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PEOPLE DETECTION IN NUCLEAR PLANTS BY VIDEO PROCESSING FOR SAFETY PURPOSE

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ABSTRACT

This work describes the development of a surveillance system for safety purposes in nuclear plants. The final objective is to track people online in videos, in order to estimate the dose received by personnel, during the execution of working tasks in nuclear plants. The estimation will be based on their tracked positions and on dose rate mapping in a real nuclear plant at Instituto de Engenharia Nuclear, Argonauta nuclear research reactor. Cameras have been installed within Argonauta's room, supplying the data needed. Both video processing and statistical signal processing techniques may be used for detection, segmentation and tracking people in video. This first paper reports people segmentation in video using background subtraction, by two different approaches, namely frame differences, and blind signal separation based on the independent component analysis method. Results are commented, along with perspectives for further work.

1. INTRODUCTION

Video surveillance has emerged as an important field, spanning through many different applications, for safety or security purposes. Some examples can be cited, as monitoring people in controlled environments, or monitoring people activities in private or public locations for security reasons. This work focuses in monitoring people in nuclear plants, which are controlled environments, to improve safety for workers during operational and maintenance activities. A case study is under implementation in an existing nuclear plant, Argonauta nuclear research reactor, at Instituto de Engenharia Nuclear, Comissão Nacional de Energia Nuclear (IEN, CNEN). Cameras have been installed in Argonauta's room to monitor workers while they execute their tasks. A person who enters this room has to be first detected and segmented, and then tracked along time. Considering the personõs tracked position and the radiation dose rate map within this room, the system can estimate the dose received by this person. This, in turn, may be used to improve safety for workers, through a better planing of the working routines, to reduce dose received by workers, fulfilling ALARA requisite [1].

This work is part of a broader R&D for virtual simulation of nuclear plants, currently under development at IEN. There are also some research groups performing virtual simulations for evaluation of dose received by personnel in nuclear plants [2]-[9]. Former results achieved by IENõs staff can be found in [10]-[12], or alternatively in a book chapter [13] that covers this research entirely. In a first stage [10], only offline dose rate mapping were available, through previous measurements performed by IENõs Radiological Protection staff. Then, the simulation was performed using also online measurements, from data collected by radiation monitors installed in Argonautaõs room, through local networking or through the Internet [11]. Later, a more detailed mapping was performed, and the dose rate was also interpolated [12]. The results of the present work will be integrated to this simulation platform.

In the present work, two approaches were tested for segmenting foreground objects in video: two-frame background subtraction, with and without background updating [14], and blind signal separation (BSS) by independent component analysis (ICA), [15]. Results are shown and compared in Section 7. The foregrounds segmented in the current stage can be roughly tracked in 2D by tracing rectangular bounding boxes around them, and thus accounting for these bounding boxes limit coordinates of for their geometrical center. However, more specific tracking methodologies are planned to be implemented in the future, including 3D tracking.

2. SIMULATION FOR SAFETY PURPOSES IN NUCLEAR PLANTS

Working in industrial plants usually involves some risk for personnel, in higher or lower degrees. Most of these risks are unavoidable, but care has to be taken through good managing and planning practices so as to minimize these risks as much as possible. In the case of personnel working in nuclear plants, receiving dose of radiation is unavoidable, so the matter is to reduce as much as possible the received dose during task execution. The ALARA principle [1], already mentioned in Section 1, treats this matter by specifying guidelines to reduce the dose received by personnel to what is strictly necessary, and when exposition justifies itself.

Planners, supervisors and trainers usually carry out training for personnel with both theoretical and hands-on stages. But considering the potentially hazardous environments such as nuclear plants, computer-based training may be employed so users can face the problems related to their working routines first in a safe environment, before entering a real one. Thus, the first training stages can be taken safely, until they acquire more skills. Computer-based training can also help trying different scenarios and improve planning of working routines so as to reduce the time spent in ñhotò locations, – regions with higher dose rates –, changing paths and optimizing the routines. From the works in [2]-[9], basically two approaches can be highlighted: (i) one making use of measurements in grids of points within nuclear plantõs rooms, and (ii) another with numerical computation of radiation dose rate; our staff has followed the former approach.

