is renumbered in such a way that patterns chosen as the last are now presented as the first ones.

6. Training patterns

For training, the *ground truth* data have been provided by *manually* marking with colours the pixels which belong to classes in the training images, made of the training batch of cores. This difficult task has been possible to fulfil only with looking at the original core. Frequently a looking glass was helpful.

The colour codes shown in Fig. 4 have been used. Please note that *artificial, boundary classes* formed with pixels lying at the boundaries between physical classes have been introduced. This has led to better accuracy, as it has become possible to perform the choice of classifier parameters for more specific class pairs.

Due to the reasons described in section 3, class 9 was merged with 6, and class 10 with

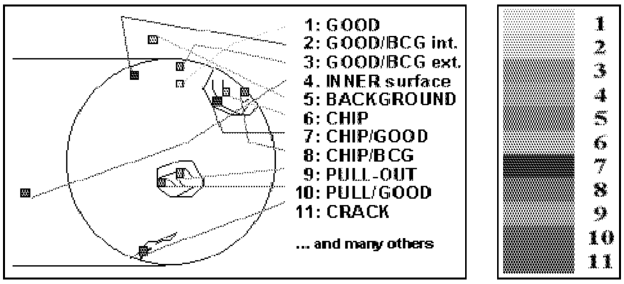

Fig. 4. Grey representation of colour codes of classes and boundary classes (see text).

class no.	class name	no. of pixels
1	GOOD	1382
2	GOOD/BCG int.	324
3	GOOD/BCG ext.	479
4	INNER surface	1195
5	BACKGROUND	1249
6	CHIP	188
7	CHIP/GOOD	181
8	CHIP/BCG	205
	Total	**5903**

Tab. 2. Numbers of training patterns (pixels) used in the presented examples.

7. Class 11 was not represented in the training batch of cores. Hence, finally there were 8 classes. In the initial experiments as much as 50,000 pixels have been used for training. Later, with the insertion of the boundary classes, less than 10,000 training pixels were used. The results presented further were obtained with the numbers of training patterns shown in Tab. 2.

7. Results of training

The performance of any type NN rule may be very often improved if data standardisation is performed. We have decided to standardise separately all reference sets for each of the component classifiers. A new feature value is obtained from the original one by subtracting its mean value and dividing the received results by the standard deviation of the feature. It is necessary to standardise also each classified object separately for each pair of classes.

The confusion matrices have been found with the leave-one-out method (Tabs. 3 and 4). The total error rate was 2.56%. From 30 available features only one has never been used (the third Laws texture [11]). We can notice that the most difficult problem

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	99.6					0.07		0.3
2		98.5	0.9	0.6				
3		0.2	98				1.7	
4		1.1	0.08	98.8				
5			0.08		99.4		0.5	
6	0.6					98		1.5
7		1.1	*6.1*		0.55		92	
8	*15.6*					**22.9**		61.5

Tab. 3. A priori error probabilities: that pixel from class i (row) will be assigned to the class j (column); in %, zero values omitted.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	97					0.4		2
2		95	0.3	*4*			0.6	
3		0.6	97	0.2	0.2		2	
4		0.2		99.8				
5					99.9		0.08	
6	0.1					95		5
7			*4*		*3*		92	
8	3					**9**		88

Tab. 4. A posteriori error probabilities: that pixel classified as class i (row) comes in fact from the class j (column); in %, zero values omitted.

was to separate the class 8 from the classes 1 and 6. Thus, our further studies should be focused on the two class pairs and in the case of success it will be sufficient to replace only the respective two component classifiers.

The effectiveness of applying the (1-NN, k-NN) rule instead of the standard k-NN one is shown in Tab. 5. For some of the class pairs this advantage is very small, mainly for the pairs 1/6, 1/8 and 6/8. For eight pairs the overlap rate, i.e. the number of objects found in the overlap area divided by the size of the reference set for suitable class pair was equal to zero. It means that for these pairs the k-NN rule in the tandem (1-NN, k-NN) will never be activated. For this reason we have blanks in the columns: 4, 5 and 6 for these pairs.

