LINEAR ALGEBRA FOR VISION-BASED SURVEILLANCE IN HEAVY INDUSTRY - CONVERGENCE BEHAVIOR CASE STUDY

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ABSTRACT

The surveillance application aims at improving the quality of technology via modelling human expert behaviour in the coking plant ArcelorMittal Ostrava, the Czech Republic. Video data on several industrial processes are captured by means of a CCD camera and classified by using Latent Semantic Indexing (LSI) with the respect to etalons classified by an expert. We also study the convergence behavior of proposed partial eigenproblem-based dimension reduction technique and its ability for knowledge acquisition. Having increased the computational effort of the dimension reduction technique did not imply the increasing quality of retrieved results in our cases.

1. INTRODUCTION

Content-based retrieval of images is used as a tool for monitoring of industrial processes in the coking plant ArcelorMittal Ostrava, the Czech Republic. A coking plant belongs to the industrial complex [3] with several various parallelly operated technologies of chemically-thermal character which are, only theoretically, in full accordance with theoretical conditions of the processes. There are more reasons of this statement:

- absence of algorithmized forms of these technologies
- insufficient knowledge concerning the possibilities of application of communication and information technology in specific conditions of industrial complexes including the influences of working environment.

General problems of integration of partial technological systems and the elimination or moderation of negative expressions described above were already described in more details in [4].

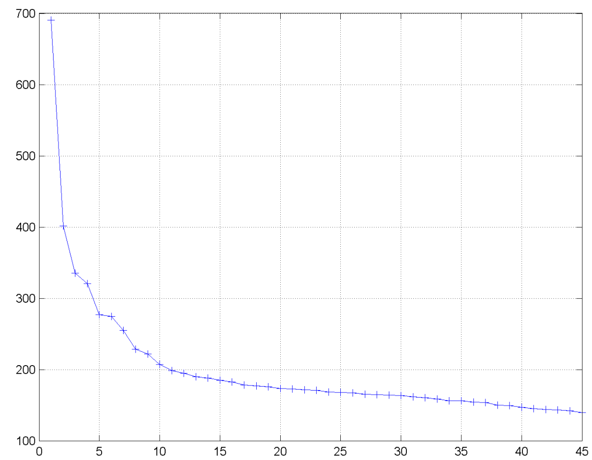

Fig. 1. The distribution of the first 45 largest singular values of the document matrix. The singular values are sorted in a descending order.

In this paper we focus on application of a content-based search technique to images taken at such a plant. In this way, a content-based analysis tool could be used for evaluation of the coking process quality, which should lead to its better surveillance. Namely, the result of the analysis provided by the tool will be the project of action interference into the heating system and project for carrying out of control of the chamber lining. This application will be interconnected with the subsystem of servicing machine controls and with the application of passport working out servings for observation of the state of lining of the coke-oven chambers. The effect of this interconnection on the technological quality of the information being obtained will be evaluated.

The final goal of any surveillance application for coke-oven (CO) analysis is an optimal decision. In practice a CO operator makes decisions using his past experience which is not formalized at all. A flexible coexistence of a human being reasoning power, computer memory and arithmetic operation

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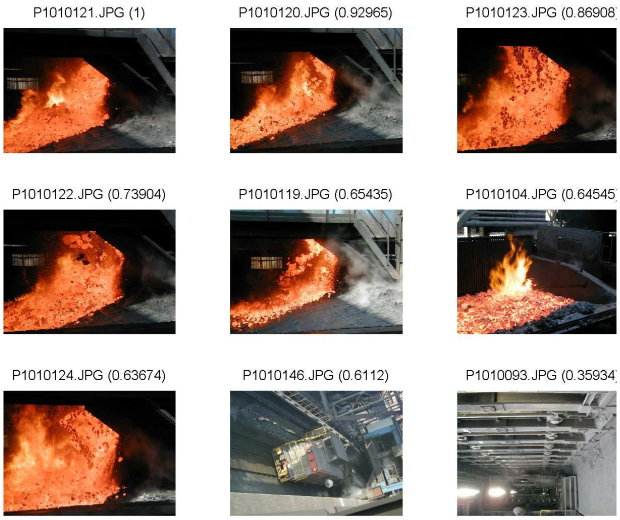

Fig. 2. An example of LSI image retrieval results: Experiment A, $k = 8$.

