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AUTOMATIC CLASSIFICATION OF ELECTRONIC COMPONENTS BASED ON THE SUPPORT VECTOR MACHINE

Summary. In this paper, we present a classification of electronic components in the electronic factory. This classification provides relevant information for correcting the manufacturing process, thereby enhancing the production fields and the quality of product. Our classification system based on the support vector machine (SVM) classifies all the used electronic components into predefined categories that are learnt from the training samples. The system has been deployed in the manufacturing line and has met the design criteria of over 90% of the classification rate and 80% of the classification accuracy.

Keywords: support vector machine, classification

AUTOMATYCZNA KLASYFIKACJA KOMPONENTÓW ELEKTRONICZNYCH OPARTA O MECHANIZM MASZYNY WEKTORÓW WSPIERAJĄCYCH

Streszczenie. W niniejszym artykule opisano automatyczną klasyfikację komponentów elektronicznych, która pozwala m.in. na ocenę jakości produktu. Klasyfikację tę przeprowadzono przy użyciu maszyny wektorów wspierających (ang. *support vector machine*, SVM). Dzięki zastosowanemu klasyfikatorowi uzyskano 80% dokładność klasyfikacji. Zbudowany system klasyfikacji został zainstalowany na linii produkcyjnej komponentów elektronicznych.

Słowa kluczowe: maszyna wektorów wspierających, klasyfikacja

1. Introduction

An automated categorization of electronic components has become increasingly important over the past decade. It is a result of the development of automatic tools for manufacturing. It

has been estimated that in very-large scale integrated (VLSI) circuits can be attributed to random visual defects up to 80% of the yield loss in the production of high-volume. Various techniques for an automated classification of electronic components have been developed. Among others, an automated rule-based classification system was built for the IBM Burlington 16 M DRAM [3].

Currently, many classification tools are available as commercial products. Some firms, such as KLA Instruments, Tencor, Orbot, etc., offer tools for classification and defect detection in the course of the manufacturing process [2, 4]. The author in [8] considered two applications of Automatic Defect Classification (ADC) to monitor and control defect density in photolithography processing. Nevertheless, such tools costs more than a million dollars, making it very expensive to use for the classification problem [3].

An automated classification process reduces the operator workload, allows us to improve the accuracy and consistency of the end products. The need for an automated classification becomes even more significant.

The main goal of this paper is present a new classifier for electronic components based on the support vector machine (SVM). The automated classification of this tool achieves 80% classification accuracy. Moreover, the presented tool is practically used in the manufacturing process. In practical terms, the introduction of the automated classifier of electronic components is favourable for an automated monitoring in the industrial control, leading to rapid and reliable results in real-time.

The rest of this paper is organized as follows: section 2 describes method of the applied classification. Section 3 presents the constructed tool. In section 4 we give some experimental results. We finish the paper with a brief summary in section 5.

2. The Support Vector Machine

The support vector machine (SVM), introduced by V. Vapnik and A. Ya. Chervonenkis [11, 9], was chosen as a classifier. It is a very good tool for classification problems with an excellent generalization ability.

A SVM works in a high dimensional feature space formed by the non-linear-mapping of the n -dimensional input \bar{x} into a K -dimensional feature space ($K > n$) through the use of function $\varphi(\bar{x})$. The equation of the hyperplan separating two different classes is given by:

$$y(\bar{x}) = w^T \cdot \varphi(\bar{x}) = \sum_{j=1}^K w_j \cdot \varphi_j(\bar{x}) + w_0 = 0 \quad (1)$$

where:

$$\varphi(\bar{x}) = [\varphi_0(\bar{x}), \varphi_1(\bar{x}), \dots, \varphi_k(\bar{x})]^T \quad (2)$$

with $\varphi_0(\bar{x}) = 1$ and \bar{w} is the weight vector given by:

$$\bar{w} = [w_0, w_1, \dots, w_k]^T. \quad (3)$$

The data vector \bar{x} fulfilling condition $y(\bar{x}) > 0$ belongs to one class. If $y(\bar{x}) < 0$, it belongs to the opposite class. The most distinctive fact of SVM is that the learning task is simplified to the quadratic programming by introducing the so-called Lagrange multipliers α_i .

