PEOPLE COUNTING SYSTEM

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Abstract: Demand for security and surveillance systems is getting bigger day after day. This work proposes a method that counts people and detects suspicious attitudes via video sequences of areas with moderate people access. A typical application is the security of warehouses during the night, on weekends or at any time when people access is allowed but no load movement is admissible. Specifically it focuses on detecting when a person passing by the environment carries any object belonging to the background away or leaves any object in the background, while only people movement is allowed in the area. In addition, it estimates the number of people on scene. The method consists of performing four main tasks on video sequences: a) background and foreground separation, b) background estimative dynamic update, c) people location and counting, and d) suspicious attitudes detection. The proposed background and foreground separation and background estimative update algorithms deal with illumination fluctuation and shade effects. People location and counting explores colour information and motion coherence. A prototype implementing the proposed method was built for evaluation purpose. Experiments on simulated and real video sequences are reported showing the effectiveness of the proposed approach.

1 INTRODUCTION

There is an increasing concern about security issues worldwide. A great deal of effort has been made in order to provide automatic systems able to detect suspicious activities. This work proposes an automatic method to estimate the number of people moving in an area monitored by a video camera, as well as to detect image changes, which are potentially due to undesired actions. A system implementing the proposed method would be primarily applied to enforce security in areas, such as warehouses.

Due to its ability to count people on an image, the method can be applied in several applications, such as layout arrangement, elevator access control, light or temperature control and others.

This method must cope with the following requirements: a) dynamic background update, b) permanent background changes, c) illumination variation, d) noise, e) shade effects, f) groups and g) partial occlusions. In addition, the method should also tolerate people passing in front of the camera as well as some deformation in the shape seen by the camera due to bending, sitting down or standing up.

Solutions meeting these requirements are proposed in the literature, but no one deals with all of them together. The systems described in (Shio) do not handle items d) and e), Piau and Ranganath (Piau) do not handle items b) and g) and Lu and Tan (Lu) fail to meet items a), b), c) and g). Rossi (Rossi) consider topics a) and b) and Wren (Wren), e) and g), but, in the same way as in (Atsushi), they consider only isolated person situations. Cai et all. (Cai) treat only item a) while Kettnaker and Zabi (Kettnaker), only items e) and f). Roh (Roh) deals with groups (f), but not with further aspects. Ramanan (Ramanan) treats only occlusions (g). Finally, works reported in (Haritaoglu) and (Wojtaszek) deal with all aspects, except for item e).

This paper is organized in three sections besides the introduction. Section 2 describes the method in details. Experimental results are shown in section 3. Finally, section 4 presents the conclusions.

2 THE SYSTEM

The task of counting people and detecting objects changes in a background is performed in this method by the following sequential steps: image

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pre-processing; background and foreground separation; dynamic background estimation; people location and counting; and suspicious attitudes detection. Each of these steps is explained in the next subsections.

2.1 Image Pre-Processing

RGB images are captured by conventional color cameras. The RGB image is converted to a color system that separates the brightness in a single component.

The CIELAB (Forsyth) color coordinates system was selected because it mimics the logarithm response of the human eye. This would permit a visual evaluation of the intermediate results, which was convenient during the development of the method. As a matter of fact any color system that expresses the brightness information in a single color component could be used in the place of CIELAB.

After the color system conversion, a bi-dimensional 3x3 median filter is applied to each color plane to reduce noise effects.

2.2 Background/Foreground Separation

This step consists in discriminating between background and foreground pixels. A variation of the technique proposed in (Kumar) is added to the conventional image subtraction approach in order to deal with background changes due to shades.

Let $\mathbf{I}_t(x,y)$ denote the image frame taken in instant t on the image coordinates (x,y). The notation used here (bold face) emphasizes that each pixel is represented by a vector in a three-dimensional color space, whereby brightness is represented by a single component ($I_t^b(x,y)$) and chromaticity by the remaining color components ($\mathbf{I}_t^c(x,y)$). Similarly let $\mathbf{B}_t(x,y)$, $B_t^b(x,y)$ and $\mathbf{B}_t^c(x,y)$ denote the corresponding background estimate, its brightness and its chromaticity in instant t. Additionally let $M_t(x,y)$ be the logical mask matrix indicating background ($M_t(x,y)$ = true) and foreground ($M_t(x,y)$ = false) pixels.