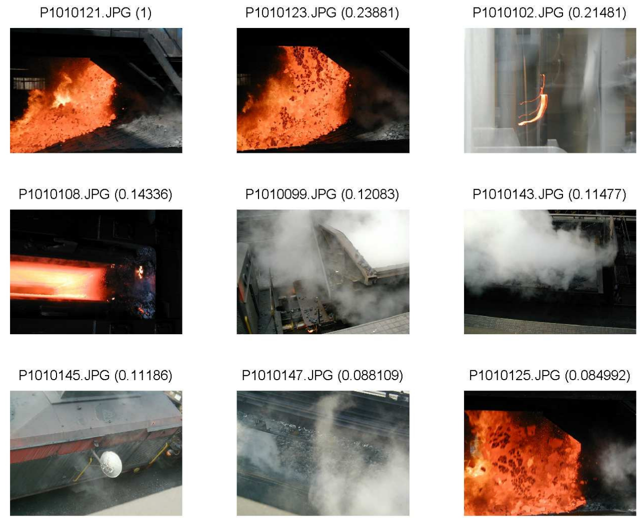

Fig. 3. An example of LSI image retrieval results: Experiment A, k=45.

velocity is an effective artificial intelligence solution.

2. TECHNOLOGICAL SITUATION

The pictures shown in Figures 2 – 9 were picked up digitally during the pushing out the coke from the coking furnaces at the coke plant in ArcelorMittal Ostrava, Czech Republic. The servicing cars (wagons) are equipped with camera systems enabling visual control of the state by service personnel of the coke-oven battery (hereinafter only CB). The measuring and information system (hereinafter only MIS) does not catch the states when there occurs changes of the heating gases flow into the coke-oven battery, for example due to the damage of lining or burners. These parts of CB are affecting to coking products and the quality of resulting product can be reduced. The existing MIS does not enable the collection, scanning, archiving and evaluation of data concerning the quality of resulting product (coke) and their utilization in the coking process management.

After completion of the coking process, which runs under temperatures above 1000^oC, the charge of CB, processed thermally and chemically, is pushed through the output opening by means of the output servicing machine. During the pushing out on the output side of CB there comes to disintegration of the coke prism which falls on the loading area of the handling wagon linked on (Figure 2, up). Due to the wagon traveling the falling coke is distributed on its loading area and is transported for cooling by water shower and, after cooling, to dumping into the chutes of the transport system of the granulation system and storage tanks.

The resulting quality of the coke produced is influenced not only by the heating regime but also by the coal charge quality. The important and up to now not utilized information source are the colored visual parameters of the surface of the coke pushed out from CB together with the character of its gassing and fragmentation before the fall on loading area of handling wagon. In practice this kind of information can be used by an experienced human expert, such as operating personnel, to make an estimation of the quality of the pushed coke. However the operator can also pass the linguistic values of estimated visual parameters observed during coke pushing to a knowledge-based system to make the final decision about quality. In some cases these parameters can also be used for maintenance diagnostic of the inner state of the coking furnace from which the coke is pushed. This visual information can be caught by visual displaying system with the CCD camera in the viewing field of which the output of chutes of the output servicing machine will be found. More detailed information can be obtained further by scanning of the discharging hopper of the coke cooled, where, after certain information processing, the parameters of granularity, fracture surfaces and color of resulting product can be monitored.

Such a displaying system consisting of a cooled high-resolution CCD camera interconnected with the computer for data pre-processing and analysing would be wireless interconnected with the control system of CB on two levels. The first one would enable the service personnel the view on the output side of CB. The second one would deliver the extracted data about the parameters of the coke production from single CB for visualization. At the same time, the file of these extracted data would serve for classification in the database system as a file of the knowledge system input data.

Fig. 4. An example of LSI image retrieval results: Experiment B, k=8.

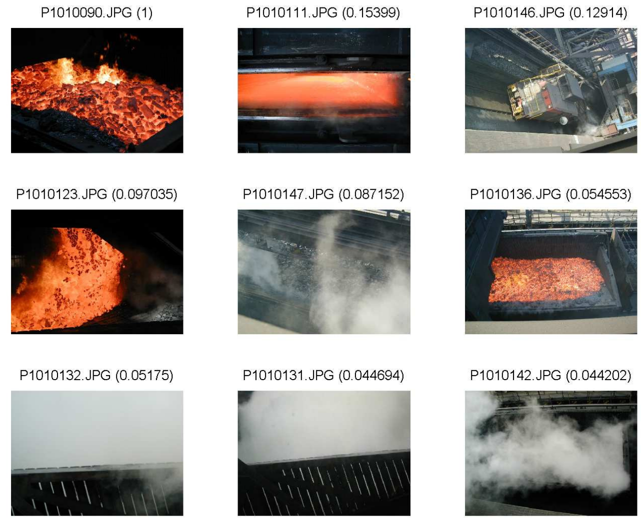

Fig. 5. An example of LSI image retrieval results: Experiment B, k=45.

