Numerical Algorithms (MU4IN910)

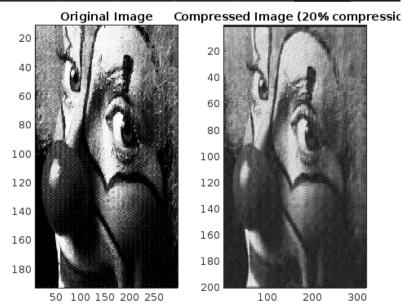
Practical 2

Assia MASTOR

Exercise 6

1-

```
load clown.mat;
% Display the original image
figure;
subplot(1, 2, 1);
imagesc(X);
colormap gray;
title('Original Image');
[U, S, V] = svd(X);
% Set a compression factor
compression_factor = 0.2;
k = round(compression_factor * min(size(X)));
% Compress the image by keeping only the first k singular values
X_compressed = U(:, 1:k) * S(1:k, 1:k) * V(:, 1:k)';
% Display the compressed image
subplot(1, 2, 2);
imagesc(X_compressed);
colormap gray;
title(['Compressed Image (', num2str(compression_factor * 100), '% compression)']
```



2- Compression ratio CR to measure the quality of the compression:

$$CR = \frac{\text{Original Data size}}{\text{Compressed Data size}}$$

Exercise 7

1- The objective is to minimize the function $||g - Kf||^2$, where $K = U\Sigma V^T$. We aim to find the solution f^* .

The function to minimize is given by:

$$||g - Kf||^2 = ||g - U\Sigma V^T f||^2$$

By using the properties of the norm operator and the singular value decomposition, we can rewrite this as:

$$||g - Kf||^2 = ||U^T g - \Sigma V^T f||^2 = ||U^T g - \Sigma w||^2$$

where $w = V^T f$.

Now, the problem becomes minimizing the norm of $U^Tg - \Sigma w$, and the solution for w that minimizes this norm is obtained by choosing $w^* = \Sigma^{-1}U^Tg$.

Revisiting the relation $w = V^T f$, we have:

$$V^T f^* = \Sigma^{-1} U^T g$$

Multiplying both sides by $V\Sigma^{-1}$, we get:

$$f^* = V \Sigma^{-1} U^T g$$

Given the expression $f^* = V \Sigma^{-1} U^T g$, we want now to show that it is equivalent to $f^* = \sum_{i=1}^n \frac{u_i^T g}{\sigma_i} v_i$, where σ_i are the singular values.

Starting with the expression $f^* = V \Sigma^{-1} U^T g$, we can rewrite it using the definition of matrix multiplication:

$$f^* = V\Sigma^{-1}U^T g = \left(\sum_{i=1}^n v_i \sigma_i^{-1} u_i^T\right) g$$

Here, we utilize the property of the inverse of a diagonal matrix Σ^{-1} , where $\Sigma_i^{-1} = \frac{1}{\sigma_i}$. Then, we get:

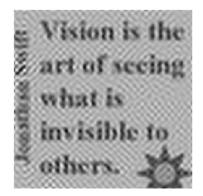
$$f^* = \sum_{i=1}^{n} v_i \sigma_i^{-1} u_i^T g = \sum_{i=1}^{n} \frac{u_i^T g}{\sigma_i} v_i$$

This confirms that the two expressions are equivalent.

2-

```
url = 'https://www-pequan.lip6.fr/~graillat/teach/anum/defloutage.mat';
websave('defloutage.mat', url);
% Load the matrices
load('defloutage.mat');
% Compute the SVD for A and B
[U_A, S_A, V_A] = svd(A);
[U_B, S_B, V_B] = svd(B);
% Choose the number of singular values to use
p = 55;
G_prime = U_B' * G * U_A;
% Compute the inverse of the first p singular values for S_A and S_B
S_A_inv = diag(1 ./ diag(S_A(1:p, 1:p)));
S_B_inv = diag(1 ./ diag(S_B(1:p, 1:p)));
% Multiply G_prime by the inverses in the truncated singular value space
F_prime = S_B_inv * G_prime(1:p, 1:p) * S_A_inv;
% Multiply by V_B and V_A^T to get the deblurred image F
F = V_B(:, 1:p) * F_prime * V_A(:, 1:p)';
% Display the deblurred image
imshow(F, []);
```

Result with p=55:



Result with p=100:



Result with p=20:



After testing with many different p, we can conclude that the p which gives the best result is equal to 55

Exercise 8

1-

To show that A is a stochastic matrix, we must show that each column sums to 1 and each term is positive.

a) Column Sum Property: If $c_i \neq 0$

$$\sum_{i=1}^{n} (A)_{ij} = \sum_{i=1}^{n} \left(\frac{pg_{ij}}{c_j} + \delta \right) = \frac{p}{c_j} \sum_{i=1}^{n} g_{ij} + n\delta = p + n \times \frac{1-p}{n} = 1.$$

If $c_j = 0$

$$\sum_{i=1}^{n} \frac{1}{n} = 1.$$

Thus, the column sum property is verified.

b) The matrix A is defined as follows if $a \neq b$ 0:

$$(A)_{ij} = \frac{pg_{ij}}{c_j} + \delta$$

Let's analyze the terms of this expression:

- The term $\frac{pg_{ij}}{c_i}$ is non-negative because p, g_{ij} , and c_j are all positive.
- The term δ is also non-negative.

Therefore, each term of the matrix A is non-negative due to the sum of two non-negative terms. This ensures that all elements of the matrix A are non-negative. We can conclude that A is a stochastic matrix, so A^T is also a stochastic matrix. Therefore, we can conclude that the largest eigenvalue of A is 1.

2

Let's start with the stochastic matrix A^T , where each element is nonnegative and the columns sum to 1. The Perron-Frobenius theorem states that there exists a positive eigenvalue ρ such that all other eigenvalues have absolute values less than or equal to ρ , for a nonnegative and irreducible matrix.

Since A^T is a stochastic matrix, $\rho = 1$ is an eigenvalue, and we can choose the corresponding eigenvector, denoted as x, to be nonnegative.

Now, consider the equation $Ax = \lambda x$, where $\lambda = 1$ (our positive eigenvalue) so the equation becomes Ax = x.

Thus, we have our nonnegative vector $x \in \mathbb{R}^n$ such that Ax = x. Additionally, since x is an eigenvector corresponding to the eigenvalue 1, it also satisfies $\sum_{i=1}^n x_i = 1$.

3-

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