In this step, the matrix $M_t(x,y)$ is computed from $\mathbf{I}_t(x,y)$ and $\mathbf{B}_t(x,y)$, as formulated by the algorithm given in Figure 1.

```
if      | I_t(x, y) − B_t(x, y) | < T_L
then      M_t(x, y) = true
elseif  | I_t(x, y) − B_t(x, y) | < T_H
   AND  | I_t^C(x, y) − B_t^C(x, y) | < T_C
then      M_t(x, y) = true
else      M_t(x, y) = false
```

Figure 1: Foreground separation algorithm.

The first if condition corresponds to pixels very similar to the background. The second if condition tolerates a rather higher disparity to the background estimate, as far as the difference in chromaticity is still moderate. This condition models shade effects in a color space where brightness is expressed by a single color component.

The threshold values T_L, T_H ($T_L < T_H$) and T_C are obtained experimentally. Following this step an open-close morphological operation is applied in the image to eliminate small regions.

2.3 Dynamic Background Estimation

In the previous step it is assumed that a background estimate is available. This section describes how these estimates are computed and updated at each new frame.

The first background estimate, used when system starts up, must be provided somehow. This may be an image stored in memory, or even an image captured as part of the initialization procedure. Starting from this first estimate, a dynamic update algorithm will correct it, at every frame, to handle illumination fluctuation as well as permanent background changes. The procedure is presented in Figure 2.

For background pixels ($M_t(x,y)$ = true) the next background estimate is given by a mixture of the current estimate and the current pixel value. The mixture factor p establishes how fast small background changes are assimilated by the estimate.

Actions for foreground pixels ($M_t(x,y)$ = false) aim at updating background estimate, at that position with the current pixel value, if it remains stable along many consecutive frames. In other words, if changes between consecutive frames, in a foreground pixel, are small, as given by parameter e_b, for $K_{máx}$ consecutive frames, this pixel is considered as belonging to the background and thus stored in its background estimate.

$$
\begin{array}{l}
\textbf{if}\ \ M_t(x, y) = true \\
\textbf{then} \\
\quad \mathbf{B}_{t+1}(x, y) = (1 - p) \cdot \mathbf{B}_t(x, y) + p \cdot \mathbf{I}_t(x, y) \\
\textbf{elseif}\ \left| \mathbf{I}_t(x, y) - \mathbf{I}_{t-1}(x, y) \right| < e_b \\
\textbf{then} \\
\quad K(x, y) = K(x, y) + 1 \\
\quad \textbf{if}\ \ K(x, y) = K_{\max} \\
\quad \textbf{then} \\
\qquad \mathbf{B}_{t+1}(x, y) = \mathbf{I}_{t+1}(x, y) \\
\qquad K(x, y) = 0 \\
\textbf{else}\ \ K(x, y) = 0
\end{array}
$$

Figure 2: Background estimation algorithm.

The algorithm in Figure 2 contains a matrix K(x,y) where the number of consecutive frames without any significant change is stored for each pixel. K(x,y) is initialized with zero at system start up.

The maximum number of consecutive frames $K_{máx}$, as well as the mixture factor p, must be defined empirically for the application.

2.4 People Location and Counting

Once the foreground is known, the system must locate and count people moving in front of it. Both tasks are performed together by the following sequential actions:

- Foreground segmentation.
- Grouping segments.

2.4.1 Foreground Segmentation

In this first step, initially, the foreground is segmented in homogeneous color regions. Actually there are many different segmentation algorithms that could probably work properly here. This section describes the watershed-based (Gonzalez) segmentation algorithm implemented in the prototype built to validate the proposed method.

The image used to extract the foreground is the one obtained after applying the smoothing filter in the pre-processing stage. To segment this image, the gradient magnitude is calculated over each color plane by using the Sobel convolution mask. A matrix G(x,y) containing the mean of the gradient magnitude across all color components is then computed for each pixel position. G(x,y) is then modified; artificial lines are created, building a square grid whose side equals to $\sqrt[2]{A_{máx}}$. Pixels located in the grid will assume the highest value of G(x,y). This action ensures that all produced segments will have an area smaller than $A_{máx}$.