The k-NN classifier ought to be used in the case of 20 out of 28 pairs and only for 6 pairs the required value of k was greater than 3. For the pairs 4 and 6 it was surprisingly large. The same ideal result could be reached also for all the lower values of k. However, the largest value was preferred since it generates a more regular separating boundary and therefore a smaller size of the final reduced reference set can be expected.

The results of the Hart's algorithm are seen in the last two columns of the Tab. 5. As we see, in most cases the lower the error rate is the smaller the size of the reduced

1	2	3	4	5	6	7	8
pair	n. fea. for min. overlap	overlap rate	optimum k	n. fea. for k-NN rule	err. for k-NN rule	ref. set power before red.	ref. set power after red.
1/2	3	4.22	12	4	0.00	1706	25
1/3	2	0.00	-	-	-	1861	2
1/4	1	2.10	18	6	0.00	2577	10
1/5	1	0.00	-	-	-	2631	2
1/6	2	79.60	1	19	2.25	2270	271
1/7	1	0.00	-	-	-	1563	2
1/8	3	97.23	3	6	4.16	1587	143
2/3	4	33.13	3	12	0.75	803	78
2/4	1	30.35	3	6	1.38	1519	57
2/5	5	1.53	49	3	0.06	1573	20
2/6	2	0.91	2	3	0.00	1212	10
2/7	7	16.63	1	8	0.20	505	43
2/8	2	2.27	1	3	0.00	529	43
3/4	2	12.13	1	17	0.18	1674	41
3/5	6	27.60	1	7	0.29	1728	45
3/6	1	1.24	43	1	0.00	1367	2
3/7	1	8.697	3	12	4.55	660	109
3/8	2	0.00	-	-	-	684	2
4/5	4	39.20	1	16	1.10	2444	159
4/6	1	0.29	805	2	0.00	2083	4
4/7	2	2.11	2	3	0.00	1376	19
4/8	1	0.29	17	1	0.00	1400	2
5/6	1	0.00	-	-	-	2137	2
5/7	3	14.69	3	10	0.77	1430	29
5/8	1	0.00	-	-	-	1454	2
6/7	2	0.00	-	-	0.00	1069	24
6/8	2	93.50	3	10	10.43	1093	258
7/8	2	0.00	-	-	-	386	2

Tab. 5. Results for component classifiers. Notations: col. 1 - pair of classes, col. 2 - no. of selected features which minimise the overlap rate, col. 3 - overlap rate, col. 4 - optimum no. of NN, col. 5 - no. of features selected for k-NN rule, col. 6 - error rate for k-NN rule, cols. 7 and 8 - size of ref. sets before and after reduction respectively. Blanks mean that k-NN rule was not applied.

set can be expected. We have checked experimentally that the reference set reduction accelerated the classification about fourteen times.

8. Examples of results

In the results below, we shall exemplify with images a number of phenomena:

1. overall quality of classification (Figs. 5-7);

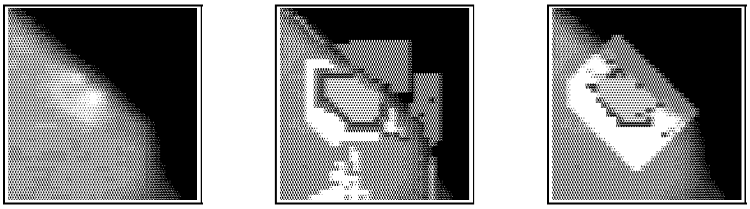

Fig. 5. Classification of trained pixels: left: original; center: training data; right: classified.

