Homomorphic Filtering

Eric Norman, Oskar Eriksson, Konstantinos Zakkas, Lovisa Landgren
RRY025/ASM420 Image Processing
(Dated: October 13, 2021)

I. INTRODUCTION

Image processing encompasses a wide range of applications. There is no common agreement regarding where image processing stops and other related areas start and setting clear-cut boundaries between the areas often cause overlapping of some fields. Gonzalez in his book *Digital Image Processing* [1] encompasses processes whose inputs and outputs are images and processes that extract attributes from images, including the recognition of individual objects. Image processing methods include image enhancement. The objective of image enhancement is to process the image so that the results are more suitable for display or for further analysis. Image enhancement methods are in general judged based on subjective image quality criteria, meaning that no objective mathematical criteria are used for optimizing processing results.

Filtering is an image processing technique with various applications. For example, you can filter an image to emphasize certain features or attenuate others. Filtering operations include smoothing, sharpening, and edge enhancement. Filtering is a neighborhood operation in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixels in the neighborhood of the input pixel.

Homomorphic filtering in particular is sometimes used as an image enhancement technique for removing multiplicative noise that has certain characteristics. It can be used in various applications like audio and speech analysis [2], deconvolution of seismic data [3] and neural coding [4] but it is most commonly used for correcting non-uniform illumination in images. The illumination of an image influences the subjective perception of image quality. The illumination-reflectance model [5] of image formation says that the intensity at any pixel, which is the amount of light reflected by a point on the object, is the product of the illumination of the scene and the reflectance of the objects in the scene. The key to this filtering approach is the separation of the illumination and reflectance components so the filter function can operate on them separately.

The goal of this project is to visually enhance the image of depicting a forest scenery in Figure 1, so that details are visible in both the bright and the dark areas, using homomorphic filtering. The design of a homomorphic filter is presented, followed up by a study of the filter's parameters and their contribution to the enhanced image. Having determined an appropriate set of parameters, the results from filtering are presented. Finally, a conclusion is made regarding whether this technique is successful with this type of application.

FIG. 1: The original image, depicting a forest scenery

II. METHOD

Homomorphic filtering utilizes the frequency-domain to improve the illumination balance of an image. According to the illumination-reflectance model (Horn, 1986)[5], the brightness of each pixel in an image, expressed as a function $f(x, y)$, can be formulated as the product of direct illumination (i) and reflected illumination (r).

$$f(x, y) = i(x, y) \cdot r(x, y) \tag{1}$$

A central idea behind homomorphic filtering is that irregularities in the brightness of an image is caused by the illumination component being uneven across the image. The reflectance component is correspondingly assumed to be a source of more evenly distributed light in the image, since reflected light is scattered a multitude of times from different surfaces. Consequently, by reducing the illumination component of the image a more level spread of brightness can be attained, with details of the

---

[1]Author contributions: Eric Norman has implemented the parameter search, generated figures and contributed to the method and results sections of the report.
Oskar Eriksson has contributed to the conclusion of the report.
Konstantinos Zakkas has written the introduction of the report.
Lovisa Landgren has taken part in the filter implementation, implemented the Butterworth filter, as well as contributed to all parts of the report, particularly the method and conclusion.

image as a result becoming more visible in both lighter and darker areas. The illumination component is typically characterized by slow variations across the spatial domain of the image while the reflectance component can vary abruptly at object edges. The image is therefore moved to the frequency (i e Fourier) domain, where the low frequencies that correspond to the illumination can be easily filtered out, and the higher frequencies that correspond to reflectance can be preserved or even amplified. This is the central idea in homomorphic filtering [1].

The homomorphic filtering in this project is implemented as follows. Firstly, the image function is transformed to the Fourier domain. By first taking the logarithm of this expression, the product of direct and reflected light becomes a sum of the two parts rather than a product.

$$\begin{aligned}\log\left(f(x,y)\right) &= \log\left(i(x,y)r(x,y)\right) = \\ &= \log\left(i(x,y)\right) + \log\left(r(x,y)\right)\end{aligned} \tag{2}$$

The expression can then be Fourier transformed by transforming the two parts of the sum separately.

$$\mathcal{F}(\log f(x,y)) = \mathcal{F}(\log i(x,y)) + \mathcal{F}(\log r(x,y))$$

To correctly transform the image to the Fourier domain, zero padding is applied beforehand to avoid wraparound errors (or aliasing).

The transformed function is filtered in the frequency domain using a highpass filter, to decrease or remove the lower frequencies up to the cutoff-frequency D_0.

To return the filtered image to the spatial domain, the inverse Fourier transform is applied and exponentiated to obtain the output image.

