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Machine Vision System for Assessment of Firing Process Parameters in Rotary Kiln

Yudin Dmitriy Aleksandrovich, Magergut Valeriy Zalmanovich and Dobrinskiy Evgeniy Pavlovich

Belgorod State Technological University named after V.G. Shukhov,
Russia, 308012, Belgorod, Kostyukova street, 46

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Abstract: Article describes developed hardware-software complex of machine vision system for assessment of firing process parameters in rotary cement kilns. Authors developed method of firing process image recognition, allowing automatically real-time assessment of the firing process in three parameters: dust, state of the material and state of the torch.Its program implementation was performed.Authors made the selection of the number of hidden layer neurons of the network trained by extreme learning machine (ELM)provided the maximum average parameters classification accuracy. Advantage of ELM for the classification of the firing process parameters compared to the other methods was showed.Comparison of functionality of the proposed system with analogs was performed and showed its advantages. Developed machine vision system is being tested at the cement kiln CJSC “Oskolcement” (Russia, Stary Oskol).Possible positive effectsof machine vision system applicationwas showed: enhancing work efficiency of kiln operators, reducing the number of accidents and damage of kiln, as well as reducing of fuel consumption.

Key words: Machine vision system · Firing process · Rotary kiln · Image recognition · Self-organizing map · Extreme learning machine

INTRODUCTION

At the rotary cement kilns of “wet” cement production operator carries out a subjective visual observation of firing process parameters and uses them to decision-making of kiln control [1]. For example, in the control of “wet” cement rotary kilns operators are taken into account the following firing process parameters: 1) dust ("normal", "furnace dusts", "heavy dust"), 2) the state of the material ("the material is overheated", "normal mode", "poorly prepared material", "defective", "coating dropping "), 3) the state of the torch ("short torch (hard)","long torch", "soft torch (with twist blades)"), 4) granulometry at sintering zone output, 5) the angle of material elevation at the kiln.

To automate the collection of visual information about the firing process can be applied industrial television system [2], which, however, does not allow you to automatically assess the firing process parameters mentioned above. Thermal imaging systems [3, 4] provide measurement of the temperature field, but they can’t assess all mentioned parameters.High cost of them and temperature measurement errors due to dust require the creation of a reliable and low-cost machine vision systems.

Articles on the methods of firing process image recognition for a variety of industries are published since 1991. Detailed overview is given in [5, 6]. Scientific publications about machine vision for rotary kilns of “wet” cement production only beginning to emerge [7, 8]. The task of finding the assessments of mentioned firing process parameters had not been solved and requires the development of a special method of image recognition and the development of a hardware-software complex of machine vision systems suitable for use in a real industrial environment and integrated into the overall kiln automation system.

Corresponding Author: Yudin Dmitriy Aleksandrovich , Belgorod State Technological University named after V.G. Shukhov, Russia, 308012, Belgorod, Kostyukova street, 46. Tel: +79202007395.
E-mail: yuddim@yandex.ru - valerymag@nm.ru.

MATERIALS AND METHODS

Machine vision system for the assessment of the firing process parameters must provide the capture and processing of high-quality images of the process with a resolution of 2 megapixels, derived from the HD-SDI-video camera and an automatic assessment of the firing process parameters in real time (every 5 seconds), software with user-friendly visual interface, the ability to system training by operator, software integration with the kiln control system.

Automatic assessment of the firing process parameters in the kiln required to provide a method of image recognition, which formally represents the task of constructing an algorithm

$A: f \rightarrow Y,$

where f - 2d image brightness function, Y- firing process assessments vector: 1) dust assessment Y_1, 2) state of material (clinker) Y_2, 3) state of the torch Y_3.

Each component of vector Y is coded with integers: assessment Y_1 can take values "normal mode" (0), "dust" (1), "heavy dust" (2); Y_2- "overheated material" (0), "normal" (1), "poorly heated material" (2), "defective" (3), "coating dropping" (4); Y_3 - short torch" (0), "long torch" (1), "soft torch (with twist blades)"(2).

