Open access • Book Chapter • DOI:10.1007/11492429_68

# Performance analysis of homomorphic systems for image change detection



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**Institutions:** Complutense University of Madrid

**Published on:** 07 Jun 2005 - Iberian Conference on Pattern Recognition and Image Analysis

**Topics:** Feature detection (computer vision) and Change detection

# Performance Analysis of Homomorphic Systems for Image Change Detection*

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**Abstract.** Under illumination variations image change detection becomes a difficult task. Some existing image change detection methods try to compensate this effect. It is assumed that an image can be expressed in terms of its illumination and reflectance components. Detection of changes in the reflectance component is directly related to scene changes. In general, scene illumination varies slowly over space, whereas the reflectance component contains mainly spatially high frequency details. The intention is to apply the image change detection algorithm to the reflectance component only. The aim of this work is to analyze the performance of different homomorphic pre-filtering schemes for extracting the reflectance component so that the image change detection algorithm is applied only to this component. This scheme is not suitable for scenes without spatial high frequency details.

## 1 Introduction

The main difficult in image change detection tasks is the illumination variations between two frames. Some existing image change detection methods try to compensate this effect by mapping data and contextual information under an energy function which is then minimized through optimization [1,2,3].

Additionally some works have used the power of homomorphic systems in order to separate the reflectance component, so that the image change detection algorithm is only applied to this component [4]. This is justified under the assumption that scene illumination varies slowly over space, whereas the reflectance component contains mainly spatially high frequency details.

The goal of this work is to analyse the behaviour of three different homomorphic filtering strategies in image change detection. They are: the low pass filtering strategy given in [4] (TOT), the frequency procedure based on butterworth filtering [5,6] (KOV) and the wavelet-based approach described in [7] (GOM).

* This work has been partially supported by the Spanish CICYT under grant DPI2002-02924.

J.S. Marques et al. (Eds.): IbPRIA 2005, LNCS 3522, pp. 563–570, 2005.

We have selected the image change detection algorithm described in [1] as the base method. It is applied with and without previous homomorphic filtering, where the homomorphic filtering is implemented according to TOT, KOV and GOM.

This paper is organised as follows: in section 2 we formulate the homomorphic framework and describe the TOT, KOV and GOM strategies. In section 3 the homomorphic performance is analyzed. Finally in section 4 the conclusions are presented.

## 2 The Homomorphic Framework

The goal for image change detection between two frames is to obtain equal illuminated frames by processing them in any way. This can be achieved through a special class of systems know as *homomorphic systems* [5]. They are based on the image perception. The images people perceive consist of light reflected from the objects. The basic nature of intensity may be characterized by two components: (1) the amount of source light incident on the scene being viewed and (2) the amount of light reflected by the objects in the scene. They are called the *illumination* and *reflectance* components and are denoted by $i_k(x,y)$ and $r_k(x,y)$ respectively, where $k$-th frame and $(x,y)$ is the pixel location. As a first approximation for Lambertian objects surfaces the intensity of the $k$-th frame in an image sequence is given by

$$f_k(x,y) = i_k(x,y) r_k(x,y) \ . \tag{1}$$

The illumination component of an image is generally characterized by slow spatial variations, while the reflectance component tends to vary abruptly, particularly at the junctions of dissimilar objects. These characteristics lead to associating the low frequencies with illumination and the high with reflectance.

The goal is to extract the reflectance component in order to minimize the illumination effects and to consider only the reflectance. This is carried out by first applying the logarithm and then extracting the high frequencies. The logarithm transforms the multiplicative relation in (1) into an additive one:

$$y_k = \log\left(f_k(x,y)\right) = \log\left(i_k(x,y)\right) + \log\left(r_k(x,y)\right) . \tag{2}$$

Although the log-nonlinearity modifies the spectral content of illumination and reflectance components, it is in practice often justified to assume the log-illumination to be still spatially slowly varying [5]. Obviously, this scheme should not be suitable for scenes without spatial high frequency details.

### 2.1 KOV: Through High-Pass Filtering

In [5,6] the homomorphic system is designed as follows: after applying the logarithm to $f_k$ in (1), the resulting image $y_k$ is fast Fourier transformed, the resulting image is high-pass filtered in the frequency domain by designing a high-pass filter based on the butterworth scheme. The filter function is obtained so that it affects the low- and high-frequency components of the Fourier transform. A trade-off must be achieved to boost the high frequencies relative to the low frequency values. We have chosen this relation as a ratio of 25% and 75% for low and high frequencies respectively. So the filter function tends to decrease the low frequencies and amplify the high frequencies. Once the filtering is carried out, the inverse fast Fourier transformation is applied to the filtered result. Exponentiation of the last resulting signal is applied to obtain the reflectance image.