After that, the extended-minima transform (Soille) is applied to G(x,y). This transform suppresses the local minima that are not deeper than a given parameter H. The purpose here is to avoid the over segmentation effect that would result from applying the watershed algorithm right away over G(x,y).

Finally the watershed segmentation procedure is carried out over the two-dimensional matrix produced by the extended-minima transform, and homogeneous color segments are obtained. The regions delimited by the bounding boxes of these segments are hereafter called interest regions.

2.4.2 Grouping Segments

People location process assumes that interest regions belonging to the same person move quite in the same way between two consecutive frames, if the variation between those frames is moderated.

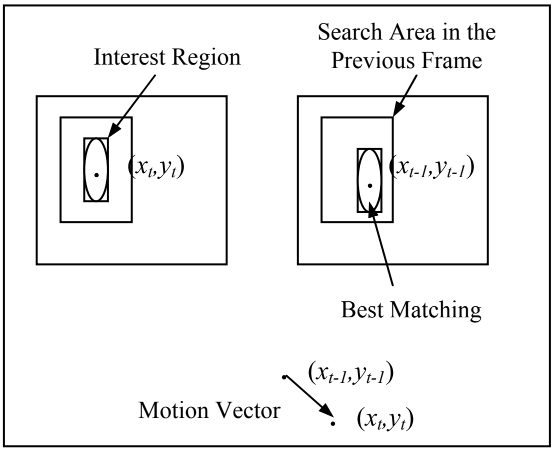
The proposed method bases on a technique known as motion coherence and is summarized in the following subsections. A more detailed description can be found in (Shapiro).

2.4.2.1 Locating Matching Segments in Previous Frame

Each segment found in the preceding stage must have a matching segment in the previous frame. Hence, the previous frame should be searched for this best matching. For computational efficiency this search is restricted to an area surrounding the current region position, as illustrated in Figure 3. The size of the search area is determined by the maximum displacement that may occur between two consecutive frames.

Similarity, between a segment and an equal shaped segment in the previous frame search area, can be measured by first computing the magnitude of color differences between all pairs of corresponding pixels and then taking the percentile of them. If the lowest similarity measure found in the search area is lower than some user defined maximum, the matching segment on the previous frame has been found.

Figure 3: Matching segments.



2.4.2.2 Computing Motion Vectors

Now vectors representing the movement of each interest region are computed. Let (x_t,y_t) and (x_{t-1},y_{t-1}) be the coordinates of the center of an interest region and its best matching in the previous frame, respectively. The corresponding motion vector is given by $(x_t - x_{t-1}, y_t - y_{t-1})$ and will be represented by its magnitude and angle.

2.4.2.3 Grouping Segments

Finally, segments should be joined in groups that represent people. Some conditions should be respected before two segments are grouped: adjacency, coherent movement and previous frame labeling. The algorithm used is presented in Figure 4. Segments for which no matching in previous frame was found will be analyzed considering only adjacency.

At the end of this process, each group will correspond to a set of adjacent coherent moving regions, which are assumed as belonging to a single person.

2.5 Suspicious Attitudes Detection

The idea underlying suspicious attitudes detection is that, if anybody moving in the environment leaves a lasting background change, this is an indication that something was carried away or something was left behind. Both situations may be relevant as far as the security is concerned. The proposed method models this reasoning.

In fact, permanent changes in the background will sign a suspicious attitude, and this condition has already been considered in the background estimate update.