Learning and testing in the SVM method are done by means of the so-called kernel function which is defined by:

$$K(\bar{x}, \bar{x}_i) = \varphi^T(\bar{x}_i)\varphi(\bar{x}). \quad (4)$$

More details about the SVM method can be found in the textbooks [1, 10]. After learning the output signal $y(\bar{x})$ of the SVM is determined as a function of the used kernel. If the value of $y(\bar{x}) > 0$, it is associated with 1. It means that the membership of the feature vector \bar{x} is with the particular class. When the value of $y(\bar{x}) < 0$, it indicates the opposite class.

Although the SVM separates the data into two classes only, the recognition of more classes is achieved by means of using either "one against one" or "one against all" method [6].

3. An Automatic Classifier of Electronic Components

In this section we present details of the constructed tool for an automatic classification of electronic components applied in the manufacturing process.

The scheme of the data flow in the tool constructed for an automatic classification is shown in Fig. 1. According to the presented scheme the data of electronic components are automatically read by a machine vision system comprised of a color CCD camera fixed on top of the autofocus system. An operator could re-examine the introduction of the input data. The structure of input data in the XML format is additionally introduced. In the automatic mode, the model of catalog group is selected. Next, the selected components are used in training process and classified. Moreover, the models of the input data are uploaded into the computer manually.

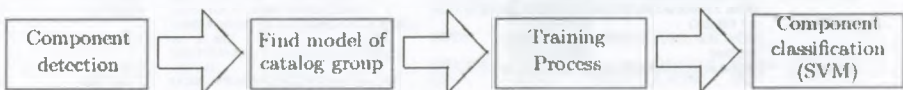


Fig. 1. Flowchart for classification of electronic components
Rys. 1. Schemat klasyfikacji komponentów elektronicznych


```

XMLCategorizationConfig config =
    new XMLCategorizationConfig(
        CATEGORIZATION_CONFIG_FILE,
        new DataMiningConfiguration(DATABASE_CONNECTION_FILE), true);
try {
    config.initConnection(DATABASE_CONNECTION_FILE);
    CategorizationDataMiningObjectNamesCreator dmObjectNamesCreator =
        new CategorizationDataMiningObjectNamesCreator(config);
    DatabaseObjectHandler dbObjectHandler =
        new DatabaseObjectHandlerImpl(config);
    DataMiningObjectsHandler dmObjectHandler =
        new SVMCategorizationDataMiningObjectsHandler(config);
    SVMCategorizationModelCreator modelCreator =
        new SVMCategorizationModelCreator(
            config, dmObjectNamesCreator,
            dbObjectHandler, dmObjectHandler);

    modelCreator.refreshTrainingTables();
    modelCreator.refreshModels();
} finally {
    config.dispose();
}

```

Fig. 2. An example of the configuration file for the model of the catalog group
Rys. 2. Przykładowy plik konfiguracyjny dla modelu grupy katalogowej