We propose method of firing process image recognition (Figure1), based on:

- Pre-treatment of image with 2d brightness function f, image partitioning into regions and calculating texture characteristics matrix X: $f \rightarrow X$;
- Segmentation of regions with Self-organizing map (SOM): $X \rightarrow S$,where each row of matrix X is aligned component of the vector S, corresponding to the segment number; set of texture characteristics X that provide the best segmentation optimized with genetic algorithm.
- Calculation of geometric and brightness features vector P on finding segments S with texture characteristics X: P: $\{X,S\} \rightarrow P$ and
- Calculation of assessments vector$Y$ with classification of features vector $P:P \rightarrow Y$. Single layer feed-forward neural network (SLFNN) trained with Extreme Learning Machine (ELM) used as classifier.

Hardware-software complex of machine vision system. To solve the task we develop the hardware-software complex of machine vision system for the assessment of the firing process parameters in rotary cement kilns. Its structure is shown at Figure 2.

Firing process Image is captured with an industrial HD-SDI-camera with high resolution (up to 1920 × 1080 pixels). To protect against high temperatures and dust the camera is placed in a special thermojacket with liquid cooling. The camera protection system is controlled by a local control module placed in control cabinet, Local

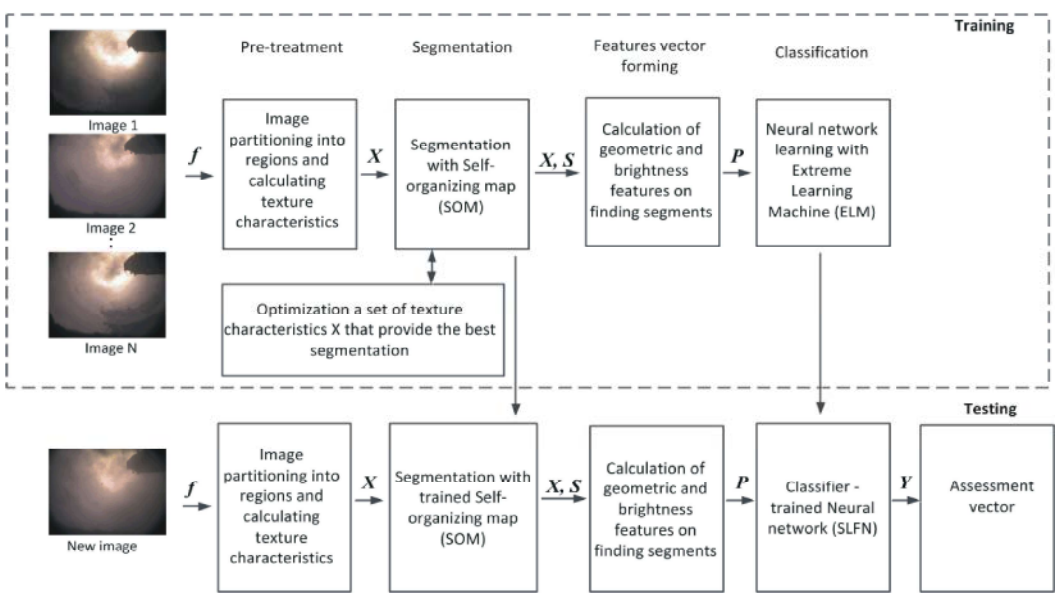

Fig. 1: Scheme of image recognition method

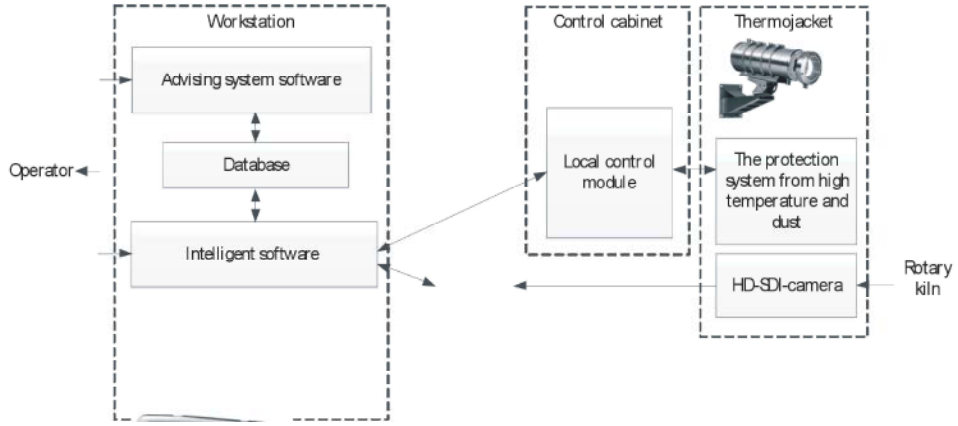

Fig. 2: Structure of hardware-software complex of machine vision system for assessment of firing process parameters in rotary cement kilns

Table 1: A comparison of features of the developed machine vision system with analogs

Feature	Developed machine vision system	DURAG System "D-VAT100-20", Germany	Video surveillance system TELESEN, Russia
Automated collection of visual data of firing process	Yes	Yes	Yes
Work at high temperatures and dust	Yes	Yes	Yes
Opportunity to study the system by operator	Yes	No	No
Visual interface	Yes	Yes	Yes
Measurement of the temperature field in the kiln	No	Yes	No
Firing process image recognition and firing process parameters assessment	Yes	No	No
Integration with the kiln automated process control system	Yes	Yes	No