Following the same idea, if an area, that does not belong do the background, stays stable for $K'_{máx}$ ($K'_{máx} \leq K_{máx}$) consecutive frames, it will be configured a suspicious modification. $K'_{máx}$ value represents how long the system takes to detect these changes and will be defined according to application characteristics.

```
/ U→ set of found segments.
/ S→ set of non grouped segments.
/ G_g → g^th formed group.
/ s_j, s_k → non grouped segments.
/ L^A_j , L^A_k → s_j, s_k previous labels.
/ L^C_j, L^C_k → s_j, s_k current labels.
/ mv_j, mv_k → s_j, s_k movement vectors.
/ D_max → maximum distance ensuring
vectors coherence.

S = U;
g = 0;
while  S ≠ ∅
   g = g + 1;
   G_g = s_j ∈ S;
   S = S – s_j;
   while  ∃ s_k ∈ S  so that
      (s_k is adjacent to s_j ∈ G_g)  AND
      ( (L^A_k = L^A_j AND |mv_k – mv_j |< D_max)
      OR s_k does not have a matching
region in previous frame)

        G_g = G_g ∪ s_k;
        S  = S  –  s_k;
        L^C_k = g;

   L^A_j = L^C_j, ∀ j so that s_j ∈ U
```

Figure 4: Grouping segments algorithm.

3 EXPERIMENTAL RESULTS

A prototype implementing the proposed model was built for evaluation purposes. Five different ambient were used to collect simulated and real video sequences. The simulated ones were used to analyze aspects of the process separately, as follows.

- *In background and foreground separation* → shade effects.
- *In dynamic background estimation* → illumination variations and background permanent changes.
- *In people location and counting* → partial occlusion and groups.

Besides, simulated sequences were also used to observe suspicious attitudes detection. Eventually, a real video sequence was applied, so that the whole process could be evaluated in a real case. The subsections below describe each of these topics.

3.1 Shade Effects

Six situations involving smooth, medium and strong shade effects were simulated. Figure 5 shows an example with medium shadow.

Figure 5: Medium shadow.

The real number of pixels relative to shade effects was compared with the one obtained by the method. The percentage of detected shade is shown in Table 1.

Table 1: Percentage of detected shade.

	Ambient 1	**Ambient 2**
Smooth	82 %	83 %
Medium	69 %	54 %
Strong	72 %	58 %

3.2 Illumination Variation

Two different lighting conditions were provided, as shown in the Figure 6 example. One of them has a higher illumination (Figure 6a) and the other a lower one (Figure 6b). Video sequences, where these conditions vary one to another, were obtained and submitted to the system. In all of them, illumination changes were incorporated in background estimate.

3.3 Permanent Changes

Video sequences where people enter in the scene, and leaves or carries away any object, were formulated, as presented in Figure 7. These situations configure permanent changes in the scene.

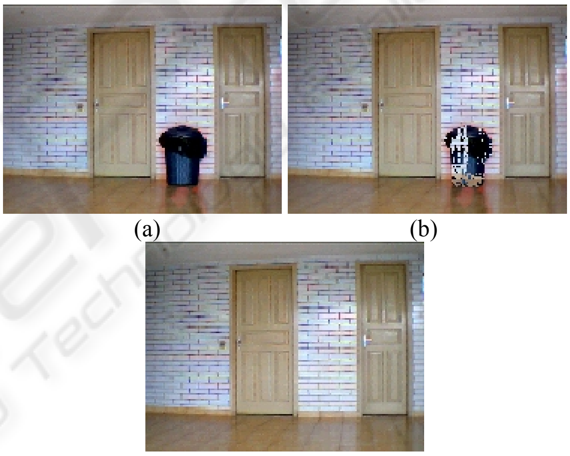
Background update corresponding to modification illustrated in Figure 7 can be analyzed in Figure 8. At first the waste bin belongs to the background (Figure 8a), but, as it was carried away (Figure 7b), slowly, background estimate eliminates the waste bin from itself (Figure 8b and Figure 8c).

(a) (b)

Figure 6: (a) High and (b) low illumination.

(a) (b)

Figure 7: (a) Original ambient. (b) After change.



(a) (b)

(c)

Figure 8: (a) Original ambient. (b) Update process. (c) After update.

3.4 Partial Occlusions

Situations involving partial occlusions (Figure 9) were also developed to evaluate system correctness. Performance metrics are described below.

- *Mean Error:* mean of the differences between the real number of people in the scene and the one obtained by the method.
- *Standard Deviation:* standard deviation of the same differences cited above.