ITEM NUMBER	DESCRIPTION	CATALOG GRP	PROBABILITY	PARENT GROUP	PROBABILITY
M1FT0001	CAPACITOR CERAMIC 100NF 10% 50V05V				
M1FT0004	0805				
M1FT0006	CAPACITOR TANTAL 1.0MF 20% 35V SMD				
M1FT0008	CAPACITOR TANTAL 10MF 10% 50V 5MD SIZE				
M1FT0011	F				
M1FT0012	DIODE SMBMCA SUPPRESSOR SMD				
M1FT0013	CAPACITOR METALLIZED FILM 100NF 5 D 1MF				
M1FT0014	100V 10% RADIAL				
M1FT0015	CAPACITOR ELECTRIC 220NF 20% 10V 4M1				
M1FT0016	CASE SIZE D4				
M1FT0017	CAPACITOR TANTAL 10MF 20% 35V SMD				
M1FT0018	DIODE 50BQ100PBF SMC				
M1FT0019	ARALDIT STANDARD/2011, A 50ML				
M1FT0020	CONNECTOR CMM 220 20 CONTACTS MALE				
M1FT0021	JACK POST				
M1FT0022	CAPACITOR CERAMIC 1NF 10% 50V 0603				
M1FT0023	RESISTOR FILM OR 0603				
M1FT0024	RESISTOR FILM 68K 1% D 1W 0603				
M1FT0025	INDUCTOR DT3316F 153ML 15H				
M1FT0026	INDUCTOR DT3316F 224ML 230H				
M1FT0027	INDUCTOR DT1904C 334ML 330UH				
M1FT0028	INDUCTOR DT1904C 334ML 330UH				
M1FT0029	INDUCTOR DT1904C 334ML 330UH				
M1FT0030	INDUCTOR DT1904C 334ML 330UH				
M1FT0031	INDUCTOR DT1904C 334ML 330UH				
M1FT0032	INDUCTOR DT1904C 334ML 330UH				
M1FT0033	INDUCTOR DT1904C 334ML 330UH				
M1FT0034	INDUCTOR DT1904C 334ML 330UH				
M1FT0035	INDUCTOR DT1904C 334ML 330UH				
M1FT0036	INDUCTOR DT1904C 334ML 330UH				
M1FT0037	INDUCTOR DT1904C 334ML 330UH				
M1FT0038	INDUCTOR DT1904C 334ML 330UH				
M1FT0039	INDUCTOR DT1904C 334ML 330UH				
M1FT0040	INDUCTOR DT1904C 334ML 330UH				
M1FT0041	INDUCTOR DT1904C 334ML 330UH				
M1FT0042	INDUCTOR DT1904C 334ML 330UH				
M1FT0043	INDUCTOR DT1904C 334ML 330UH				
M1FT0044	INDUCTOR DT1904C 334ML 330UH				
M1FT0045	INDUCTOR DT1904C 334ML 330UH				
M1FT0046	INDUCTOR DT1904C 334ML 330UH				
M1FT0047	INDUCTOR DT1904C 334ML 330UH				
M1FT0048	INDUCTOR DT1904C 334ML 330UH				
M1FT0049	INDUCTOR DT1904C 334ML 330UH				
M1FT0050	INDUCTOR DT1904C 334ML 330UH				
M1FT0051	INDUCTOR DT1904C 334ML 330UH				
M1FT0052	INDUCTOR DT1904C 334ML 330UH				
M1FT0053	INDUCTOR DT1904C 334ML 330UH				
M1FT0054	INDUCTOR DT1904C 334ML 330UH				
M1FT0055	INDUCTOR DT1904C 334ML 330UH				
M1FT0056	INDUCTOR DT1904C 334ML 330UH				
M1FT0057	INDUCTOR DT1904C 334ML 330UH				
M1FT0058	INDUCTOR DT1904C 334ML 330UH				
M1FT0059	INDUCTOR DT1904C 334ML 330UH				
M1FT0060	INDUCTOR DT1904C 334ML 330UH				
M1FT0061	INDUCTOR DT1904C 334ML 330UH				
M1FT0062	INDUCTOR DT1904C 334ML 330UH				
M1FT0063	INDUCTOR DT1904C 334ML 330UH				
M1FT0064	INDUCTOR DT1904C 334ML 330UH				
M1FT0065	INDUCTOR DT1904C 334ML 330UH				
M1FT0066	INDUCTOR DT1904C 334ML 330UH				
M1FT0067	INDUCTOR DT1904C 334ML 330UH				
M1FT0068	INDUCTOR DT1904C 334ML 330UH				
M1FT0069	INDUCTOR DT1904C 334ML 330UH				
M1FT0070	INDUCTOR DT1904C 334ML 330UH				
M1FT0071	INDUCTOR DT1904C 334ML 330UH				
M1FT0072	INDUCTOR DT1904C 334ML 330UH				
M1FT0073	INDUCTOR DT1904C 334ML 330UH				
M1FT0074	INDUCTOR DT1904C 334ML 330UH				
M1FT0075	INDUCTOR DT1904C 334ML 330UH				
M1FT0076	INDUCTOR DT1904C 334ML 330UH				
M1FT0077	INDUCTOR DT1904C 334ML 330UH				
M1FT0078	INDUCTOR DT1904C 334ML 330UH				
M1FT0079	INDUCTOR DT1904C 334ML 330UH				
M1FT0080	INDUCTOR DT1904C 334ML 330UH				
M1FT0081	INDUCTOR DT1904C 334ML 330UH				
M1FT0082	INDUCTOR DT1904C 334ML 330UH				
M1FT0083	INDUCTOR DT1904C 334ML 330UH				
M1FT0084	INDUCTOR DT1904C 334ML 330UH				
M1FT0085	INDUCTOR DT1904C 334ML 330UH				
M1FT0086	INDUCTOR DT1904C 334ML 330UH				
M1FT0087	INDUCTOR DT1904C 334ML 330UH				
M1FT0088	INDUCTOR DT1904C 334ML 330UH				
M1FT0089	INDUCTOR DT1904C 334ML 330UH				
M1FT0090	INDUCTOR DT1904C 334ML 330UH				
M1FT0091	INDUCTOR DT1904C 334ML 330UH				
M1FT0092	INDUCTOR DT1904C 334ML 330UH				
M1FT0093	INDUCTOR DT1904C 334ML 330UH				
M1FT0094	INDUCTOR DT1904C 334ML 330UH				
M1FT0095	INDUCTOR DT1904C 334ML 330UH				
M1FT0096	INDUCTOR DT1904C 334ML 330UH				
M1FT0097	INDUCTOR DT1904C 334ML 330UH				
M1FT0098	INDUCTOR DT1904C 334ML 330UH				
M1FT0099	INDUCTOR DT1904C 334ML 330UH				
M1FT0100	INDUCTOR DT1904C 334ML 330UH				

