Low-loss image compression techniques for cutting tool images: a comparative study of compression quality measures

Técnicas de Compressão com Baixa Perda de Imagens de Ferramentas de Corte: um estudo comparativo de medidas de qualidade de compressão

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This work accomplishes a comparative study between two distinct image compression techniques, namely the Lifting technique and the Principal Components Analysis (PCA), in order to determine what of these two approaches is more appropriate for cutting tool wear images analysis. Lifting and Principal Components Analysis were applied in original images of a cutting tool for producing a low resolution version, while keeping the more important details of the image. The low-loss image compression quality provided by these techniques was expressed in terms of the compression factor (ρ), the Mean Square Error (MSE) and the Peak Signal-to-Noise Rate (PSNR) provided by the image compression process. The tests were accomplished using the high-performance language for technical computing MATLAB®, and the results shown that the PCA technique presented the best values of PSNR with low compression rates. However, with high values of compression rates the lifting technique gave the highest PSNR.

Key words: Cutting tool. Image compression. Lifting technique. Principal Components Analysis.

Este trabalho realiza um estudo comparativo entre duas diferentes técnicas de compressão de imagens, a técnica de Lifting e a Análise de Componentes Principais (PCA), visando determinar qual das duas abordagens é mais apropriada para a análise de imagens de ferramentas de corte desgastadas. As técnicas de Lifting a PCA foram aplicadas em imagens de ferramentas de corte para produzir versões de baixa resolução, mantendo os detalhes mais importantes da imagem. A qualidade da compressão de baixa perda da imagem para ambas as técnicas foi expressa em termos do fator de compressão (ρ), do Erro Quadrático Médio (MSE) e a Relação Sinal-Ruído de Pico (PSNR) gerado pelo processo de compressão. Os testes foram realizados usando a linguagem de computação numérica de alto desempenho MATLAB, e os resultados mostram que a técnica PCA apresenta os melhores valores de PSNR para baixas taxas de compressão. Entretanto, para altos valores de taxas de compressão a técnica de lifting produziu maiores valores de PSNR.

Palavras-chave: Análise de Componentes Principais. Compressão de imagens. Ferramenta de corte. Técnica de lifting.

1 Introduction

In recent years, the use of computer vision-based systems and artificial intelligence techniques as such, artificial neural network, to estimate tool's lifetime in metal cutting process has been aimed by many researches (ALAJMI et al., 2005; PATRA et al., 2007; CHAO and HWANG, 1997; ALAJMI and ALFARES, 2007; VOLKAN ATLI et al., 2006; GADELMAWLA et al., 2008; INOUE, KONISHI and IMAI, 2009; WANG et al., 2009). Usually, the lifetime is predicted by detecting visible – sometimes very small – degeneration in images of a cutting tool, which is supplied by a typical experiment in the turning process. In order to make visible small changes or degenerations in a cutting tool, this experiment tends to generate high-resolution images. Finding patterns in high-resolution images can be a hard and time consuming task to the most artificial neural network approaches (HAYKIN, 1999). So, in order to obtain relevant enhancement in patterns recognition performance, before using images as input cases in the neural network training processes, it is common to apply some low-loss image compression techniques.

In this context, wavelet decomposition is recognized as a powerful tool for image analysis and data compression. In fact, many works has shown how to use wavelets transform for creating data compression methods with great potential to compress large-scale, three-dimensional image data files, while keeping the most important information necessary to find patterns in the data (GRGEĆ et al., 2000; LO et al., 2003; O'ROURKE and STEVENSON 1995; UHL, 1997). However, despite its good properties the numerical performance of the wavelet transforms can be improved through the lifting technique.

The lifting technique is a method introduced by W. Sweldens (1996), which allows to create an wavelet transform algorithm with smaller memory requirement and a reduced number of floating point operations, if long filters are used, keeping the efficiency of the technique (SWELDENS, 1996; DAUBECHIES and SWELDENS, 1998). Thenceforth, the lifting-based wavelet transform has been applied in many applications worldwide (SPIRES, 2005; PIELLA, PAU and PESQUET-POPESCU, 2005; VASUKI and VANATHI, 2007; MATHEW and SINGH, 2009; ROJALS, 2006; MATÍNEZ-TRINDAD, OCHOA and KITTLER, 2006). Although this great success of the lifting technique, its use in the cutting tool image analysis practically does not exist (PEREIRA et al., 2009).