Working in the simulator mode	Yes	No	No

control module is connected to the workstation by Ethernet-interface. HD-SDI video signal is converted by the converter to the Full HD format 1920x1080 and comes to the workstation. The workstation is a computer with the operating system Microsoft Windows 7 and intelligent software of machine system vision system that provides automatic firing process image recognition with the display and archiving in the database of images and found assessments of the process parameters.

In developing the structure of the system considered as the modern requirements for automation systems design and existing developments in the field of machine vision systems. We analyzed the functionality of some existing developments and compare them with the features of the proposed machine vision system (Table 1). DURAG System "D-VAT 100-20" [4] (company Durag GmbH, Germany) and video surveillance system TELESEN (company Telesen, Russia) [2] are considered.

In accordance with the data from Table 1 it should be noted that the Russian system has no intelligent features of image recognition and process parameters assessments and could not integrate to the kiln control system. Germany system allows to obtain objective data on temperature fieldof the firing process, however, as noted above, these data are not sufficient for firing process parameters assessment. Additionally, the system DURAG has high cost of implementation and follow-up support and maintenance.

The proposed machine vision system can take into account the specifics of rotary kilns for "wet" cement production and provide automatic visual assessment of the firing process parameters with special developed method of image recognition. If necessary, it is possible to train machine vision system during of its operation in real time, it is provided the opportunity to use machine vision system in a simulator mode.

The machine vision systems software for the firing process parameters assessment has a simplified structure shown in Figure 3 [7].

Module "Operator Form" provides the displaying of video images from the camera, changing the image size, displaying of information from the temperature sensor in a protective camera housings, with the alarm threshold is exceeded at + 50°C, the displaying of firing process

