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Analysis of thermographic images of thin metal layers using grouping algorithms

Abstract: *In this paper the authors attempt to perform the analysis of the thermographic images of thin metal layers obtained in PVD (physical vapor deposition) process as the part of the working textronic system. The authors also briefly characterize algorithms applied in data classification: algorithm k medium, COBWEB algorithm and the grouping algorithm. The identification of defects of thin film structures using image recognition algorithms are presented.*

Streszczenie. *W artykule autorzy dokonują analizy obrazów termograficznych cienkich warstw metalicznych wykonanych w procesie PVD (physical vapor deposition) jako części roboczej systemu tekstronicznego. Scharakteryzowano również krótko algorytmy zastosowane przy klasyfikacji danych: algorytm k średnich, algorytm COBWEB oraz algorytm grupujący. Wykorzystując zaprezentowane algorytmy rozpoznawania obrazów dokonano identyfikacji defektów struktur cienkowarstwowych.* ***(Analiza obrazu termograficznego cienkich warstw metalicznych przy użyciu algorytmów grupujących)***

Słowa kluczowe: rezystancja warstw cienkich, algorytm k-średnich, algorytm COBWEB, algorytm grupujący.
Keywords: resistance of thin layers, K –means algorithm, COBWEB algorithm, grouping algorithm.

Introduction

Textronics is one of the most modern areas of scientific research. One of the methods of validation of working of conductive elements which are an integral part of their studies might be infrared measurement. Analysis of thermographic images can be done using grouping algorithms.

The main task of image recognition is to extract membership of different types of objects to certain classes. It may therefore be used in the absence of a priori information on the objects belonging to the various classes. The only usable information is the information contained in the learning sequence. The process of image recognition can be divided according to the way of inference into feature-based recognition and model-based recognition.

The initial stage of the recognition process is the measurement of the characteristics of the recognized objects. Further actions are focused on analyzing the extracted features which may depend on the type of object or specific task.

Materials and methods

The tests have been subjected to electrically conductive paths that are integral part of the textronic system. In the PVD process Ag layer was created on a flexible composite textile - material made of nylon strands coated with polyurethane - known under the trade name Cordura.

In spite of keeping the constant process conditions during creating the layers, the surface is not homogeneous. This is the result of a stochastic vapor deposition of metals and stresses resulting from mounting the substrate in a vacuum chamber.

The thin Ag layers created during the process can be defected and the changes in local resistance and temperature can be observed.

To find out the heterogeneity or discontinuity of electroconductive layers preliminary microscope studies were carried out using the scanning microscope with a magnification of 400×. The result of that kind of research of the thin layer structure is presented in Fig. 1.

Due to the fact that the microscopic images cover a small area of created structures and do not provide a basis for drawing conclusions about the entire layer, produced samples were tested thermographically. Steady thermal state of the samples obtained 10 minutes after switching the 200 mA current on. Thermographic images were made using a FLIR thermal imaging camera T650sc, in the Military Institute of Medicine in Warsaw. The stand for thermographic study is presented in Fig. 2.

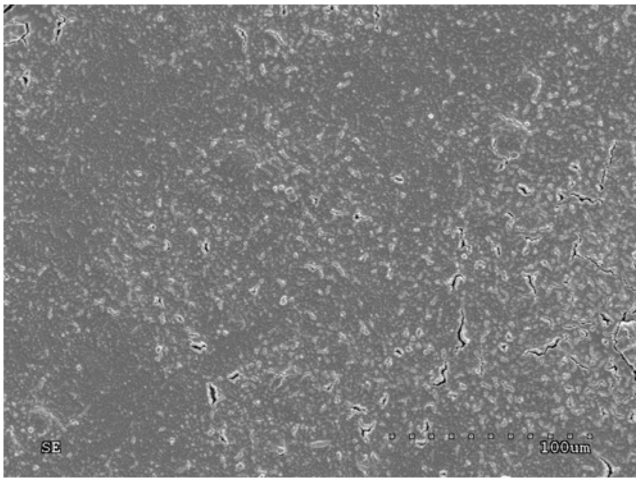

Fig. 1. The SEM image of thin metal layer created on the surface of composite in the PVD process, the magnification 400x, (the surface is made of nylon threads with poliuretan cover - Cordura)