On the other hand, there are some statistical techniques that also can provide a powerful tool for data dimension reduction and pattern recognition. As the dimensionality reduction problem is directly related to image compression, these techniques are often used in image processing. Principal component analysis is one of those statistical techniques and it has been widely applied in the area of image compression in various forms (HUHLE, 2006; NA et al. 2007; KIM, FRANZ and SCHOLKOPF, 2005; KIM, 2007). Also in this case, as for the cutting tool image analysis, the results are very incipient (QIXIN, 2008; KHANDEY, 2009; KARACAL, CHO, and YU, 2009).

In this work, we accomplish a comparative study between the Lifting technique and the Principal Components Analysis, in order to determine what of these two approaches is more appropriate for cutting tool wear images analysis. Lifting and PCA were applied in an original image of a cutting tool for producing a low resolution version, while keeping the more important details of the image. The low-loss image compression quality provided by these techniques was expressed in terms of the compression factor (ρ), the Mean Square Error (MSE) and the Peak Signal-to-Noise Rate (PSNR) provided by the image compression process. The tests were accomplished using the high-performance language for technical computing MATLAB®, and the results shown that the PCA technique presented the best values of PSNR with low compression rates. However, with high values of compression rates the lifting technique gave the highest PSNR.

2 Principal Components Analysis – PCA

2.1 Dimensionality reduction provided by PCA

The PCA scheme is a formulation that projects a dataset $\boldsymbol{X}$ of vector $x \in R^N$ onto an orthonormal base in R^N, defined as a set of M eigenvectors $e_i \in R^N$, $i = 0,1,\ldots M$-1, of the covariance matrix of $\boldsymbol{X}$, such that the base is oriented in the direction that provides the maximum variance of $\boldsymbol{X}$ in R^N (CASTRO, 1996; SMITH, 2002).

The most important application of PCA is the dimensionality reduction of a dataset $\boldsymbol{X}$. The principle of dimensionality reduction is the representation of the dataset $\boldsymbol{X}$ in terms of eigenvectors $e_i \in R^N$ (components) of its covariance matrix (SMITH, 2002). The eigenvectors oriented in the direction with the maximum variance of $\boldsymbol{X}$ in R^N carry the most relevant information of $\boldsymbol{X}$. These eigenvectors are called principal components. The dimensionality reduction consists of choosing the eigenvectors that carry, the least significant components, i.e., with the least variance, to leave out the dataset $\boldsymbol{X}$ (JIEPING, JANARDAN and LI, 2004).

Assume that n images in a set are originally represented in matrix form as $U_i \in R^{r \times c}$, i = 1, ..., n, where r and c are, repetitively, the number of rows and columns of the matrices. In vectorized representation (matrix-to-vector alignment) each U_i is a N = $r \times c$ -dimensional vector a_i computed by sequentially concatenating all of the lines of the matrix U_i. Considering the matrix-to-vector alignment n images can be represented by only one single matrix $U \in R^{n \times N}$, where each line corresponds to a single image U_i in form of vector $a_i \in R^N$.

To compute the Principal Components the covariance matrix of U is formed, namely $\Sigma = U^T U$, where T addresses the matrix transpose operation, and eigenvalues, with the corresponding eigenvectors, are evaluated. The eigenvectors forms a set of linearly independent vectors, i.e., the base $\{\phi\}_{i=1}^{n}$ which consist of a new axis system (JIEPING, JANARDAN and LI, 2004).