Fig. 3. The model of the exemplary data set used in training process
Rys. 3. Model przykładowego zbioru danych użyty w procesie uczenia

```

CategorizationConfig config = null;
CsvTableDefinitionInputStructure structure = null;
try {
    Configuration configuration =
        new DataMiningConfiguration(DEFAULT_CONNECTION_FILE);
    config = new XMLCategorizationConfig(
        CATEGORIZATION_CONFIG_FILE, configuration, false);
    config.initConnection(DEFAULT_CONNECTION_FILE);

    DatabaseObjectHandler dbObjectHandler =
        new DatabaseObjectHandlerImpl(config);
    DataMiningObjectsHandler dmObjectHandler =
        new SVMCategorizationDataMiningObjectsHandler(config);
    DataMiningObjectNamesCreator dmObjectNamesCreator =
        new CategorizationDataMiningObjectNamesCreator(config);

    dbObjectHandler.dropTrainingTable(
        dmObjectNamesCreator.getApplyTextTableName());
    CategorizationModelApplier modelApplier =
        new CategorizationModelApplier(
            config, dmObjectNamesCreator,
            dmObjectHandler, dbObjectHandler);
    InputStructure resultStructure =
        modelApplier.applyModel(structure.getTableNames());
}finally{
    config.dispose();
}

```

Fig. 4. An example of the classification program using the SVM classification model
Rys. 4. Przykładowy program dla klasyfikacji, używający modelu klasyfikacji SVM