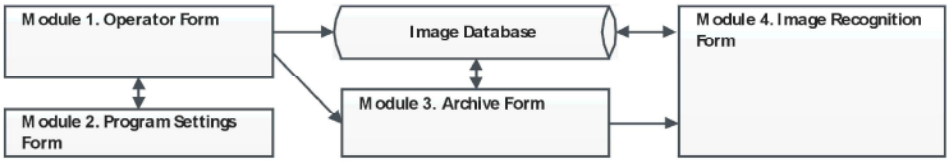

Fig. 3: Structure of machine vision system software

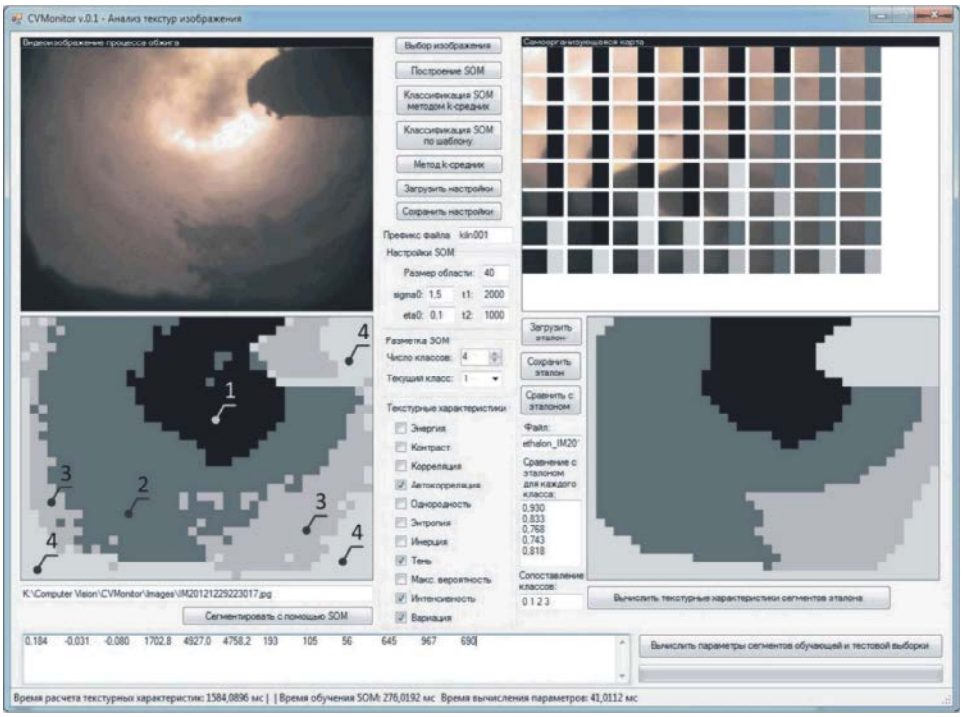

Fig. 4: Screen ofModule "Image Recognition Form".

parameters assessments, the ability to train the system due to changes in parameters assessments by the operator, saving to the database of images, assessments, the temperature in the thermojacket.

The module "Program Settings Form" allows you to specify the path to the database software package, the path to the saved images, image processing interval, adjust the image size.

Module "Archive Form" provides displaying the firing process image stored in the specified date and time, displaying of assessments and temperature on the specified date and time, interactive selection and display the date and time of saving image, the ability to step through the images, the possibility of teaching system due to changes in parameters assessments, the ability to select stored images for the training set, going to the module “Image Recognition Form”.

In the module "Image Recognition Form" provides a choice of an arbitrary image from a file or database, image segmentation implemented with a self-organizing map (SOM) or the k-means method, capability of self-organizing map marking both manually and automatically using a template or k-means method, the change, save and load algorithm settings. The module provides a choice a number of texture characteristics of an image, the ability to calculate of the image features and parameters assessments, the possibility of classifier training with stored in the database examples of images.

Image segmentation [8] into segments "torch" S1, "material" S2, "liners" S3, "kiln burner and corps" S4 is performed on base of texture characteristics vector X with the construction of Kohonen self-organizing map (SOM) trained with etalon. For a similar taskless descriptive method of multivariate image analysis (MIA) [5, 6] is used. Example ofimage segmentation with self-organizing map (SOM) shown in Figure 4, which shows the screen of the module "Image Recognition Form".

Top l - the original image; top right - Kohonen Self-organizing map with 8×8 neurons; down left -the SOM segmentation: 1 - torch, 2 - material, 3 - lining, 4 - kiln

burner and corps; down right - the etalon segmentation: 1 - torch, 2 - material, 3 - lining, 4 - kiln burner and corps.