To perform the dimensionality reduction, the entire matrix $\boldsymbol{U}$ is projected onto the base $\{\phi\}_{i=1}^{n}$ that is, assuming $U = (a_1,\ldots,a_n)$, its coordinates on a new axis system are $(U\phi_1,\ldots,U\phi_n)$. By choosing p eigenvectors corresponding to the largest p eigenvalues, such that p is less than n, an authentic decreasing in dimension is performed and the coordinates of U projected in this reduced p-dimension sub-space are $(U\phi_1,\ldots,U\phi_p)$.

The aim of PCA is finding the maximum variance of the projections of U onto the p-dimension sub-space $\{\phi_1,\ldots,\phi_p\}$, i.e., if $G = [\phi_1,\ldots,U\phi_p]$ is one matrix of eigenvectors corresponding to the largest p eigenvalues of Σ, then G is the solution of the following optimization problem (SMITH, 2002):

$$G = \arg \max_{G \in \mathbb{R}^{N \times p} : G^T G = I_p} \frac{1}{n-1} \sum_{i=1}^{n} \left\| (a_i - m) G \right\|_2^2 \quad (1)$$

where a_i are the rows of matrix U, $m = \frac{1}{n} \sum_{i=1}^{n} a_i$ is the mean, I_p is the pxp identity matrix and $\| \, \|_2$ denotes the norm two of a vector. In the solution provided by G, the projections of data image U onto the p-dimension sub-space $\{\phi_1,\ldots,\phi_p\}$ have the largest variance (largest energy stored) $\mathrm{var}(x) = \frac{1}{n-1}\sum_{i=1}^{n}\left\|a_i - m\right\|_2^2$ among all the p-dimension axes systems.

2.2 PCA Image compression scheme

For image compression purpose an image $I \in R^{r \times c}$, where r and c are repetitively the number of rows and columns of the matrix, is divided into n sub-image $\{sub_{r' \times c'}\}_{j=1}^{n}$, where $r' < r$ and $c' < c$. The matrix U is formed by vectorazing all of $\{sub_{r' \times c'}\}_{j=1}^{n}$ such that each line of U is a matrix-to-vector alignment of a particular $\{sub_{r' \times c'}\}_{j=1}^{n}$. As mentioned before, the energy stored in a particular direction (the variance of the projection of U onto the p-dimension sub-space $\{\phi_1,\ldots,\phi_p\}$) is the eigenvalue associated to eigenvectors in this direction. Therefore it is possible to exclude some directions (sub-spaces) defined by eigenvectors which the eigenvalue is less significant than other eigenvalues.

As the sub-spaces with the least energy are excluded a low-loss data compression of U is performed (SMITH, 2002), because the leaved out sub-spaces generally carry irrelevant information of U. In this sense, U had a dimensionality reduction because initially it was represented in $R^{n \times N}$ and, after removing the least significant sub-spaces, U became U' a dataset represented in a dimension less than $n \times N$ with low-loss of information.

According to (SMITH, 2002) the low-loss image compression provided by PCA method can be expressed in terms of the compression factor (ρ), the Mean Square Error (MSE) in approximating U by U' and the Peak Signal-to-Noise Rate (PSNR) provided by the image compression process i.e., the ratio between the maximum possible component of U and the power of MSE (noise) that affects the fidelity of the approximation. The compression factor is defined as

$$\rho = \frac{\text{The total storage unit need to represet } U'}{\text{The total storage unit need to represet } U}, \qquad (2)$$

while the MSE of approximating U by U' is:

$$MSE = \sum_i (a_i' - a_i)^T (a_i' - a_i), \qquad (3)$$

and PSNR is defined as

$$PSNR = 10\log\left(\frac{(\max comp\{U\})^2}{MSE}\right). \qquad (4)$$

3 Lifting Technique

The mathematical analysis and the signal processing communities have created several algorithms of compactly supported wavelet. In fact, many other areas of science such as engineering, and mathematics have also contributed to the development of the wavelet field (DAUBECHIES and SWELDENS, 1998; SWELDENS and SCHRÖDER, 1996; SWELDENS, 1996; COHEN, DAUBECHIES, and FEAUVEAU, 1992; UYTERHOEVEN, ROOSE, and BULTHEEL, 1997).