Fact Categories		Result Categories			
ITEM NUMBER	DESCRIPTION	CATALOG	PROBABILITY	PARENT GROUP	PROBABILITY
MF70001	CAPACITOR CERAMIC 100PF 50V 50X20	CAPACITORS		ELECTRONIC PASSIVE	
MF70004	CAPACITOR TANTAL 1.00W 20% 33V SMD	CAPACITORS		ELECTRONIC PASSIVE	
MF70006	CAPACITOR TANTAL 10MF 10% 35V SMD SIZE 8	CAPACITORS		ELECTRONIC PASSIVE	
MF70008	DIODE SMD/PCA SUPPRESSOR SMD	DIODES	MEDIUM	ELECTRONIC ACTIVE	MEDIUM
MF70011	CAPACITOR METALLIZED FILM 90W / 5 0.1MF 100V 10% RA/MAL	CAPACITORS	MEDIUM	ELECTRONIC PASSIVE	MEDIUM
MF70012	CAPACITOR EL LYTRC 220MF 20% 10V SMD	CAPACITORS		ELECTRONIC PASSIVE	
MF70011	CAPACITOR TANTAL 10MF 10% 35V SMD	CAPACITORS		ELECTRONIC PASSIVE	MEDIUM
MF70015	DIODE SMD/PCA SMC	DIODES		ELECTRONIC ACTIVE	
MF70016	Accessories (994 220 30 CONTACTS WALL	ACCESSORIES		MECHANICAL CATALOG	LOW
MF70018	Accessories (994 220 30 CONTACTS WALL	ACCESSORIES		MECHANICAL CATALOG	LOW
MF70021	CAPACITOR CERAMIC 1NF 10% 50V 0603	CAPACITORS		ELECTRONIC PASSIVE	
MF70022	RESISTOR FILM OR 0603	RESISTORS		ELECTRONIC PASSIVE	
MF70023	INDUCTOR 4.7mH 1% 1W 0603	INDUCTORS		ELECTRONIC PASSIVE	
MF70024	INDUCTOR 0.033MF 10% 10V	INDUCTORS		ELECTRONIC PASSIVE	LOW
MF70025	INDUCTOR 0.015MF-250V 125M	INDUCTORS		ELECTRONIC PASSIVE	LOW
MF70030	INDUCTOR 0.15MF-250V 125M	INDUCTORS		ELECTRONIC PASSIVE	LOW
MF70031	WIRE 0.55mm2 30 9 (55A902-30-0) AWG30	WIRES		WIRES	LOW
MF70032	WIRE 0.55mm2 30 9 (55A902-30-0) AWG30	WIRES		WIRES	LOW
MF70033	INDUCTOR 0.011 COMMON MODE CHARGE	INDUCTORS		ELECTRONIC PASSIVE	MEDIUM
MF70033	IC32 99424-54731130 3.3V 15V 1W	ICS	MEDIUM	ELECTRONIC ACTIVE	LOW

Fig. 5. The output data of the classified electronic components

Rys. 5. Uzyskane wyniki dotyczące sklasyfikowanych komponentów elektronicznych

These models are used in the learning process. An example of the configuration file for the model of the catalogue group is shown in Fig. 2. On the basis of the models we used the SVM method implemented in the Oracle Data Mining 11g in order to create the object of the SVM Categorization Model Create. Further, by means of the training method or refreshing the training method the model of the actually used data set is learnt (see Fig. 3). An example of the classification program using the SVM classification model is shown in Fig. 4.

As a result we obtained the output data of the classified electronic components, which shown in Fig. 5. The green color indicates the good classified data and the yellow color shows the medium classified data according to introduced model. The classification accuracy reached 80%.

In this paper, the verification performance is evaluated by means of the receiver operating characteristic (ROC) curves. Fig. 6 presents the ROC curve of the SVM classifier trained with some training sets. It is evident that the performance of any training data set achieved a remarkable level.