### 2.2 TOT: Through Low-Pass Filtering

In TOT [4] the homomorphic system works as follows: after applying the logarithm to $f_k$ in (1), the resulting $y_k$ of (2) is low-pass filtered and then subtracted from the logarithmic original $y_k$, yielding a high-pass component. The low-pass filtering can be carried out through different filter kernels; we have used a Gaussian one with size 31 $x$ 31 and standard deviation of 14 as in [4].

This filter has to trade-off the reduction of illumination and the retention of the image structure. Note that the standard deviation is decisive in the filter design. A high value of this parameter involves a high filter dimension affecting the high components in the image.

Exponentiation of the filtered signal is applied to obtain the reflectance image. In the reflectance image illumination effects are strongly suppressed while object information is preserved. In the illumination image, however, the light-spot is very prominent whereas object details are blurred. Of course, the illumination image still contains low-frequency parts from the reflectance and thus separation of the two components is only an approximation. Nevertheless this suffices for the intended image change detection.

### 2.3 GOM: Wavelet-Based Filtering

This is the scheme described in [7]. As before, the goal is to obtain the reflectance component. The process is as follows: first of all we must separate the illumination and reflection components. The logarithm applied to $f_k$ converts the product from (1) to $y_k$ which is a sum with two components that are low pass and high pass respectively. Then, these components are separated by using the Discrete Wavelet Transform (DWT). The DWT performs a low and high pass filtering using the scheme proposed by Mallat [8]. The scheme can be repeated over the approximation image. So we get a multiresolution approximation to the original image. The more we repeat the decomposition scheme the more we concentrate the low frequencies energy in the approximation image. After several decompositions (depends on image size) the approximation image is a representation of illumination of the image. In our approach we have used a five level decomposition.

Now, the illumination is in the approximation image of the DWT. If we want to obtain the same illumination in the both frames under processing, the next step is to cancel the approximation image and recover the whole image without illumination, i.e. only with the reflection component.

So, after the five level decomposition we replace the approximation image with a zero image of the same size that the approximation image at such level. After this replacement we apply the Inverse Discrete Wavelet Transform (IDWT) scheme using the reconstruction filters.

The resulting image is now with no illumination. Now a constant illumination level is added. This constant level is set log(128) that corresponds to the mean grey level in the byte images representation used in this work. Then, the image can be recovered, i.e. the logarithm is undone by using the exponential. As before the exponentiation could be avoided for the image change detection pouposes.

## 3 Comparative Analysis and Performance Evaluation

In order to analyse the performance of the *homomorphic systems*, we have considered two different data sets: a synthetic data set artificially generated and a real data set corresponding to consecutive frames in indoor and outdoor environments where the images are captured under different illumination conditions.

### 3.1 Synthetic Data Set

We used as the image reference a region of 400 $x$ 400 pixels from a remote sensing image acquired by the commercial IKONOS satellite. This image contains mainly high frequency components and was assumed to be the $t_1$ reference image in the full sequence (i.e. the image acquired at time $t_1$).

Then we generate five new synthetic images $t_i$; $i = 2,\ldots,6$ from $t_1$ by adding changes, noise and illumination variations as follows:

$t_2$: only controlled changes without noise and without illumination variation;

$t_3$: Gaussian noise ($\sigma^2$=2.5);

$t_4$: Gaussian noise ($\sigma^2$=5) and illumination variation;

$t_5$: salt and pepper noise (density = 0.05);

$t_6$: salt and pepper noise (density = 0.10) and with illumination variation.

Hence, five pairs of images are built with each $t_i$ and the reference $t_1$.

The illumination variation is achieved by shifting the original histogram, so that different light conditions can be simulated between the image with the original histogram and the image with the shifted histogram. Figure 1($a$) and ($b$) show the $t_1$ and $t_4$ images. Figure 1($c$) shows the mapping of the controlled changes. Figures 1($d$) and ($e$) are obtained from ($a$) and ($b$) respectively by applying the homomorphic KOV scheme. We can see that the illumination is compensated between both images, i.e. the differences in the original images are minimized.

### 3.2 Real Data Set

Real data sets for aerial or satellite images are only available in dedicated companies which have previously paid the corresponding royalty.