Due to the different origins of wavelets, their properties and construction can be motivated and understood in different ways. Lifting technique is one of these ways and it has some structural advantages in relation to traditional approaches (DAUBECHIES and SWELDENS, 1998; SWELDENS and SCHRÖDER, 1996).

The lifting technique allows some improvements on the properties of existing wavelet transforms. The basic idea of this technique is to exploit the correlation present in most real life signals to build a sparse approximation. In contrast to traditional approach, which relies heavily on the frequency domain, the lifting scheme derives all constructions in the spatial domain (DAUBECHIES and SWELDENS, 1998; SWELDENS and SCHRÖDER, 1996). This feature allows that the lifting algorithms can easily be generalized to higher dimensions and complex geometric structures.

For a simple introduction of the lifting scheme we considered a finite signal of length 2^j, which is represented here as:

$$\mathbf{s}^j = \{s_1^j, s_2^j, s_3^j, \ldots, s_{2^j}^j\} \quad (5)$$

The lifting scheme assumes that the numbers $S_i^j, i = 1,\ldots,2^j$, are not randomly distributed, but contain some correlation between the sample and its neighbors. Then an odd sample S_{2k+1}^j can use the average of its two even neighbors for its prediction. The detail d_k^{j-1} is defined as the difference between the odd sample and its computed prediction (Jensen and la Cour-Harbo, 2001), as expressed by:

$$d_k^{j-1} = s_{2k+1}^j - (s_{2k}^j + s_{2k+2}^j)/2 \quad (6)$$

Therefore, if the sample and its neighbors have almost the same value, then the difference is of course small, and the prediction is good.

To preserve the average value of the original signal the values of the difference are redistributed to the computed averages issued from the prediction phase. This operation is called update and is defined by (7).

$$s_k^{j-1} = s_{2k}^j + (d_{k-1}^{j-1} + d_k^{j-1})/4 \quad (7)$$

This prediction and update steps are of order two. In this case, the prediction will be exact, if the original signal is linear and the update will preserve the average and the first moment. This idea is illustrated in Figure 1.

The procedure defined by (6) and (7) is only one example that can be used for constructing wavelet transforms and it is part of a large family of so-called biorthogonal wavelet CDF(2,2)

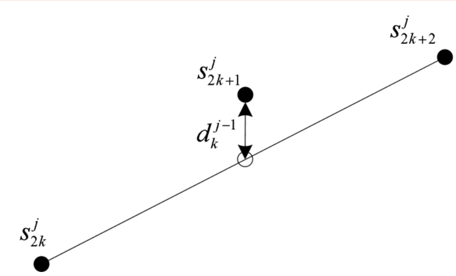


Figure 1: Prediction is correct for a linear signal and the correction is the difference between the real middle sample value and its computed prediction
Source: The authors.

transforms (COHEN, DAUBECHIES, and FEAUVEAU, 1992).

As another example of CDF transforms, which have been taken from (COHEN, DAUBECHIES, and FEAUVEAU, 1992), the detail d_k^{j-1} defined in the expression (6) above can be defined again as

$$d_k^{j-1} = s_{2k+1}^j - \left(9s_k^{j-1} + 3s_{k+1}^{j-1}\right)/8 \quad (8)$$

where,

$$s_k^{j-1} = s_{2k}^j - \frac{1}{3}s_{2k-1}^j \quad (9)$$

In all these examples of wavelet transforms each pair of prediction and update step is inverted separately, as illustrated in Figure 3. It is known in the literature that the generalization of this procedure is crucial for application purposes (UYTERHOEVEN, ROOSE, and BULTHEEL, 1997). In this generalization a prediction step is followed by an update step and by another prediction and update steps. In this approach the detail d_k^{j-1} can be defined as (10)

$$d_k^{j-1} = \frac{\sqrt{3}+1}{\sqrt{2}} \tilde{d}_k^{j-1} , \tag{10}$$

where,

$$\tilde{d}_k^{j-1} = s_{2k+1}^j - \frac{1}{4}\sqrt{3}s_k^{j-1} - \frac{1}{4}(\sqrt{3}-2)s_{k-1}^{j-1} , \tag{11}$$

and

$$s_k^{j-1} = s_{2k}^j + \sqrt{3}s_{2k+1}^j . \tag{12}$$

The operations (10)-(12) are part of one step in the discrete wavelet transform based on Daubechies 4 filters (UYTERHOEVEN, ROOSE, and BULTHEEL, 1997).