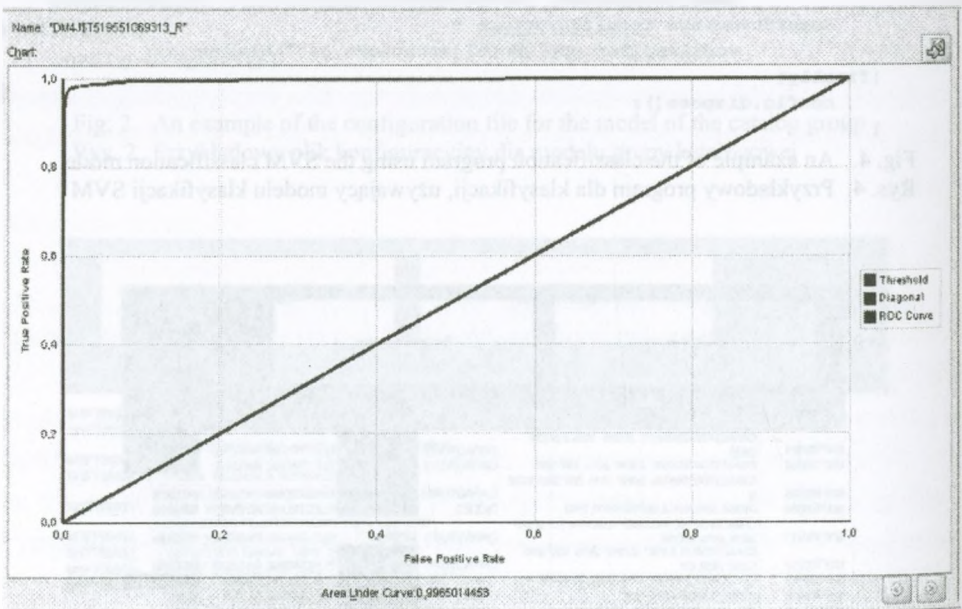


Fig. 6. The ROC curve of the SVM classifier trained with the some training sets
Rys. 6. Krzywa ROC dla klasyfikatora SVM uczonego pewnym zbiorem danych

4. Conclusion

In this paper we presented a new classifier based on the SVM method for the electronic components classification. The built system reaches ca. 80% classification accuracy. Moreover, this system was implemented in an industrial manufacturing process. It simplifies the

process of reading and classification of all the data sets of the used electronic components, hardware elements, etc. needed in the automatic manufacturing process.

Our classifier will be improved the next stage of the system exploitation. We hope that an ideal classifier will have the ability to deal with the problem of high dimensionality, adapt to the changes of environment (lighting, various speed of the moving components, etc.). Furthermore, we believe that the building of an ideal classifier is possible by means of additional AI methods, such as the fuzzy logic systems and the neural networks.

BILIOGRAPHY

1. Burges C.: A Tutorial on Support Vector Machines for Pattern Recognition, [in:] Fayyad U. (ed.): Knowledge Discovery and Data Mining. Dordrecht, Kluwer 2000, p. 1-43.
2. Burggraf F.: Defect Inspection: Wafers In, Process Control Out. Semiconductor International, Vol. 14, 1991, p. 58-62.
3. Chou P. B., Ravishankar Rao A., Sturzenbecker M. C., Wu F. Y., Brecher V. H.: Automatic Defect Classification for Semiconductor Manufacturing. Machine Vision and Application, Vol. 9, 1997, p. 201-214.
4. Chin R.: Survey of Automated Visual Inspection: 1981 to 1987. Computer Vision Graphics and Image Processing, Vol. 41, 1988, p. 346-381.
5. Cortes C., Vapnik V. N.: Support-Vector Networks. Machine Learning, Vol. 20, No. 3, 1995, p. 273-297.
6. Cramer K., Singer Y.: On the Learnability and Design of Output Codes for Multi-class Problems. Int. Conf. Computational Learning Theory, 2000, p. 35-46.
7. Dom B., Brecher V. H.: Recent Advances in Inspecting Integrated Circuits for Pattern Defects. IBM Research Report, RJ 9602, Yorktown Heights, N.Y. 1993.
8. Stinson G.: Applications of Automatic Defect Classification in Photolithography. Advanced Semiconductor Manufacturing Conference and Workshop, IEEE/SEMI, 1999, p. 270-274.
9. Vapnik V. N.: The Nature of Statistical Learning Theory. Springer, Berlin-Heidelberg-New York 1995.
10. Vapnik V. N.: Statistical Learning Theory. John Wiley & Sons, New York 1998.
11. Vapnik V. N., Chervonenkis A. Ya.: On the Uniform Convergence of Relative Frequencies of Events to Their Probabilities. Soviet Math. Dokl., Vol. 9, 1968, p. 915-918.

Wpłynęło do Redakcji 16 stycznia 2013 r.

Omówienie

W niniejszym artykule przedstawiono automatyczny system do klasyfikacji komponentów elektronicznych. Pozwala on na ich identyfikację oraz umożliwia wyszukiwanie elementów wadliwych lub uszkodzonych. W artykule opisano budowę systemu automatycznej klasyfikacji komponentów elektronicznych, którego działanie oparte jest na maszynie wektorów wspierających (ang. *support vector machine*, SVM). Na podstawie zadanych wzorców, klasyfikator SVM uczy się modelu aktualnie produkowanych komponentów elektronicznych, a następnie dokonuje ich klasyfikacji. Dzięki użytej metodzie klasyfikacji uzyskano 80% dokładność klasyfikacji komponentów elektronicznych. Zbudowany system został zainstalowany na linii produkcyjnej komponentów elektronicznych.

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