Sometimes the error can be negative, since the system counts less people than, in fact, it should do. On the other hand, when the error is positive, it means that the system counted more people than it should.

The estimated error must be greater than the difference between the mean error and the standard deviation and smaller than the sum of them.

Video sequences used to evaluate the method present between 0 and 4 people and it is expected that system error stays between 0,5 and 1,5 person.

Figure 9: Partial occlusion situation.

The mean error and the standard deviation for tests involving partial occlusions are presented in Table 2. Results obtained in ambient 2 were not very good, since the error reached almost 2 people and there was only one person in the scene. However, in ambient 1, the error was about 1 person and, in ambient 3, less than 0,5 person, considerably better.

Table 2: Mean error and standard deviation for occlusion situations.

	Ambient 1	Ambient 2	Ambient 3
Mean Error	0,36	0,95	0,11
Standard Deviation	0,67	0,90	0,31

3.5 Groups

For group's evaluation, three conditions were considered: an isolated person circulating, groups' formation and groups splitting.

Table 3 presents reached results for isolated person situations. As can be seen, ambient 3 allowed for good results; the error was under 1 person. Ambient 2 was still satisfactory, but ambient 1, did not, since it had an error over 2 people.

Table 3: Mean error and standard deviation for isolated person situations.

	Ambient 1	Ambient 2	Ambient 3
Mean Error	1,20	0,42	0,22
Standard Deviation	1,14	0,80	0,59

In group's formation analysis, ambient 1 presented an error about 2 people. For 3 or 4 people in the scene, this error is acceptable, however with only 2 people, it is not so good. In ambient 2, except for groups with 2 people, results were quite good. In ambient 3, results were better, since the error was less than 1 person for groups with 2 people and less than 1,5 person for groups with 3 or 4 people. Table 4 displays these data.

Table 4: Mean error/standard deviation for group formation situations.

Number of People	Ambient 1	Ambient 2	Ambient 3
2	0,79 / 1,28	1,23 / 1,21	-0,20 / 0,58
3	1,06 / 0,99	0,49 / 1,05	-0,67 / 0,73
4	0,90 / 1,28	0,00 / 1,42	0,50 / 0,96

Lastly, Table 5 presents results for group's splitting. Ambient 2 allowed for better results; the error was about 1 person for groups with 2 or 3 people and about 1,5 for groups with 4 people. Ambient 3 had almost the same result. Nonetheless, ambient 1 had not similar results; the error was over 2 people for all cases.

Table 5: Mean error/standard deviation for group splitting situations.

Number of People	Ambient 1	Ambient 2	Ambient 3
2	1,00 / 1,31	0,40 / 0,58	-0,06 / 0,79
3	1,32 / 1,29	-0,11 / 0,99	-
4	1,26 / 1,48	0,34 / 1,34	-0,63 / 1,25

3.6 Suspicious Attitudes

Ten different video sequences concerning suspicious attitudes were captured and, for all of them, the system alarmed as expected. Figure 10 shows an example of a suspicious attitude, where someone carries an object away.

Figure 10: Suspicious attitude.

3.7 Real Situation

Finally a video sequence illustrating a real situation, that is, without any kind of control, captured in a newsstand (Figure 11), was submitted to the system. Results can be seen in Table 6.

Figure 11: Real situation.

Table 6: Mean error and standard deviation for the real situation.

	Real Situation
Mean Error	0,88
Standard Deviation	1,02

In this video sequence, there were also between 0 and 4 people in the scene and the error high limit was almost 2 people. With 4 people in the scene, this error is acceptable, nevertheless for 1 person, it could be smaller.

4 CONCLUSIONS

A method to monitor the number of people moving in front of a video camera, as well as to detect suspicious image changes was developed. The method is intended to enforce security in areas like warehouses.

This model meets some requirements that have not been completely met by previous works. It performs dynamic background update during system operation and tolerates image changes due to variation of illumination, to noise and to shade effects. Permanent background changes are also managed by the method.

The process has been validated by experiments carried out on a prototype that produced good results, although there are still some aspects to enhance to improve results in group analysis and in partial occlusions, such as motion coherence and grouping segment criteria's.

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