3. ARGONAUTA NUCLEAR RESEARCH REACTOR

Argonauta nuclear research reactor is a swimming pool type reactor with typical and maximum operating power levels of 300 W and 5 kW, respectively. It has been used for research purposes since 1965, mainly for: (i) non-destructive evaluation using gamma or neutron radiation, (ii) as support for graduate courses in nuclear physics and nuclear engineering, and (iii) for radioisotope production to be used as radiotracers for industrial applications [10].

Considering a typical operation for non-destructive materials evaluation, a user has to put a material sample in the reactor's output radiation channel, removing it after the radiation process finishes. This output radiation channel is shown in Figure 1, and the region around it is the hottest area within Argonauta's room.

Dose rate mapping is available since the former works [10]-[12]. Obtaining the users' tracked positions is the current focus of this work.

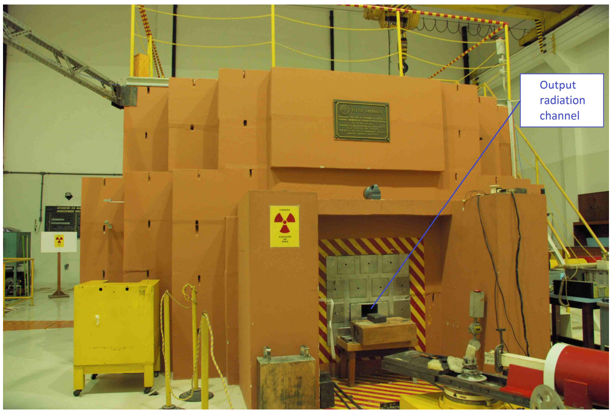


Figure 1. Argonauta research reactor with its output radiation channel indicated.

4. SURVEILANCE IN VIDEO

Surveillance in video became a broad research field, with many different approaches and applications, as object detection and tracking. The reader can refer to [16]-[22] for a review of this type of research. Basically, object tracking in video usually involves three main stages, comprising: (i) detection, (ii) segmentation and (iii) tracking itself [16], [17]. First, the object to be tracked has to be detected automatically in the scene; second, the object (foreground) has to be segmented from the background; finally, the position of the segmented object has to be tracked online along time. This work concentrates in the segmentation stage in a previously selected video interval; automatic detection and tracking will be dealt with in the future.

The most basic method used for object segmentation is frame differencing, where video frames are simply subtracted from one another. If there is no foreground object in the scene, the difference results in small amplitude noise, because both frames have essentially the same content, the background. But if a foreground object appears in the scene in a given frame, simple difference between this frame and one with background only results in the foreground object itself, the background being eliminated from this processing. However, this does not work in the case of a more complex behavior, such as variable background due to undesired object movement, variable illumination or camera motion, among other reasons. To cope with such situations, there are approaches other than simple frame differencing. Examples of more robust algorithms can be found in [14].

Alternatively, the object to be tracked may be identified in the scene by matching features of interest extracted from this object. The location of these features can then be tracked along time. An example of this later approach is the SIFT (scale invariant feature transform) method [23]-[25], that is robust to scale, 2D rotation and illumination changes, and also to clutter and partial occlusions. There are other methods similar to SIFT, such as SURF (speed up robust features) method [26], [27]. Due to the processing in the scale-space, both SIFT and SURF have shown superior performance over methods based on single scale.

There are also other important methods for object tracking in video reported in the literature. Optical flow [28], [29] estimation is a good choice for object tracking. This method is a pixel-based inter-frame processing that estimates the velocity vectors of moving pixels whose movement is detected between subsequent frames; background does not present any significant change, since its pixelsô velocities are very small, while moving pixels have their estimated velocities well above a given threshold. Another method well suited for object tracking in video is the Kalman filter [30], [31], that is used to estimate and track an objectôs movement.