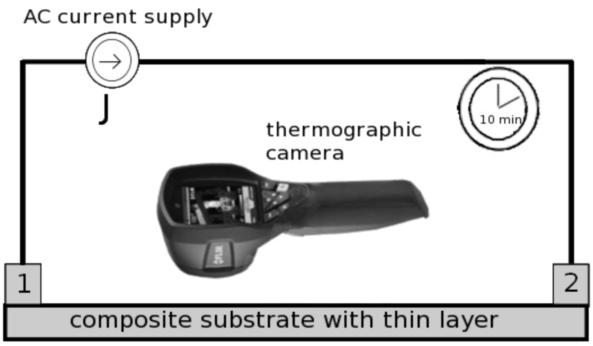

Fig. 2. The stand for taking the thermographic images of thin metal layer - the part of working textronic system

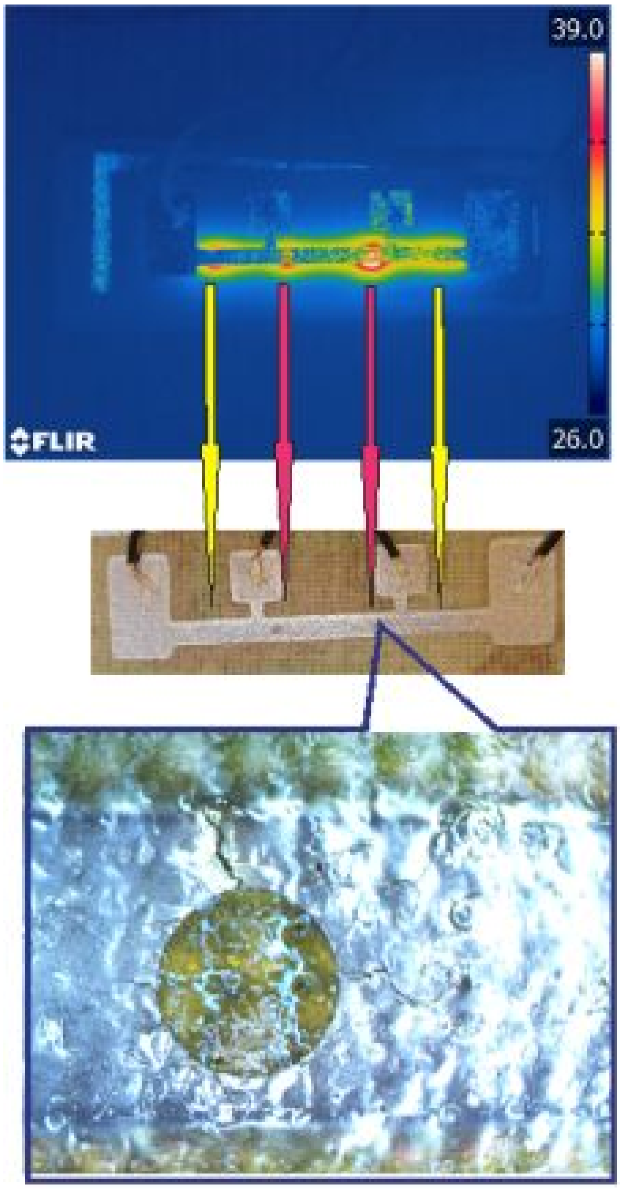

Fig.3. The layer with defect done with laser
a) Thermographic images of electroconductive thin layers 10 minutes after switching current on
b) Macroscopic images of tested samples
c) Microscopic images of defected area - magnification 20x