There are many other examples to build wavelet transforms and some of them can be found in (DAUBECHIES and SWELDENS, 1998). Overall, the direct lifting transform can be defined as

$$\begin{aligned} \mathrm{d}_{j\text{-}1} &= odd_{j-1} - P(even_{j-1}) \\ \mathrm{s}_{j\text{-}1} &= even_{j-1} + U(\mathrm{d}_{j-1}) \end{aligned} , \tag{13}$$

where P and U are, respectively, the prediction and update step and the entries s_j are sorted into even and odd entries (of course, in effective implementations the entries are not separated).

The prediction and the update lifting steps are shown in Figure 2 and the direct and inverse lifting steps in Figure 3. As can be observed from Figure 3, the inverse transform is easily found by flipping the order of the operations and inverting its signs. This is an important structural advantage of lifting (SWELDENS, 1996).

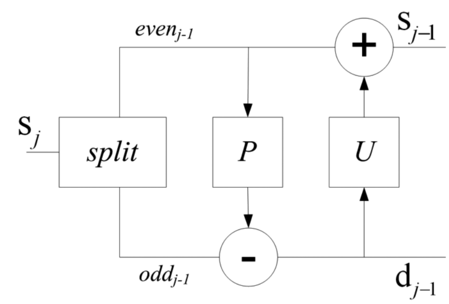


Figure 2: Block diagram of prediction and update lifting steps
Source: The authors.

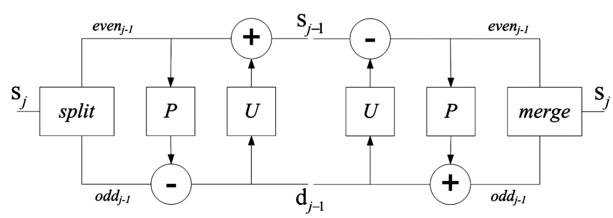


Figure 3: Direct (left side) and inverse (right side) lifting steps
Source: The authors.

3.1 Lifting image compression method

In two-dimensional case the lifting process defined by the equations (10)-(12) are applied in the rows and columns of the matrix. In this case, the lifting transform generates a matrix formed by four types of coefficients: the approximation coefficients (A), the horizontal (H), the vertical (V), and the diagonal (D) details coefficients. These coefficients are called image sub-bands. The approximation coefficients keep the most important information of the matrix, whereas the details coefficients possess very small values, close to zero. Then, it is possible to choose a value of threshold and set to zero all the details coefficients that are below that value. As result, it is formed a low-loss version of the original image after accomplishing the inverse lifting transform. This decomposition process is part of a multiresolution approach and can be continued using the output approximation coefficients in the current level as an input signal in the next level.

To illustrate the lifting process an example of a single-level lifting decomposition, for a simple synthetic image, is presented in Figure 4. In this Figure, the upper left plot (a) shows the original image, which is based on a 128 x 128 matrix where the entries with value 1 correspond to black pixels and all others entries have value zero. The coefficients obtained from a lifting transform with a Daubechies 2 wavelet are shown in upper right plot (b). The bottom left plot (c) shows the inverse transform for each coefficient. In this case a component of the composition is selected, the other three components are replaced by zeroes and the lifting inverse transform is applied. The rebuilt image is presented in bottom right plot (d).