3. IMAGE RETRIEVAL USING LSI

3.1. Principles of LSI

The numerical linear algebra, especially Singular Value Decomposition (SVD) is used as a basis for information retrieval in the retrieval strategy called Latent Semantic Indexing (LSI), see [5]. Originally, LSI was used as an efficient tool for semantic analysis of large amounts of text documents. The main reason is that more conventional retrieval strategies (such as vector space, probabilistic and extended Boolean) are not very efficient for real data, because they retrieve information solely on the basis of keywords; polysemy (words having multiple meanings) and synonymy (multiple words having the same meaning) are thus not correctly detected, see [1, 2]. LSI can be viewed as a variant of the vector space model with a low-rank approximation of the original data matrix via the SVD or the other numerical methods [5].

The "classical" LSI application in information retrieval algorithm has the following basic steps:

i) The Singular Value Decomposition of the term matrix using numerical linear algebra. SVD is used to identify and remove redundant information and noise from data.

ii) The computation of similarity coefficients between transformed vectors of data and thus reveal some hidden (latent) structures of data.

Numerical experiments proved that some kind of dimension reduction, which is applied to the original data, brings to the information retrieval two main advantages: (i) automatic noise filtering and (ii) natural clustering of data with "similar" semantic.

Recently, the methods of numerical linear algebra, especially SVD, have also been successfully used for diverse applications such as general image retrieval [8, 9], face recognition and reconstruction [7], iris recognition [11], information retrieval in hydrochemical data [12], and even as an support for information extraction from HTML product catalogues [6]. A comparison of two approaches for classification of metallography images from a steel plant is presented in [13].

3.2. Image coding

In our approach [8, 9, 10, 11], a raster image is coded as a sequence of pixels. Then the coded image can be understood as a vector of a m-dimensional space, where m denotes the number of pixels (attributes). Let a symbol A denote a $m \times n$ term-document matrix related to m keywords (pixels) in n documents (images). The (i, j)-element of the term-document matrix A represents the color of i-th position in the j-th image document.

3.3. Implementation details

Let the symbol A denote the $m \times n$ document matrix related to m pixels in n images. The aim of SVD is to compute the decomposition

$$A = USV^T, \tag{1}$$

where $S \in R^{m\times n}$ is a diagonal matrix with nonnegative diagonal elements called the singular values, $U \in R^{m\times m}$ and $V \in R^{n\times n}$ are orthogonal matrices[1]. The columns of matrices U and V are called the left singular vectors and the

[1] A matrix $Q \in R^{n\times n}$ is said to be *orthogonal* if the condition $Q^{-1} = Q^T$ is satisfied.

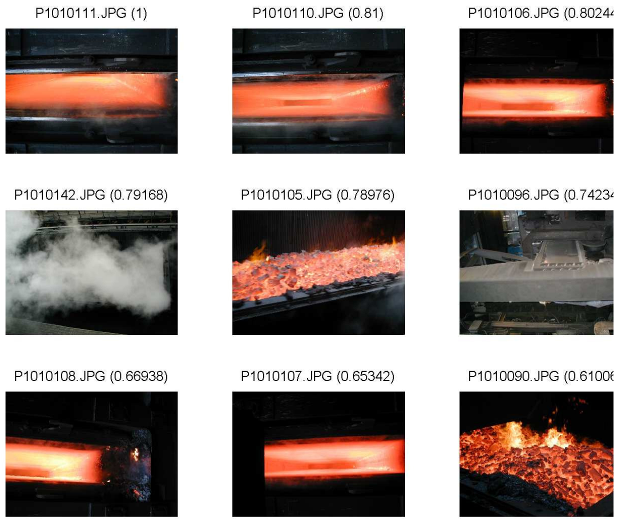

Fig. 6. An example of LSI image retrieval results: Experiment C, k=8.