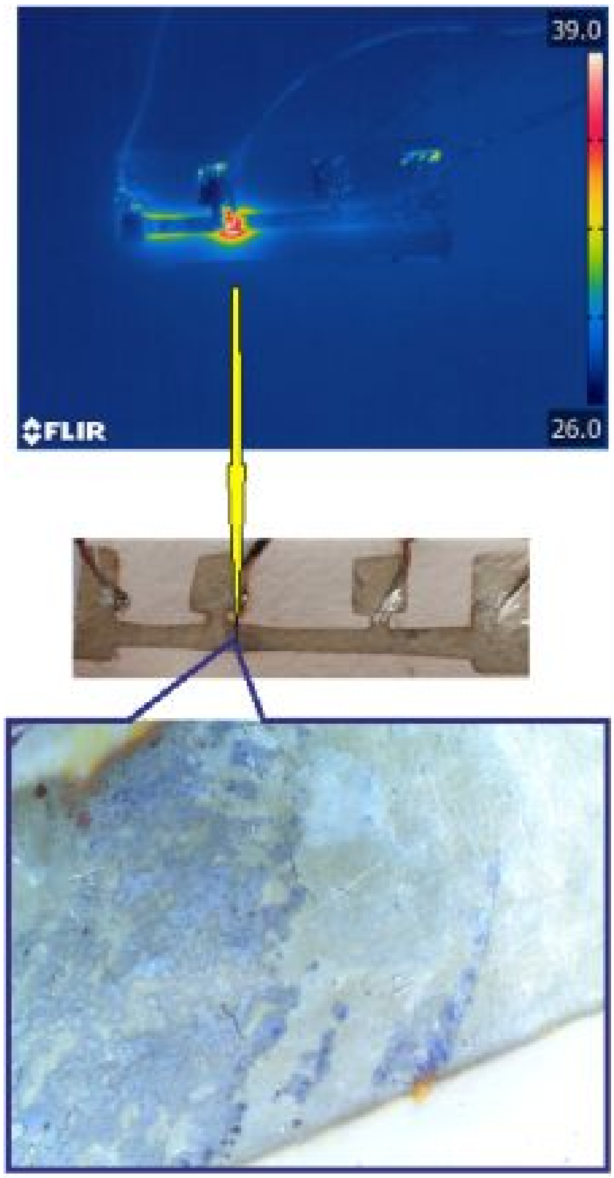

Fig.4. The layer with abrasion
a) Thermographic images of electroconductive thin layers 10 minutes after switching current on
b) Macroscopic images of tested samples
c) Microscopic images of defected area - magnification 20x

In Figs 3 and 4 the images of thin electroconductive layer with defected areas are presented. The difference between them is the kind of defect. In the sample presented in Fig. 3, the defect was done with the laser specially for the research. In Fig. 4 there is presented the sample with abrasion. In the section a of both figures the thermographic images of created samples are presented, which are shown in the section b. The defected areas can be observed in microscopic images depicted in the section c. The microscopic images were taken with Delta Optical SZ-630T - magnification 20x.

Clustering algorithms

Pattern recognition theory describes a number of methods of decision making on the basis of a set of characteristics. Therefore, the selection of appropriate characteristics which are defined and selected for the image recognition algorithm is very important. Object recognition is strongly dependent on the features used for its characterization. Thus, their choice should be carefully considered. Quantitative properties are easy to use. They can easily be measured, quantified and visualized on the axes of the coordinate system of the feature space. In the case of measurement of designated features of the analyzed object and visualize their values on the axes of the three-dimensional coordinate system, in the space described by these features there will be designated a point which in further considerations may also represent a specific object. If a collection objects is subjected to analysis, then each object is assigned a point in the feature space. The location of this point will clearly identify the object and will differentiate it from other objects. A well-built feature space has such a property that different images of the same object will determine the points located close to each other, while the points corresponding to images of other objects will be located in another area.