This example clearly shows the averaging, and the emphasis of vertical, horizontal, and diagonal lines, respectively, in the four components of the output image. In this example, no value of threshold has been used and the inverse lifting transform rebuilt the original image without any loss of information. In order to be able to see the details, the grey scale has been adjusted in each of blocks of the transform, such that the largest value in block corresponds to black and the smallest value in a block to whi

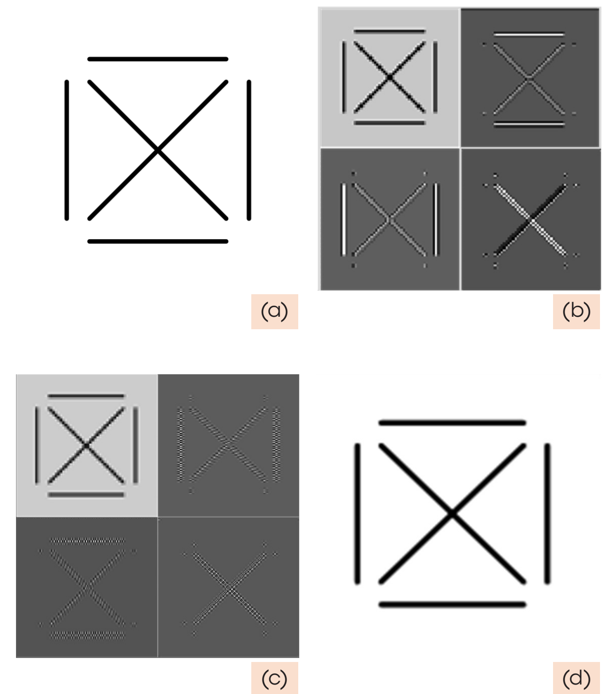


Figure 4: Single-level lifting transform for a simple synthetic image. (a) The original image, (b) the coefficients obtained from a lifting transform with a Daubechies 2 wavelet, (c) the inverse transform for each coefficient and (d) the rebuilt image

Source: The authors.

4 Experimental Results

Lifting and PCA techniques were applied to some cutting tool images in order to produce low resolution versions of them. The quality of compressed images was measured in terms of distortion measures such as reconstruction error, Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR), as defined in (2)-(4).

Both techniques were applied to the original cutting tool image presented in Figure 5. Details related to the resolution, format and memory request for the original image are shown in the second column of the Table 1.

Three values of compression rate were previously selected and the resulting compressed images were analyzed by comparing distortion measures mentioned above. These experimental results are shown in Table 1-3. Table 1 presents the results for a compression rate of, approximately, 0.190. The corresponding illustrations for this value of compression rate are shown in Figure 6. The com-

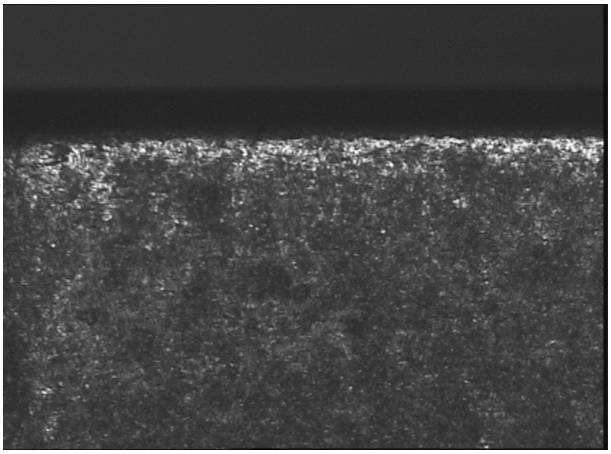


Figure 5: The original 768x576 pixel cutting tool image

Source: The authors.

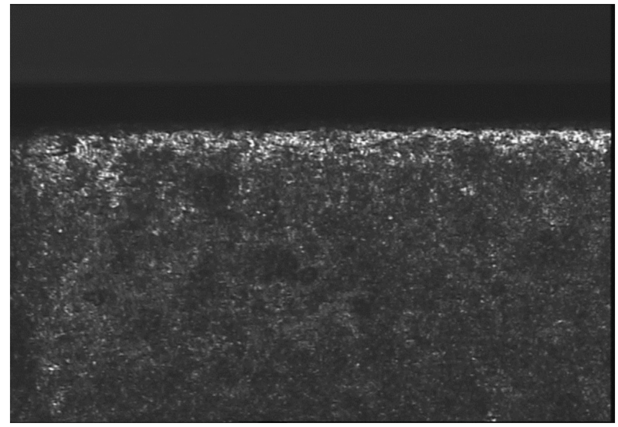
Table 1: Results with a compression rate of approximately 0.1900