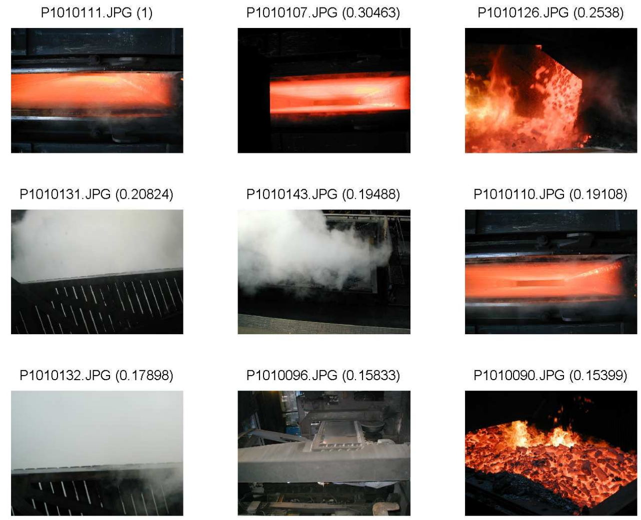

Fig. 7. An example of LSI image retrieval results: Experiment C, k=45.

right singular vectors respectively. The decomposition can be computed so that the singular values are sorted in a decreasing order. The full SVD decomposition is a memory and time consuming operation, especially for large problems. Moreover, the matrices U and V have a dense structure and our experiments show that computation of very small singular values and associated singular vectors can damage image retrieval results, see Figure 3, Figure 5, Figure 7 and Figure 9. Due to these facts, only a few k-largest singular values of A and the corresponding left and right singular vectors are computed and stored in memory. We implemented and tested LSI procedure in the Matlab system by Mathworks. The document matrix A was decomposed by the Matlab command *svds*. Using the *svds* command brings following advantages:

- The document matrix A can be effectively stored in memory by using the Matlab storage format for sparse matrices.
- The number of singular values and vectors computed by the partial SVD decomposition can easily be set by the user.

Following [5] the Latent Semantic Indexing procedure can be written in Matlab by the following way.

Procedure LSI [Latent Semantic Indexing]

function sim = lsi(A,q,k)

Input:

A ... the $m \times n$ matrix

q ... the query vector

k ... Compute k largest singular values and vectors; $k \leq n$

Output: sim ... the vector of similarity coefficients

[m,n] = size(A);

1. **Compute the co-ordinates of all images in the k-dim space by the partial SVD of a document matrix A.**
   [U,S,V] = svds(A,k);
   Compute the k largest singular values of A; The rows of V contain the co-ordinates of images.

2. **Compute the co-ordinate of a query vector q**
   *qc = q' * U * pinv(S);*
   The vector qc includes the co-ordinate of the query vector q; The matrix $pinv(S)$ contains reciprocals of nonzeros singular values (a pseudoinverse); The symbol ' denotes a transpose superscript.

3. **Compute the similarity coefficients between the co-ordinates of the query vector and images.**
   for i = 1:n Loop over all images
   *sim(i)=(qc*V(i,:)')/(norm(qc)*norm(V(i,:)));*
   end;
   Compute the similarity coefficient for i-th image; $V(i,:)$ denotes the i-th row of V.

The procedure *lsi* returns to a user the vector of similarity coefficients sim. The i-th element of the vector sim contains a value which indicates a "measure" of a semantic similarity between the i-th document and the query document. The increasing value of the similarity coefficient indicates the increasing semantic similarity. The algorithm can be implemented very effective when the time consuming SVD of LSI is replaced by the partial symmetric eigenproblem [9, 11].

Fig. 8. An example of LSI image retrieval results: Experiment D, k=8.

Fig. 9. An example of LSI image retrieval results: Experiment D, k=45.

4. SUMMARY OF EXPERIMENTS

There is no exact routine for selection of the optimal number of computed singular values and vectors [1]. For this reason, the number of extreme singular values and associated singular vectors used for LSI was estimated experimentally according to the distribution of singular values of the document matrix, see Figure 1. We have extended experiments [10] by a subjective evaluation of results related to these two different settings: In the first case, $k = 8$ largest singular values is assumed, whereas in the second case $k = 45$ largest singular values were used for LSI. For each experiment, query image represents a different industrial process. Image retrieval results are presented by decreasing order of similarity. The query image is situated in the upper left corner. The similarity of the query image and the retrieved image is written in parentheses. In order to achieve well arranged results, only 9 most significant images are presented. The computation of very small singular values and associated singular vectors can damage retrieval results. Analysing Figure 1, we set the number of computed singular values and vectors by $k = 8$ for final evaluation. The properties of the document matrix and LSI processing parameters are summarized in Table 1.