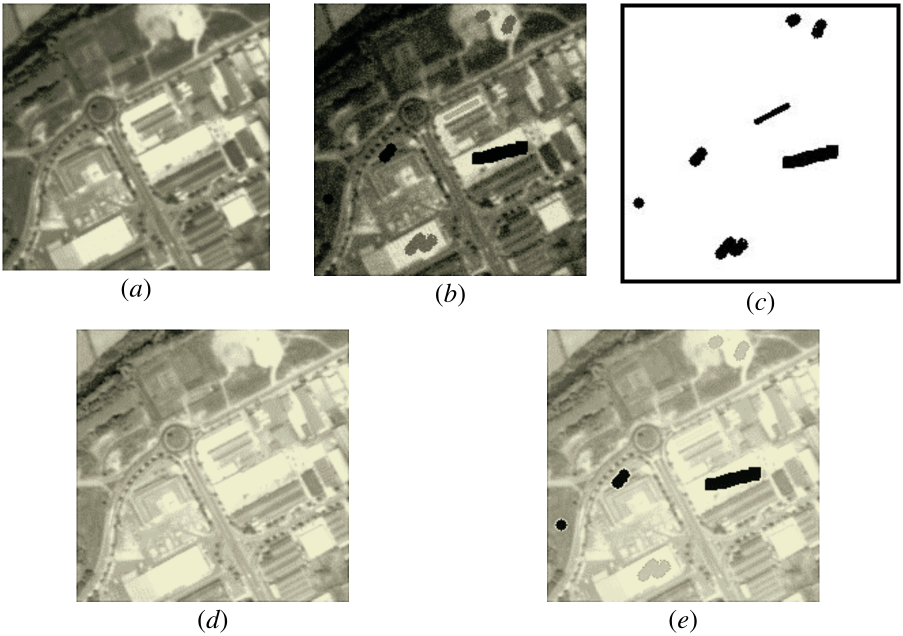


**Fig. 1.** Synthetic data set used in the experiments. (*a*) $t_1$ *o*riginal image, (*b*) $t_4$ image with controlled changes and Gaussian; (*c*) map of the areas with simulated changes used as the reference map in the experiments; (*d*) and (*e*) illumination compensation by homomorphic filtering

Hence, the real data set used in the experiments consisted of a first group of ten pairs of indoor images captured under different illumination conditions. Indeed, we have varied the illumination in two ways:

*a*) by changing the internal artificial illumination switching on and off different indirect lights,

*b*) by moving a blind window, i.e. by changing the external illumination conditions.

Two representative images of this kind of data are shown in the figure 2(*a*) and (*b*). In the image (*b*) we have changed the mobile computer position and the two little objects placed between the mobile computer and the big monitor. Moreover, the image (*b*) is captured by increasing both, the internal and external illumination conditions. Figures 2(*d*) and (*e*) are obtained from (*a*) and (*b*) respectively by applying the homomorphic KOV approach. We can see once again that the illumination is compensated between both images.

The second group of real data is captured from an outdoor environment and consists of eight pairs of images; Figures 2(*c*) and (*f*) show two representative images. In this group the illumination is similar as they are captured in the same instant of time.

### 3.3 Evaluation

To evaluate the performance quantitatively, we used the change detection approach described in [1] and define the correct detection rate (CDR) and the false alarm rate (FAR) as follows [9].

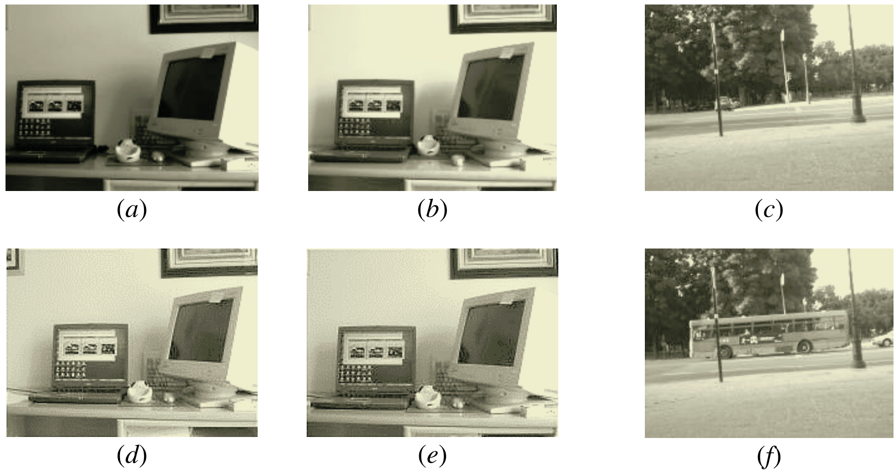


**Fig. 2.** Real data sets: (*a*) and (*b*) *o*riginal indoor images under different illumination conditions; (*d*) and (*e*) illumination compensation by homorphic filtering; (*c*) and (*f*) *o*riginal outdoor images under similar illumination conditions

CDR: the probability of claiming an Area of Interest (AOI) is changed when AOI is actually changed or claiming AOI is unchanged when AOI is actually unchanged.

