ROBUST AND ILLUMINATION INVARIANT CHANGE DETECTION BASED ON LINEAR DEPENDENCE FOR SURVEILLANCE APPLICATION

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ABSTRACT
The subject of this paper is to provide an illumination invariant moving object detector for indoor surveillance applications. Furthermore we want to treat the illumination change as a mathematical/physical transformation procedure on images. Therefore the intention to this paper could also be defined as to provide an operator, which is invariant to transformations. The proposed detector relies on a model assigning a vector to every pixel location of the reference and the current image. The vector represents information on the neighborhood region of that pixel. Based on the above definition, the theorem of linear dependence of vectors is used to describe an operator for the detection of objects. For the purpose of an objective evaluation, the proposed technique is compared to the state-of-the-art Statistical Change Detection method. The proposed operator proved to be robust to noise as well as global illumination changes and local shadows and reflections.

1 INTRODUCTION
In this paper changes of lighting conditions are treated as a transformation/translation of the pixel values. Transformations could be seen as some kind of remodeling/conversion of an existing object (mathematical or physical) from an initial state to another state. In general this conversion or transformation obeys strict rules.

In the case of this work, the objects under consideration are images. The initial and the final state of the images are well known whereas the transformation or more generally the mathematical rules and/or the physical process behind this transformation have to be investigated. For the sake of simplicity the initial and the final state of the image are called reference \( I_r \) and current \( I_c \) image respectively.

Once a rule for the transformation is found, a mathematical operator could be formulated to describe this transformation. Using this operator, changes in the images, which are not due to the transformation, are detected. Examples of such changes are structural/physical changes such as moving persons.

This work was motivated by the object detection deficiencies of state-of-the art change detection methods in the presence of illumination changes. The Statistical Change Detection is taken as a reference state-of-the-art change detection algorithm. This method begins with the difference image

\[ d_x = I_r(x) - I_c(x) \]

between a reference image and a current image respectively. The calculation of changes between images is made on sliding windows of certain size over all pixels of the considered images. The main idea is to find a statistical description of an ensemble of pixels which enables the detection of changes [1].

In the following section 2 the different types of interaction of light with surfaces will be treated and a motivation for the description of all image pixels as vectors is given. In section 3 the new Linear Dependence Change detector is presented. The implementation along with the results are given in section 4 and 5 respectively. A conclusion is added in section 6.

2 ILLUMINATION EFFECTS AND VECTOR REPRESENTATION

Illumination variations pose a great problem on change detection algorithms. Since the variation of illumination introduces a change in pixel values as it the case for moving object. Thus the interaction of light with surfaces will be investigated in the following subsection. The result of this investigation will help to define a model for the representation of the images, which considers the interaction of light on a surface.

2.1 Interaction of Light with Surfaces

When a ray of light hits a surface it gets reflected. An ideal surface reflects all the light that hits it and each ray hitting a point on the surface is reflected in one direction, such that the incidence and reflection angles are equal. If a viewer happens to be in that direction, looking at the surface, he will see a reflection of the light source on the surface (in the color and the shape of the light source and not the surface). Such an ideal reflection is called specular [2]. Calculating the specular reflection from a point on a surface requires the knowledge of the normal to the surface at that point, and the position of the viewer. An approximate example of an ideal surface is a mirror.

An ideal dull surface reflects each ray of light equally in all directions since microscopic surface roughness causes reflection in various directions depending on the slope distribution of the reflection facets. A viewer always sees the same intensity from a given point, regardless of his position. He still sees different reflections from different points, since some
points may have a greater distance from the light source, or may be pointing away from it. This type of reflection is called \textit{diffuse} [3]. Opalescent glasses come close to the definition of an ideal dull surface.

Every point on a surface emits mainly these two types of light: diffuse and specular light. Each ray leaving the surface is a sum of these contributions. The amount of contribution of each type of reflection however can vary depending the structure and the distance to the surface.

In the case of video-surveillance the viewer is a video-camera, which is observing an area of interest. We will concentrate on indoor surveillance applications with a fixed video-camera. The information provided by the camera is a composition of reflections and global illumination changes in each image. In the case of video-surveillance the viewer is a video-camera, which is observing an area of interest. We will concentrate on indoor surveillance applications with a fixed video-camera. The information provided by the camera is a composition of reflections and global illumination changes in each image.