	Original Image	Compressed Image through Lifting	Compressed Image through PCA
Resolution (pixel)	768x576	768x576	756x576
File format	TIFF	Int type	Int type
Memory request (bytes)	1327620	–	–
Memory request (int type store unit)	430276	351410	352800
Compression factor	–	0.8100	0.8102
Compression rate	–	0.1900	0.1898
PSNR (dB)	–	48.220	80.037

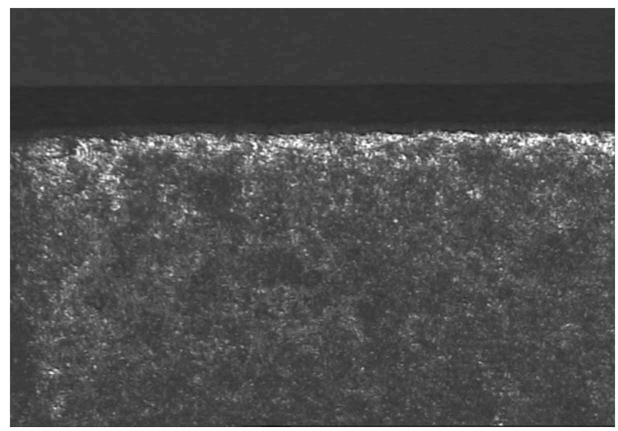
Source: The authors.

pression rate is defined as *1-compression factor*, which is calculated as (2).

Tables 2 and 3 present similar results with compression rates of 0.5950 and 0.9190, respectively. For these cases, the corresponding illustrations are shown in Figures 7 and 8. Despite the low PSNR, the PCA image compressed with compression rate of 0.9190 looks better than the Lifting one, as can be seen in Figure 8.



Lifting compressed image - 0.1900 compression rate



PCA compressed image - 0.1898 compression rate

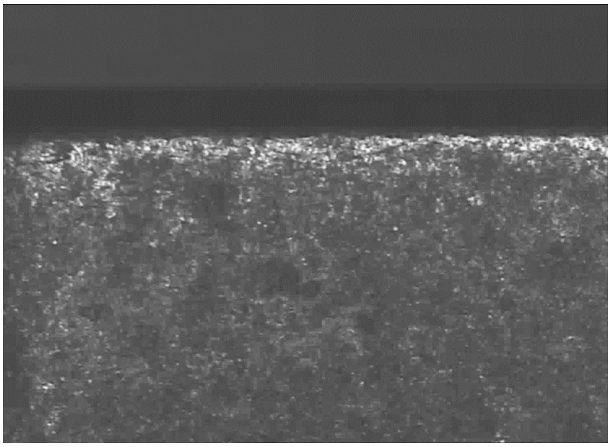
Figure 6: Compressed images for results shown in table 1

Source: The authors.

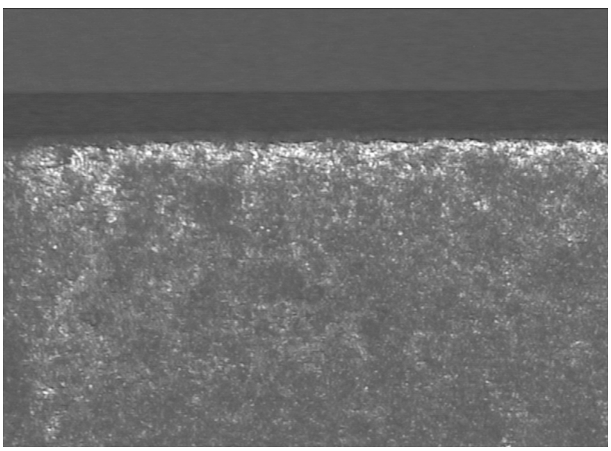
Table 2: Results with a compression rate of approximately 0.5950

	Compressed Image through Lifting	Compressed Image through PCA
Resolution (pixel)	768x576	756x576
File format	Int type	Int type
Memory request (bytes)	–	–
Memory request (int type store unit)	176382	176400
Compression factor	0.4028	0.4051
Compression rate	0.5972	0.5949
PSNR (dB)	33.410	45.011

Source: The authors.