FAR: the probability of claiming AOI is changed when AOI is actually unchanged or claiming AOI is unchanged when AOI is actually changed.

We have started our experiments with the synthetic data sets, because the changes are well controlled. Figure 3(*a*) and (*b*) shows graphically the percentage of CDR and FAR results for each pair of images obtained through the change detection method in [1] with homomorphic filtering (KOV, TOT and GOM) and without homomorphic filtering (WHF).

From results in figure 3, we can infer the following conclusions:

1. The best performance is achieved when KOV is applied, particularly for images including differences in the illumination (pairs 3 and 5).
2. In noisy images the homomorphic filtering does not contribute to the improvement of the results.
3. The worst results are obtained by GOM; we have verified that this is due to the removing of the approximation coefficients in the last decomposition level. This implies that in the reconstruction process appears some kind of artifacts, affecting the changes.

Now, taking into account the best performance achieved by using the KOV hommorphic filtering scheme, we have processed the real data set (indoor and outdoor) considering the results obtained under this filtering as the reference results for comparison purposes with the remainder homomorphic filtering schemes. We have averaged the CDR and FAR percentages over each set of data groups. Table 1 summarizes the results obtained for the indoor and outdoor environments for each homorphic filtering scheme.

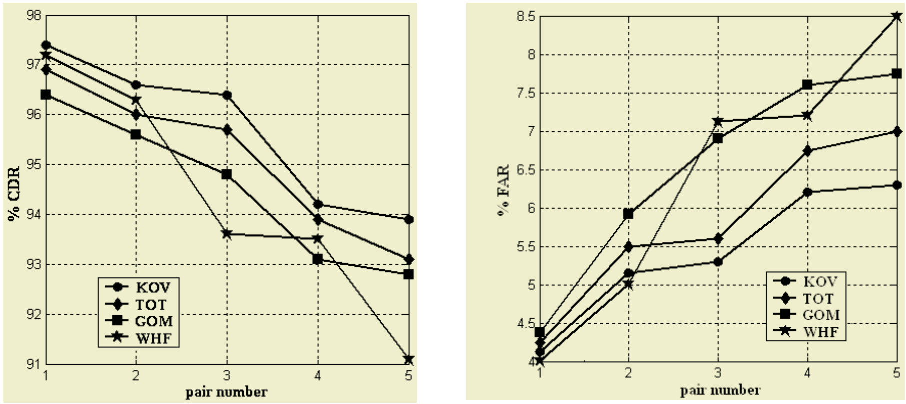


**Fig. 3.** Behaviours of the change detection error (%) with (KOV, TOT, GOM) and without (WHF) homomorphic filtering; (*a*) and (*b*) CDR and FAR respectively against the pair number

**Table 1.** Averaged CDR and FAR percentages for indoor and outdoor image sequences

| | indoor environment | | outdoor environment | |
|---|---|---|---|---|
| | **CDR** | **FAR** | **CDR** | **FAR** |
| **KOV (reference)** | 100 | 0 | 100 | 0 |
| **TOT** | 92.86 | 6.67 | 99.21 | 1.12 |
| **GOM** | 88.12 | 9.87 | 96.66 | 2.46 |
| **WHF** | 83.32 | 14.01 | 98.51 | 1.11 |

From results in table 1, the following conclusions can be inferred:

1. In the indoor images, including changes in the illumination, the homomorphic filtering improves the final results.
2. There are still artifacts affecting the performance when GOM is used.
3. In the outdoor images, without significant illumination changes, the homomorphic filtering is irrelevant. Only some slight improvement is achieved, but without filtering the results are equally acceptable in the outdoor environment.

## 4 Conclusions

We have shown the performance of the homomorphic filtering for image change detection in image sequences. This is particularly valid with images displaying high illumination variability, i.e. for scenes with spatial high frequency details. We have also verified that the underlying noise in the images does not affect the final results. This works provides the guidelines for applying homomorphic filtering for change detection methods.

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