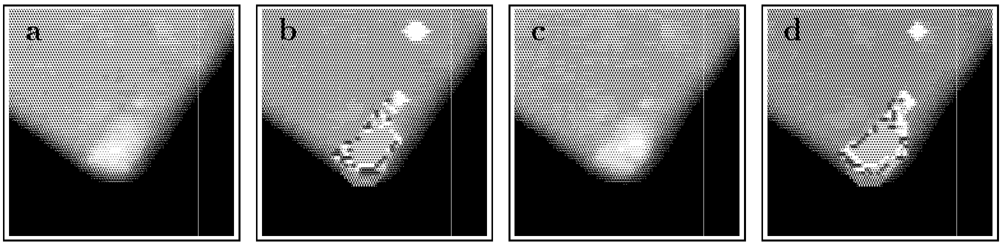

Fig. 6. Generalisation power of the classifier and invariance to small lighting changes: a, b: light I; c, d: light II; a, c: originals; b, d: classified. Results for light I and II do not differ much.

2. generalisation power of the classifier: correct results for pixels not used for training (Figs. 6, 7);
3. invariance to small lighting changes (besides that light stability is guaranteed) (Fig. 6);
4. invariance of results to rotation and shift (Fig. 7).

The time of classification of 1000 pixels was about 7 s (Pentium 200 Mhz, 32-bit software – GNU C). In a typical $512 * 512$ image, about 800 pixels are selected for classification by the detection algorithm. In Figs. 6 and 7, the classified pixels are those selected.

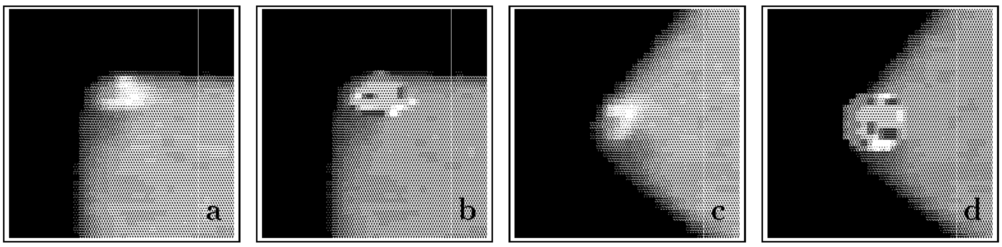

Fig. 7. Generalisation power of the classifier and invariance to position of tested object: a, b: position I; c, d: position II; a, c: originals; b, d: classified. Results for pos. I and II do not differ much.

9. Conclusion

A computerised optical inspection system for detection and classification of defects (called irregularities) on mating surfaces of ferrite cores has been designed and implemented. The system has been found to work properly in a series of tests. Quantitative nature of the results make it possible to carry out various kinds of analyses of the production process.

The obtained results have shown the usefulness of the various classification rules combinations. By the use the (1-NN, k-NN) rule it was possible to constrain the use of the more sophisticated classifier to more "difficult" objects. In this way the training stage could have been accelerated since the optimum numbers k of NN were found faster. The use of the parallel net has enabled better fitting of the feature combinations to the local class distribution in the feature space. In consequence, the parallel net of the (1-NN, k-NN) two-decision classifiers has occurred to be a very powerful tool, mainly in the training stage.

Although the reference set reduction for all the component classifiers was significant, it has been noticed that better perspectives than those offered by the Hart's approach still exist, since a minimum possible reduced reference set has not been reached. Other algorithms existing in the literature are too slow for our case. Our further studies will concern the more effective reference set reduction methods. Other experiments which, according to our opinion, are worth interest, consist in replacing the k-NN rules with their fuzzy versions. We shall also look for new features to improve the performance for those class pairs for which the errors were the largest. In these investigations the training process will concern only the respective component classifiers, while the other ones will remain unchanged. The proposed improvements in the Nearest Neighbour classifier are related to classification tasks in general. The concept of parallel classification in class pairs can be applied also in other pattern recognition approaches. The defect detection methodology is applicable to defects on flat surfaces of numerous materials, not necessarily similar to such black ceramic as ferrite. The system under consideration is planned to be developed up to an industrial level.

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