Lifting compressed image – 0.5972 compression rate



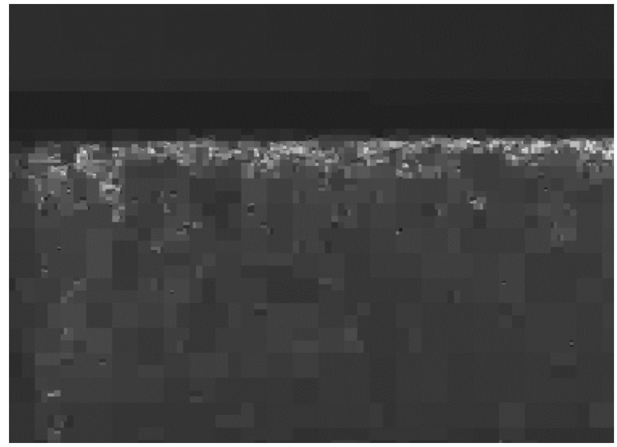
PCA compressed image – 0.5949 compression rate

Figure 7: Compressed images for results shown in table 2
Source: The authors.

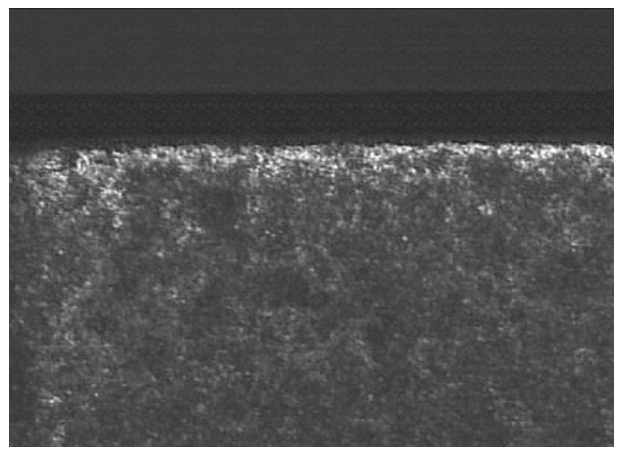
Table 3: Results for values of compression rate of approximately 0.9190

	Compressed Image through Lifting	Compressed Image through PCA
Resolution (pixel)	768x576	756x576
File format	Int type	Int type
Memory request (bytes)	–	–
Memory request (int type store unit)	35042	35280
Compression factor	0.0804	0.0810
Compression rate	0.9196	0.9190
PSNR (dB)	26.140	10.3605

Source: The authors.



Lifting compressed image – 0.9196 compression rate



PCA compressed image – 0.9190 compression rate

Figure 8: Compressed images for results shown in table 3
Source: The authors.

5 Conclusions

This work accomplishes a comparative study between two distinct low-loss image compression techniques, i.e., the Lifting technique and the Principal Components Analysis, in order to select the more appropriate image compression technique for reducing the memory size to store cutting tool images, keeping the main important features.

These compression techniques were applied to a 768x576 pixel cutting tool image and results were compared in terms of image reconstruction error: Mean Square Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). PCA technique presented the best values of PSNR with low compression rates. However, with high values of compression rates the lifting technique gave the highest PSNR. Despite the low PSNR, the PCA image compressed with compression rate of 0.9190 looks better than the Lifting one, as can be seen in Figure 8.

Here, the lifting transform was accomplished using the Daubechies 2 wavelet. Although there are other wavelet functions, recent results have shown that this wavelet function is the best one for this specific case (PEREIRA et al., 2009). Further works have been carried out applying both techniques to a new set of cutting tool images. In these works, the quality of resulting compressed images will be evaluated regarding the maintenance of the principal features using a pattern recognition system based on artificial intelligence techniques.

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