The filter primarily used is a slightly modified Gaussian highpass filter, as proposed by Gonzalez and Woods [1].

$$H(u,v) = (\gamma_H - \gamma_L)\left(1 - e^{-c(D^2(u,v)/D_0^2)}\right) + \gamma_L \tag{3}$$

The unmodified Gaussian filter is as follows:

$$H(u,v) = \left(1 - e^{-(D^2(u,v)/D_0^2)}\right) \tag{4}$$

The modification made is thus the inclusion of the parameters γ_H, γ_L and c. γ_H and γ_L, serve to decrease the contribution of the low frequencies and increase the contribution of the higher frequencies when set so that $\gamma_H > 1$ and $\gamma_L < 1$. The constant c is included to modify the transition between them [1].

$D(u,v)$ is the distance from the origin to (u,v) in the frequency domain. D_0 is the cutoff frequency for filtering out the illumination range of frequencies is a positive constant.

The parameters γ_H and γ_L serve to constrict the low frequencies in the image, primarily caused by illumination, and in turn enhance the higher frequencies that correlate to the reflectance [1].

The Gaussian filter was also compared with a similarly modified Butterworth filter.

$$H(u,v) = (\gamma_H - \gamma_L)\left(1 - \frac{1}{1 + (D^2(u,v)/D_0^2)^n}\right) + \gamma_L \tag{5}$$

The Butterworth filter presents a compromise between a Gaussian filter and an ideal filter, when the order parameter n is small it is closer to a Gaussian and approaches an ideal filter as n is increased.

A. Parameter search

Suitable parameters are found by isolating them one at a time, fixing all the others, and generating a few images where the value is changed. They are changed by orders of magnitude to see significant changes. Each set of images is judged subjectively and the best one is selected. This was repeated for every parameter until a satisfactory result was reached.

A brief analysis of the parameters in the equation yields that the c and D_0 parameters are dependent on one another. Together they form the parameter $-c/D_0^2$, which multiplies the D part of the filter. As such, it was decided to set c to 1 and only search for an optimal D_0.

III. RESULTS

The parameter search yielded the following parameters; $D_0 = 32$, $\gamma_L = 0.5$ and $\gamma_H = 1.4$.

The results from the filtering with these parameters can be seen in Figure 2.

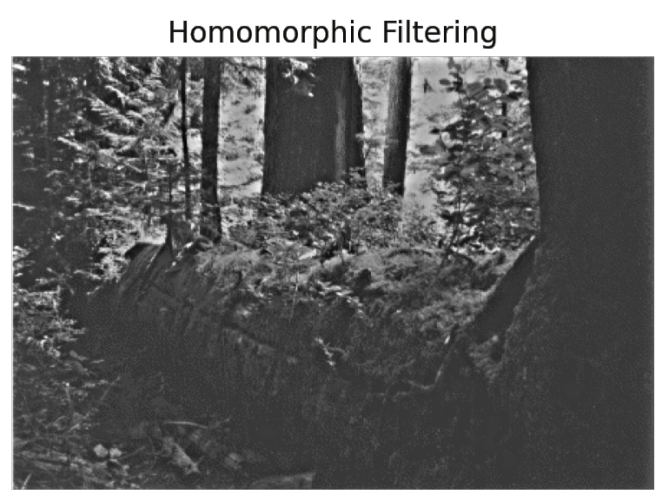

FIG. 2: The filtered image using the parameters $D_0 = 32$, $\gamma_L = 0.5$ and $\gamma_H = 1.4$

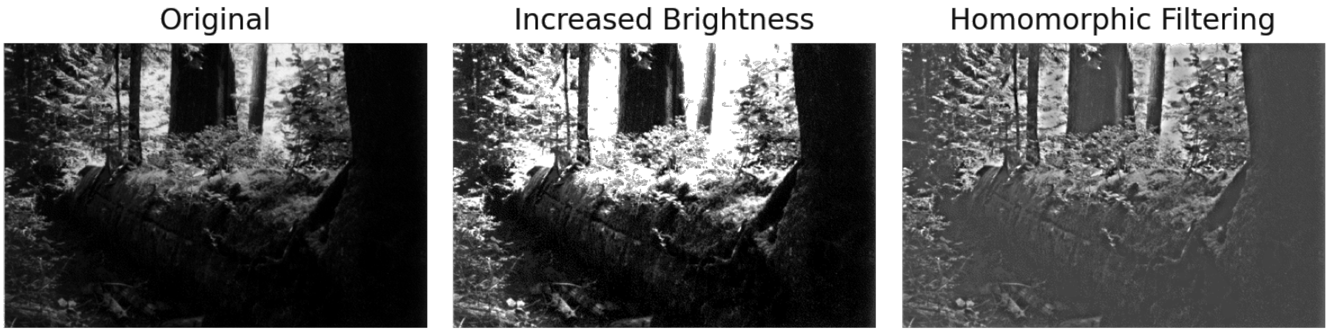

FIG. 3: A comparison between the original (left), only increasing the brightness of the image (middle) and homomorphic filtering (right).