Features are calculated on found segments "torch" S1 (1), "material" S2 (2) and "lining" S3 (3):

- Average pixels brightness of k-th segment, k = 1,2,3:

$$T_{Mk} = \sum_{(i,j)\in k} f(i,j) \Big/ N_k ,$$

where $f(i,j)$ - pixel brightness at point (i,j), N_k- number of pixels at k-th segment, k = 1,2,3; -the relative pixels brightness, which is calculated as the relative distance of the average pixels brightness of segment from its center of the histogram

$$R_{Mk} = (T_{Mk} - (f_{2k} + f_{1k})/2)/(f_{2k} - f_{1k}),$$

where [f_{1k}, f_{2k}] - brightness range of k-th segment; - root-mean-square deviation of the average value

$$\sigma_k = \sqrt{\sum_{f=f_{1k}}^{f_{2k}} \left(G_{fk} - G_{??k}\right)^2 \Big/ (f_{2k} - f_{1k})} ,$$

where G_{fk} - histogram of the brightness distribution on the k-th segment, [f_{1k}, f_{2k}] - brightness range of k-th segment, the average value of the histogram calculated by the formula

$$G_{??k} = \sum_{f=f_{1k}}^{f_{2k}} G_{fk} \Big/ (f_{2k} - f_{1k}) \cdot$$

- the equivalent diameter of the torch

$D_F = \sqrt{4N_1/\pi}$, where N_1 - total number of pixels on segment 1 «torch» (its area); -the center of mass of segment S3 “lining”

$$X_F = \sum_{(i,j)\in S3} j \Big/ N_3 , Y_F = \sum_{(i,j)\in S3} i \Big/ N_3 ,$$

where X_F and Y_F- the abscissa and the ordinate of the "center of mass" segment 3 "liner" on the vertical axis, N_3- total number of pixels in the segment 3 "lining" (its area).

Thus calculated feature vector P has 12 components: $P_1 = R_{M1}$, $P_2 = R_{M2}$, $P_3 = R_{M3}$, $P_4 = \sigma_1$, $P_5 = \sigma_2$, $P_6 = \sigma_3$, $P_7 = T_{M1}$, $P_8 = T_{M2}$, $P_9 = T_{M3}$, $P_{10} = D_F$, $P_{11} = X_F$, $P_{12} = Y_F$.

Classifier is trained by supplying N = 200 predefined examples (images), each of which is given pair (P_i, Y_i), i = 1,... N, where P_i - i-th input feature vector comprising M = 12 components, where M - total number of features and Y_i - i-th output vector classes of 3 components. Testing of the classifier was also conducted with 200 pre-prepared examples of test set.

Single layer feed-forward neural network (SLFNN) used as classifier. It has 12 input neurons, 3 output neurons and depended on the task number of hidden neurons. There are a lot of training methodsof this network for classification task [9]. Extreme learning machine (ELM-method) allows to train a three-layer neural network (with one hidden layer) without iterative procedure [10]. Neural net has hidden layer with a sigmoidal activation function G and the output layer which emits a weighted sum of its inputs. The input weight ω_j and threshold b_j for each j-th neuron of the hidden layer are set with random variables. The matrix H is the output values of hidden layer neurons has a dimension $N \times L$, where N - number of examples, L - the number of hidden layer neurons. Elements of matrix Hcalculates as $h_{ij} = G(w_j P_i + b_j)$.

Network training is calculation the matrix of output weights of the hidden layer neurons of the formula

$$\beta = H^+ Y ,$$

where $H^+ = (H^T H)^{-1} H^T$ - pseudo inverse Moore-Penrose matrix for the case of non-singular matrix H.According to [11] matrix$H^+$is the best approximate solution of equation $Y = H\beta$ by the least squares method. It allows avoid local minima in network training. High classification speed with the extreme learning machine is achieved due to the absence of iterative calculation and makes this method attractive for use in the real time algorithms, in particular to the task of firing process image recognition.

The hidden layer of neural network trained by the ELM has 45 neurons with sigmoid activation function. For the chosen network structure and the method of training this number of neurons provides the maximum classification accuracy the on the test sample and acceptable accuracy on the training set - respectively 76.33% and 75.83%, as shown in Figure 5.