2.2 Vector Representation

Most natural surfaces are neither dull nor ideal and therefore some part of the reflected light is diffuse. Each pixel from the sequence of images will have some of its information faded to the neighboring pixels. Therefore a subset of pixels for each pixel of an image has to be investigated in order to come close to the original surface information. A window defines the shape of the subsets, and their values are defined by the given image to the original surface information. The window can have different sizes in Fig. 1 an example of size 3, 33. The window is sliding over the whole reference and current images.

The shape of the window \(W\) used in this paper is rectangular. The window can have different sizes in Fig. 1 an example of size 3, 33. \(W_{3x3}\) is given for its first position in the image. The window is sliding over the whole reference and current images. The elements of the windows from the reference and current image are constituting the elements of the corresponding vectors, \(1\,1\,\vec{a}_r = (111, a_{r1}, 111, a_{r2}, 111, a_{r3})\) and \(1\,1\,\vec{a}_c = (111, a_{c1}, 111, a_{c2}, 111, a_{c3})\). The image is now no more represented by pixels but rather represented by vectors. The number of vectors equals the number of pixels in the original image. With this newly proposed vector representation some part of the faded surface information can be recovered.

3 THE LINEAR DEPENDENCE CHANGE DETECTOR

The transformation considerations and image vector-model developed in the previous sections are the bases for the Linear Dependence Change Detector which will be presented in this section. The changes are calculated between a reference image \(I_r\) and a series of current images \(I_c\) and the vectors \(\vec{a}_r \in I_r\) and \(\vec{a}_c \in I_c\). We first start by the

\begin{align*}
\begin{bmatrix}
11\,a_{r1} & 11\,a_{r2} & 11\,a_{r3} & \cdots & 11\,a_{r9} \\
11\,a_{r4} & 11\,a_{r5} & 11\,a_{r6} & \cdots & 11\,a_{r9} \\
11\,a_{r7} & 11\,a_{r8} & 11\,a_{r9} & \cdots & 11\,a_{r9} \\
\end{bmatrix} & \begin{bmatrix}
11\,a_{c1} & 11\,a_{c2} & 11\,a_{c3} & \cdots & 11\,a_{c9} \\
11\,a_{c4} & 11\,a_{c5} & 11\,a_{c6} & \cdots & 11\,a_{c9} \\
11\,a_{c7} & 11\,a_{c8} & 11\,a_{c9} & \cdots & 11\,a_{c9} \\
\end{bmatrix}
\end{align*}

\begin{figure}[h]
\centering
\begin{tabular}{c c}
\begin{tabular}{c c c c c c c c c c}
11$a_{r1}$ & 11$a_{r2}$ & 11$a_{r3}$ & $\cdots$ & 11$a_{r9}$ \\
11$a_{r4}$ & 11$a_{r5}$ & 11$a_{r6}$ & $\cdots$ & 11$a_{r9}$ \\
11$a_{r7}$ & 11$a_{r8}$ & 11$a_{r9}$ & $\cdots$ & 11$a_{r9}$ \\
\end{tabular} & \begin{tabular}{c c c c c c c c c c}
11$a_{c1}$ & 11$a_{c2}$ & 11$a_{c3}$ & $\cdots$ & 11$a_{c9}$ \\
11$a_{c4}$ & 11$a_{c5}$ & 11$a_{c6}$ & $\cdots$ & 11$a_{c9}$ \\
11$a_{c7}$ & 11$a_{c8}$ & 11$a_{c9}$ & $\cdots$ & 11$a_{c9}$ \\
\end{tabular}
\end{tabular}
\caption{The top left corner of a reference and a current image are drawn in this figure. The index r stands for reference and c for current.}
\end{figure}

\textbf{Definition 3.0 (Linear Dependence)} [4][5]: A finite subset \(\{\vec{a}_1, \ldots, \vec{a}_n\}\) of a vector space \(V\) is called linearly dependent if the zero vector, \(\vec{0}\), can be written as a non-null linear combination of those vectors, that is, if

\(3.0 \quad \vec{0} = k_1\vec{a}_1 + \cdots + k_n\vec{a}_n \quad \text{with} \quad \sum_{i=1}^{n} |k_i| \neq 0.\)

In the case of two vectors \((n=2)\), \(\vec{a}_r, \vec{a}_c\) and \(k_i \in R\), this definition leads to \(\vec{0} = \vec{a}_r - k \cdot \vec{a}_c\) which can be also expressed as:

\(3.1 \quad \frac{a_{r1}}{a_{c1}} = \frac{a_{r2}}{a_{c2}} = \frac{a_{r3}}{a_{c3}} = k\)

Where \(a_{r1}\) and \(a_{c1}\), with \(a_{r1} \neq 0 \forall i\), are denoting the components of each vector. In case Eq. 3.1 is valid then the vectors \(\vec{a}_r, \vec{a}_c\) are parallel: \(\vec{a}_r \parallel \vec{a}_c\). Eq. 3.1 is also valid for more than three-dimensional vectors. Since all the component ratios are the same, it follows that the variance of them must be zero:

\(3.2 \quad \sigma^2 = \frac{1}{n-1} \sum_{i=1}^{n} \left(\frac{a_{r1}}{a_{c1}} - \mu\right)^2, n = \dim V\)

\footnote{From now on we will omit writing the left index (position of the window in the image) from the vectors in order to ease the reading of this paper. Every time a vector is given it should be noted that it has an intrinsic position index.}
The mean is defined by:

\[ \mu = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{a_n}{a_c} \right) \]

Consequently an invariance operator for the detection of changes has been found: The Linear Dependence Detector or LDD. This operator has been derived from the linear dependence theorem and provides a powerful tool for detection of changes, which can be seen in Fig. 2.2. Following the ideas above a criterion for change between two images can be introduced:

- When \( \sigma^2 \approx 0 \) no change has occurred between two images;
- When \( \sigma^2 > 0 \) the vectors \( \vec{a}_r \) and \( \vec{a}_c \) are not parallel and hence a change has occurred.

To summarize, an invariance operator \( \sigma^2 \), which is based on the linear dependence definition, is derived. This operator is invariant to transformation of type:

\[ \tilde{a}_r = k\tilde{a}_c \]

4 IMPLEMENTATION

In practice, first the mean \( \mu \) and then the variance \( \sigma^2 \) are calculated on a window \( W \) which is sliding over images \( I_r \) and \( I_c \). Tests were performed for windows with sizes \( W_{3x3}, W_{5x5}, W_{7x7} \) and \( W_{9x9} \). The resulting variance value \( \sigma^2 \) is given to the center pixel of the preliminary mask. In case the variance is greater than the Linear Dependence Detection Threshold \( T_{LDD} \) \( (\sigma^2 \geq T_{LDD}) \) a change is detected and the center pixel gets the value 255 in the final mask, otherwise it is supposed to be 0. Typical thresholds in the performed tests were 0.05, which led to the best results in the cases studied. Obviously, with increased size of the window \( W \) and increased value of the threshold \( T_{LDD} \) the results become less noisy. Unfortunately this process has two drawbacks:

- Increasing the window size \( W \) increases the calculation time and smoothes out the change detection mask;
- Increasing the threshold value \( T_{LDD} \) results in a miss of certain changes.

Therefore, a good compromise between the size of \( W \) and the value of \( T_{LDD} \) must be found for the best possible detection of changes.

5 RESULTS

The results show that the contours of the objects detected are closed, see Fig. 2.2 (b). Although the LDD detects the contours the object interior have some not detected areas, which can be improved by using a larger window to detect the changes, (see Fig. 2.2 (d), (e) and (f)). Since the more the window size is increased the more information from the original surface is collected. This surface information is faded on the image plane due to diffuse reflection as pointed out in section 2. The LDD method is less affected by noise than classical change detection methods (see Fig. 2.1 (e) and Fig. 2.2 (c)). The problem of the detection of curtains is not resolved even if the LDD method copes better with it than the mentioned statistical approach, (see Fig. 2.1(f) and Fig. 2.2 (c)).
The proposed method is illumination invariant (see Fig. 2.2 (a) and a comparison of Fig. 2.1 (b) with Fig. 2.1 (e), and Fig. 2.2 (e)) shows that it is also removing reflection. The removal of small objects is also detected as can be seen in Fig. 2.3 (d).

The methods [6] and [7], which are not treated in this paper, have good illumination invariance performance. Nevertheless in contrast to the LDD they have problems with the detection of contours.

In [8] a multi-feature segmentation method is proposed to remove the noise and false detection of the previously presented Statistical Change Detection Algorithm. Even this improvement fails in presence of illumination change since it is based on an illumination sensitive approach.

**REFERENCES**