A recently reported approach for object segmentation in video involves BSS based on ICA, [15]. In this approach, foreground and background are modeled as corresponding to different statistically independent signals to be estimated, and different scene frames are used as mixtures from which the signals are estimated. Good results are reported in [32].

5. CASE STUDY: ARGONAUTA RESEARCH REACTOR

Some criteria had to be used for selection among different video processing methods, as cited in Section 4, based on the case study in hand. Argonautaôs environment has some particular characteristics as quasi-static background, as explained in the sequel.

Argonautaôs environment is a closed room, thus illumination change can be neglected in most situations, since illumination provided by lamps is constant. Also, the entrance door is closed most of the time for safety and security reasons. Further, the cameras installed can compensate for slow illumination change by adjusting brightness. The only problems related to illumination would be a sudden burning lamp, or a blinking defective lamp.

Since Argonautaôs room is a controlled environment where only authorized people enter, there are no unwanted people from the general public walking there, thus the system has not to differentiate between authorized and non-authorized people movements. In addition, there is no other moving object or machine in its room, unless introduced there by authorized personnel.

From the considerations above, the background can be considered quasi-static, thus enabling beginning this R&D by using methods directed towards static background, such as frame differencing without background updating. But, as verified during this R&D project, some unwanted background variation can occur in the following cases (some already mentioned):

1- Illumination change:

Illumination can rarely change due to opening the entrance door, or to defective lamps, but in this case the cameras can partially compensate for this. For blinking lamps, a more complex method should be used to overcome periodic illumination change [14].

2- Object modification in the scene:

This is the most common change for the background. In typical operations, workers have to place sample material in front of the Argonautaĝs output radiation channel, which requires opening the later in the beginning of the radiation process and closing it at the end. These actions result in changes between subsequent frames, which appear in simple frame difference without background updating. Of course such detection is unwanted, and must then be disregarded and considered as background.

Users may also enter Argonautaĝs room with a piece of equipment, such as radiation monitors or laptops for processing measurements, and may even leave them there. These changes must also be disregarded and considered as background. Therefore, methods that deal with changing background should also be considered in the future.

3- Standing still user in the scene:

The situation of a standing still worker in Argonautaĝs room is also frequent. Examples of this occurrence are: (i) while handling the material samples in front of the output radiation channel, or (ii) while performing measurements, which requires the user to be static in each position for some time for dose rate integration by instruments. Users in these situations cannot be considered as background, because the received dose must be estimated anyhow.

Therefore, intermediate solutions have to be found to consider as the background unwanted object changes, but to keep tracking of people even when they are static, or quasi-static, in the scene.

6. METHODOLOGIES

As already mentioned in Section 4, this work concentrates currently in the segmentation stage. Among the available methodologies for this task, two have been tested: (i) frame differences, and (ii) BSS. In the former case, two different algorithms have been implemented, considering or not a background updating, while in the later case an ICA algorithm has been used.

6.1. Frame Difference

Frame difference can be implemented in distinct modes. First, difference may be performed between subsequent frames, or between the current frame and a reference one; in the later case, the background may be either updated along time or not.

Performing difference between subsequent frames results naturally in robustness to background variation, because background is updated every frame. Thus, any unwanted object change (such as opening the output radiation channel) is considered as background; but standing still people are considered as background, what is not desired at all.

Performing frame difference considering a reference frame requires first that this reference concerns the background only, so that a current frame with any person results in the segmented foreground. This case is the very opposite to that of subsequent frame difference; standing still people are not considered as background. But neither object change is considered as background, what can also cause misdetections.

Therefore, two frame difference algorithms have been implemented: (i) considering static background; (ii) with background updating. The former performs simple frame difference between the current frame and a predefined reference one (background only source). The later requires a background update model and it is robust against complex background variations [14].

6.2. Blind Signal Separation

Blind signal separation aims at estimating the original source signals from given signal mixtures. Among the available methods, (linear) ICA is a very efficient one, and thus largely used, given its powerful capabilities for signal estimation allied to its fast execution.