The method of extreme learning machine (ELM) [10] was selected for use in a software after comparing it with the other most popularclassification methods (Table 2): the method of support vector machine (SVM) [12], the method of back-propagation training of a neural network with one hidden layer (BP) [9]. In the computer

Fig. 5: Averageclassificationaccuracywithdifferentnumberofhiddenneuronsinneuralnetwork, trainingwithELM

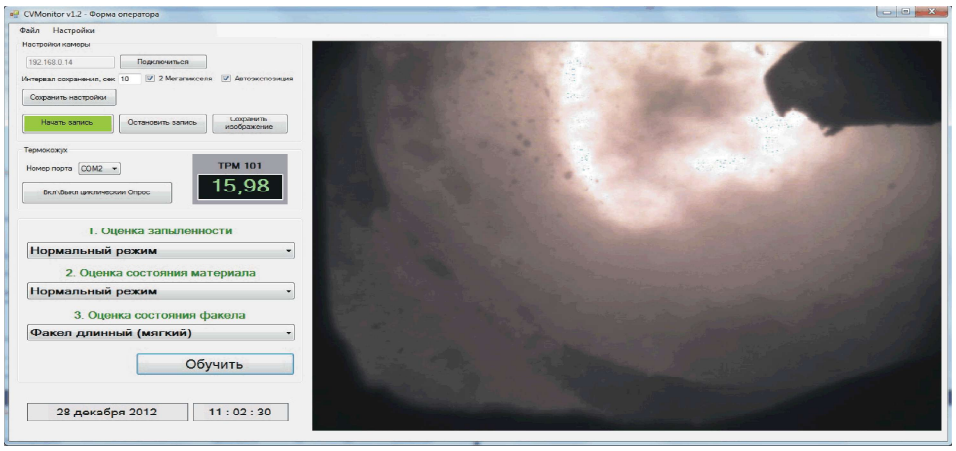

Fig. 6: Screen of Module "Operator Form

(a) (b)

Fig. 7: Hardware-software complex of machine vision system: a) camera thermojacket; b) operator workstation

Table 2: Classification methods comparison

		Classification accuracy on testing set, %				Classification accuracy on training set, %				
No	Classification method	Dust	Material state	Torch state	Average accuracy	Dust	Material state	Torch state	Average accuracy	Training time, ms
1	Extreme leaning machine (ELM)	80,0	76,0	73,0	76,33	78,0	77,5	72,0	75,83	124,8
2	Backpropagation (BP)	77,5	67,6	61,4	68,83	88,8	77,9	70,4	79,03	826,8
3	Support vector machines (SVM)	72,5	68,0	64,5	68,33	100,0	100,0	100,0	100,00	12,5

ScreenofModule “OperatorForm” isshownin figure6.

simulations in Matlab ELM showed at least 10% higher classification accuracy on the test sample compared to other methods. Network training time with ELM is about 120 ms.

Machine vision system is being tested at the cement kiln CJSC "Oskolcement" (Russia, Stary Oskol). Developed hardware-software complex of machine vision system is shown in Figure 7.

Summary: Recognizing of 2 megapixel image requires time over 2000 ms when software work in training mode, in testing mode - 1650 ms. The main expenditure of running time occurs at the first algorithm stage - image pre-treatment with texture characteristics calculation. Running time specified for the computer with a quad-processor Intel Core i5-2500S with a frequency of 2.7 GHz, 4 GB RAM, running a 64-bit operating system Windows 7. Assessment of the firing process must be carried out every 5 seconds, so the obtained results meet the requirements to machine vision system. The software developed in Microsoft Visual Studio 2010 with the C# language and image recognition results are stored in a local database SQLite, which provides integration with overall kiln control system.

In accordance with the structure and method of firing process image recognition a prototype of hardware-software complex was developed. It is currently being tested in a cement rotary kiln # 1 CJSC "Oskolcement" (Russia, Stary Oskol). Training and test sets of recognition algorithms formed on the data obtained from the real object.

CONCLUSION

Application of machine vision system will enhance the efficiency of the kiln operators, provide the on-line monitoring and control of the firing process, include the visual assessments of the process at the entire kiln control system. That will reduce the number of accidents and damage of kiln, as well as reducing fuel consumption. This system also allows to create an intellectual simulator for kiln control of "wet" cement production which based on visual assessments of the firing process parameters. That will provide effective training and re-training of operators.

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