K –means algorithm

The idea behind the K –means method is to assign the elements in such a way as to minimize variation within the designated clusters and maximize the variability between clusters. What takes place in this case is the assignment of n objects to a set number of clusters K (groups) separately for each value of K. Let us assume that all the features are quantitative of real numbers. Let C_K mean the function assigning each object the number of cluster to which it was assigned. The algorithm can be reduced to the following points:

1) Randomly distribute n objects in K clusters. Let function $C_K^{(1)}$ describe this distribution.
2) For each of the K clusters calculate the average vector $\bar{x}_k$, (k=1,2,…,K).
3) Arrange the objects in K clusters in such a way that:

$$C_K^{(l)}(1) = \arg \min_{1 \le k \le K} \rho_2(x_i, \bar{x}_k) \quad (1)$$

4) Repeat steps 2 and 3 until the assignment of objects to clusters is constancy, that is until

$$C_K^{(l)} = C_K^{(l-1)} \quad (2)$$

It should be stressed that in order to avoid a situation in which each element in a data set is a cluster, an explicitly specified number of clusters should be used. This algorithm is greedy. It has a low computational complexity, which is O(iKn). Computational complexity depends on the number of iterations i, and the number of groups K. It also has small memory requirements.

Expectation Maximization algorithm

Expectation Maximization algorithm represents the clusters as a multi-dimensional probability distributions. Objects from the data set are assigned to the cluster on the basis of the probability, the origin of the element of the distribution associated with that cluster. Partitioning of a set of data into K clusters is equivalent to the distribution built from the sum of K normal distributions. Such a distribution is called mixture of Gaussians.

The algorithm comes down to performing two alternating steps:

1) Estimation (expectation). For the current estimated distribution of parameters of examples, assign the examples of probability the membership to groups.

2) Replace the current distribution parameters for those that lead to a model more in line with the data (distribution of examples). In order to do this, use the probability of belonging to the groups obtained in step 1.

EM algorithm is particularly effective for data sets with attributes of numerical values. However, it has a high computational complexity of O(n2).

COBWEB algorithm

The COBWEB algorithm belongs to hierarchical algorithms for grouping data with nominal attributes. It was developed by Professor Douglas H. Fisher in 1987, and it is very popular. This algorithm creates a hierarchy of the group in a form of a tree by estimating the probability occurrence of equal values of attributes for the current node.

The tree which begins the analysis by Cobweb algorithm is a tree built from a single node. The number of nodes of the tree increases with the analysis of the subsequent elements (examples).

Processing of further examples causes the following modifications to the tree:

1. Creating a new class (node) for a particular example
2. Classification of example into an existing class
3. The merging of the two categories into one
4. The division of a category into several new ones

The creation of a new node depends on the goodness measure of the category; if creating a new node results in a better goodness measure than in case of the inclusion of the considered item to an existing node (class), the algorithm adds a new node to an existing tree.

The process of merging nodes is associated with the liquidation of a particular node to the junction one the level n and connecting its children with the node on the n-1 level which was their grandfather. The division of a node is an inverse process to connecting of nodes.

The principle of operation of the COBWEB algorithm can be reduced to the following steps:

1. Update the probability values in the current node k (root)
2. Is the node a leaf?

Yes – expand the current leaf (add a new node that will be the parent for the current leaf and the new example) to create a node for the new of example p

No – find the best possible child node of the particular node k and perform the appropriate operation (the result of which gives the best goodness measure of the category):

Create a new node - add a new child to the node k

Merge the nodes – merge nodes and invoke algorithm recursively for the new node

Divide the node – divide nodes (remove unnecessary nodes) and perform the algorithm recursively for the node k

Invoke the algorithm recursively for the particular child

Undoubtedly, the advantage of this algorithm is the possibility to analyze and create a tree with missing values. This is very important in determining outliers in the analyzed set. Additionally, the obtained tree can act as a classifier. It should be noted, however, that the algorithm can classify only objects with qualitative characteristics and class structure created by the algorithm is highly dependent on the order of appearance of examples.