The SVD-free LSI algorithm seems to be fast. The analyses of 166.4 MB of data required less than 1.5 seconds, see Table 1.

In fact, LSI made it possible to distinguish between different layouts of objects on the scene. It seems that we could thus e. g. detect inadequate positions of coke with a respect to the chamber observed by the given camera, see Experiment A at Figure 2. The query image describes the situation of coke pushing out the coking furnaces. All of the 6 most similar images except one are related to the same topic. These images are automatically sorted in the same way as it would be sorted by a human expert. Another example of LSI image retrieval results related to the same query image is at Figure 3. In this case, $k = 45$ largest singular values were computed. The most similar image is relevant, but its similarity to the query is only 0.23881. The following 6 images are not related to the same topic at all.

In Experiment B, the query image includes cinders, see Figure 4. The image with the same content is only one in the image database and its similarity coefficient is 0.97074. The third most similar image is not related to cinders at all but has similarity coefficient with a significantly smaller value

Properties of the document matrix *A*	
Number of keywords:	640×480 = 307 200
Number of documents:	71
Size in memory:	166.4 MB
The SVD-Free LSI processing parameters	
Dim. of the original space	71
Dim. of the reduced space (k)	8
Time for $A^T A$ operation	1.031 secs.
Results of the eigensolver	0.235 secs.
The total time	1.266 secs.

Table 1. Image retrieval using the SVD-free Latent Semantic Indexing method; Properties of the document matrix (up) and LSI processing parameters related to a PC system with Pentium(R) 4, 3GHz CPU with 2 GB RAM (down).

(0.68403). Another example of LSI image retrieval results related to the same query image is at Figure 5. In this case, $k = 45$ largest singular values were computed. The retrieved images are not related to the same topic at all.

In Experiment C, the query image includes a view into the opened coke furnace, see Figure 6. The images with the same content as the query image are at positions 2, 3, 7 and 8. The images at positions 4, 5 and 6 include images with similar shapes of contours as the query image, i. e. two thin lines. Another example of LSI image retrieval results related to the same query image is at Figure 7. In this case, $k = 45$ largest singular values were computed. The most similar image is relevant, but its similarity to the query is only 0.30463. The following images (except one image) are not related to the same topic at all.

In Experiment D, the query image includes a detailed view of coke, see Figure 8. All of the 8 most similar images are related to the same topic. Another example of LSI image retrieval results related to the same query image is at Figure 9. In this case, $k = 45$ largest singular values were computed. The retrieved images are not related to the same topic at all.

5. CONCLUSIONS

In our application of a content-based search technique in a heavy industry environment, we experimented with the LSI method applied on image bitmaps. It seems that for the specific setting of coking plant surveillance, the LSI method may provide interesting results, and mimic the behaviour of the human operator. Our results also indicate that the LSI method can automatically recognize the type of industrial process found in our image database. We have studied the quality of image retrieval results. Having increased the computational effort of LSI did not imply increasing quality of retrieved results.

Soft computing approaches will be applied to achieve the more effectiveness of CO processing, namely technological and failure diagnostics and states prediction, optimal decision-making, reasoning and control. In addition to the general rules of the CO process even the subjective knowledge of the CO operator has to be applied. The expert systems are considered here, namely, as a mean for the diagnostics of the investigated route with prediction of development of its selective condition and steps to be taken to avoid any unfavorable development. The applied knowledge systems enable to design such a control system than will be open for future development.

Future research in our application area should concentrate on the discovery of more explicit mapping from low-level video features to semantic abstractions, which can be used for human interpretation of underlying processes.

Recently, we also experimented with the sparse image representation for automated image retrieval. Although images can be represented very effectively by sparse coefficients based on FFT, the sparsity character of these coefficients is destroyed during the LSI-based dimension reduction process represented by the sparse partial eigenproblem. In our approach, we keep the memory limit of the decomposed data by a statistical model of the sparse data [14]. We successfully used this new sparse approach for a large-scale similarity task in NIST TRECVid 2007 competition as a member of K-Space team [15].

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