IV. CONCLUSIONS

A. Discussion of implementation

The goal of the homomorphic filtering process is to even out the varied illumination in the original image, to enhance details in both light and dark areas. This effect can be seen by comparing the filtering to only increasing the brightness as shown in Figure 3. One side effect of this is that the overall contrast in the image becomes lower, but the local contrast in the bright and dark areas is increased. When comparing the filtered images generated with different parameters, it was evident that images where γ_H was close to γ_L in general looked quite good. The term $(\gamma_H - \gamma_L)$ is close to zero in these cases, making the filter ineffective. The term $+\gamma_L$ remains, which only serves to increase the brightness of the image a bit. The images with raised brightness and low filtering look "good" in a sense, if the image being filtered is rather dark to begin with. When the parameters are tuned so that the Gaussian filter is in function, the details of the input image are enhanced in both the darker and the lighter areas. This can be more difficult to appreciate with the eye due to the gray impression, even when the details are much enhanced compared to the original image. This further illuminates the difficulty in judging the quality of the filter. Images with a high overall contrast may look better in one way, than images with lower total contrast but enhanced detail visibility, i e higher contrast surrounding the contours in the image. The goal when filtering is usually not to make the image more visually appealing, but to strengthen the contours so that features of the image stand out more to the eye. An area where this is useful is in x-ray scans, where pathological signs may need enhancement to be noticeable to the analysts.

B. Discussion of improvements

The result of the filtering is inherently difficult to evaluate, because human observation is in general the only way to decide whether the filtered image meets the set demands. The parameters used for the forest image in the examples are therefore also tuned for that particular image. Adapting the filter to give a good result for any other image would require a new parameter search. Improvements on the project would involve a much more extensive parameter search to achieve an optimal filter. More thorough filter comparisons between the Gaussian, Butterworth and possibly others as well would also be needed to find the best filter. Additionally, a more objective measurement of the success of the filtering would be useful to properly judge how the filtering performs. Given that the goal of the filtering is to enhance the visibility of the details in the lighter and the darker areas of the image, a measure of the success might be the distinctness of the contours in the image. One suggestion for a way of measuring the degree of success would be measuring the brightness of the filtered image, run through a highpass filter. For example, counting the number of white pixels (pixel value over some threshold) and subtracting the number of white pixels in the original image run through a highpass filter, should give a positive number if the details of the pictures were successfully enhanced.

C. Final conclusions

The homomorphic filtering of the forest image can be deemed successful, as the filtered image shows greater visibility and clarity in the details both the light and dark areas of the image.

V. ACKNOWLEDGEMENTS

Special mention goes to the examiner Alessandro Romeo in the Image Processing course that this project was done in and Team 3 in the same course; namely Anjali Poornima Karri, Shreyash Kad, Torbjörn Nur Olsson and Kuvalaya Datta Jukanti for sharing some thoughts with us.

[1] R. E. Rafael C. Gonzalez, *Digital Image Processing*, 3rd ed. Pearson Education, Inc., 2008.

[2] K.-F. L. Alex Waibel, *Readings in Speech Recognition*. Morgan Kaufmann Publishers Inc., 1990.

[3] J. Tribolet and A. Oppenheim, "Deconvolution of seismic data using homomorphic filtering," p. 11, 08 1977.

[4] S. Orcioni, A. Paffi, F. Camera, F. Apollonio, and M. Liberti, "Automatic decoding of input sinusoidal signal in a neuron model: Improved snr spectrum by low-pass homomorphic filtering," *Neurocomputing*, vol. 267, pp. 605–614, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925231217311578

[5] B. Horn, *Robot vision*. McGraw-Hill, New York, 1986.

Appendix A: Matlab code

```
clear all;
close all;
clc;
% parameters
yL = 0.5; % gamma low (should be < 1)
yH = 1.4; % gamma high (should be > 1)
D0 = 32; % D0 is the cut-off frequency
c = 1; % c is dependent on D0, set to 1 for simplicity

addpath("/home/lumo/Documents/Chalmers/ImagePro/RRY025/");
load("forest.mat"); % loads to forestgray
I = im2double(forestgray); % normalize and cast to double
log_im = log(1 + I); % logarithm of 1 + pixel value

% zero padding
M = 2*size(I,1) + 1;
N = 2*size(I,2) + 1;

% find center of padded image
[X, Y] = meshgrid(1:N,1:M);
centerX = ceil(N/2);
centerY = ceil(M/2);

% H function according to book:
% create gaussian high-pass filter
Dsqr = (X - centerX).^2 + (Y - centerY).^2; % filter squared
H = exp(-c * Dsqr ./ (D0^2));
H = (yH - yL) * (1 - H) + yL;

H = fftshift(H); % center filter


If = fft2(log_im, M, N); % fourier transform
Iout = H .* If; % filter image in fourier domain
Iout = real(ifft2(Iout)); % inverse transform, real part
Iout = Iout(1:size(I,1), 1:size(I,2)); % reverse the size change of padding
Iout = exp(Iout)-1; % get back from log domain

imshowpair(I, Iout, 'montage')
```

Appendix B: Matlab code for butterworth filter

```
% Butterworth filter
H = Dsqr ./ (D0^2);
H = 1 ./ (1 + H.^n);
H = (yH-yL) * (1-H) + yL;
```