Results

The largest image had dimensions of 600 x 600 pixels, resulting in 360 000 pixels to analyze. Each pixel is described by feature vector VV = {x, y, red, green, blue} where: x– is a pixel location relative to the x-axis, y - is the pixel location relative to the y-axis, red –color component of the pixel responsible for the red color, green - color component of the pixel responsible for the green color, blue - color component of the pixel responsible for the blue color. Each of the thermographic images of resistance was analyzed by the three algorithms discussed in the previous section, namely the k-means algorithm, Expectation Maximization (EM) algorithm and COBWEB algorithm. For each algorithm the parameters were determined i.e. the number of clusters, the number of iterations. Also threshold of ignoring black and navy blue was established. In the case of K-means algorithm two distance measures were used, namely the Euclidean distance and Minkowski's distance.

In case of analyzing the thermographic images of resistance using the k-means algorithm it was noted that with the increase in the number of clusters the thermographic changes were more accurate. They became more central subareas. The greater the number of iterations, the smaller area was the focus. Input parameters had an impact only on the size and accuracy of the selected area. No differences were noted when changing the distance measure from Euclidean distance to Minkowski's distance. The COBWEB algorithm created the largest number of clusters for the analyzed thermographic images of resistance.

The study also took into account the time of operation of the algorithms. The shortest time was obtained for the K-means algorithm. The duration of processing using the EM algorithm is the biggest. It is comparable with the time of operation of the COBWEB algorithm. Examples of results are given in Table 1 and Fig. 5

Table 1. Average time of operation of algorithms for thermographic images.

	k-mean	EM	Cobweb
Image 1	1,034300	18,565000	2,825000
Image 2	1,006500	20,060000	2,636150
Image 3	1,693100	19,565000	4,038200
Image 4	0,511350	17,865000	3,560000
Image 5	0,079700	22,900000	1,399875

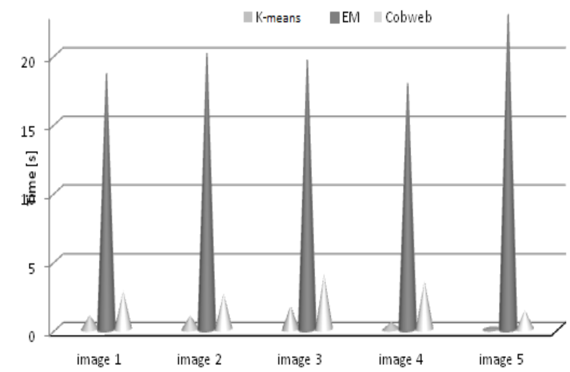

Fig. 5 Graph of the average time of processing thermographic images of resistance for the three algorithms.

The study shows that in all analyzed thermographic images of resistance using the three algorithms, there is correct division of thermographic areas. Automated analysis of resistance images is therefore possible.

Conclusions

In this paper the authors attempt to perform the analysis of the thermographic image of thin metal layers as the part of the working textronic system. The authors use the methods of extracting information as a result of which is possible to receive numeric or symbolic data. The aim of the study was to perform image segmentation in terms of color and intensity of the image followed by the correct interpretation and classification of the local temperature as the consequence of the local resistance. Image analysis begins with the pre-processing and segmentation. On the basis of the information received in the result of segmentation feature extraction was made. During the performed tests after the image segmentation, discontinuity and heterogeneity of the created thin layers can be identified.

The analysis of thermal images of resistance was carried out in four stages: pre-processing, segmentation, features extraction and detection of changes in resistance.
The paper presents the results of research based on the use of the proposed method for detecting changes in the local behavior of samples.

The study showed that it is possible to analyze thermographic images of resistance using the k-means algorithm, EM algorithm and COBWEB algorithm. All algorithms have succeeded in correct selection of specific areas of resistance, they differed in number clusters and duration of operation.

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