ICA relies on higher-order statistics evaluation. This gives ICA higher signal separation capability over the well-known second-order statistics based methods, such as principal component analysis (PCA) or whitening [15], which are based on the correlation matrix computation. It is well known that signal separation based on second-order statistics can only result in uncorrelated signals, estimating independent components only for Gaussian processes.

One solution to perform BSS is using non-linear PCA (NLPCA), [15], which results in non-linearly uncorrelated signals. Another solution comes from the central limit theorem [33], which states that mixtures of non-Gaussian signals tend to be more Gaussian than the original sources. Thus, maximizing non-Gaussianity tends to lead to the original statistical independent signals. It is also known that the fourth-order statistics is related to the non-Gaussianity of a signal; particularly, the normalized kurtosis, shown in Equation 1, is a parameter derived from the fourth-order statistics for which a Gaussian signal has null normalized value, while non-zero normalized kurtosis means the signal is non-Gaussian (negative normalized kurtosis defines sub-Gaussian signals, and positive one concerns super-Gaussian signals).

$$kurt(x) = \frac{E\{x^4\}}{[E\{x^2\}]^2} - 3. \tag{1}$$

ICA performs an optimization (maximization) of the normalized kurtosis, which finishes in very few iterations with the FastICA algorithm, [15], [34]. The basic relation between the (linear) mixtures and the original source signals is given by Equation 2a. ICA performs an estimate of the separating matrix **W**, as given by Equation 2b.

$$\mathbf{x} = \mathbf{A}\mathbf{s}. \tag{2a}$$

$$\tilde{\mathbf{s}} = \mathbf{W}\mathbf{x}. \tag{2b}$$

where:

- **s**: column vector with the original signals;
- $\tilde{\mathbf{s}}$: estimate of **s**;
- **x**: column vector with the mixtures;
- **A**: mixing matrix;
- **W**: separating matrix, $\mathbf{W} = \mathbf{A}^{-1}$.

For background subtraction, ICA is applied to estimate the separated source signals, (the foreground and the background), from the available video frames, which are considered resulting from mixtures. This work follows the approach reported in [32], where the authors used as the two mixtures: (i) the current frame with the foreground (person), and (ii) the background-only reference frame. The first stage in ICA processing is to estimate the separating matrix. Once estimated, one has just to apply it to incoming frames, to obtain the estimation of the foreground in the target frame. This method should be robust against standing still objects, as independent sources are continuously extracted.

6.3. Further Processing

In both cases, additional processing has been performed to improve results, as follows:

1- <u>Binarization</u>:

The difference image was binarized, the foreground resulting in white and the background in black. The threshold for binarization influences the result in the following way: (i) lower thresholds tend to capture more connected body parts, but also results in a larger number of small-area regions corresponding to background noise; (ii) higher thresholds tend to reduce the background noise, but also results in disconnected body parts. Thus, an intermediary threshold has been chosen by trials.

2- <u>Background noise filtering</u>:

Background noise resulting from the binarization process has been eliminated by a mathematical morphology [35], [36] operation. Basic morphological operations are erosion and dilation, and both make use of a structuring element that is a mask for filtering. The former (erosion), eliminates foreground (white) areas smaller than the structuring element, while reducing wider areas; therefore, this reduces background noise by eliminating small-area regions, but reduces also the human body area. The later operation (dilation) tends to widen foreground regions according to the structuring element. This thus tends to widen background noise areas, but also to reconnect eventually disconnected human body regions.

Composite morphological operations are opening and closing; the former comprises erosion followed by dilation, while the later comprises dilation followed by erosion. In this work, opening was used to filter background noise: the initial erosion reduces background noise by eliminating small-area regions, and the subsequent dilation recovers the original human body area.

3- Reconection of human body parts:

The disconnected human body parts, resulting from the binarization process, must be reconnected. In this work, this was performed by the closing morphological operation: the initial dilation reconnects the human body parts (now free from noise amplification problem), while the subsequent erosion recovers the original human body area.

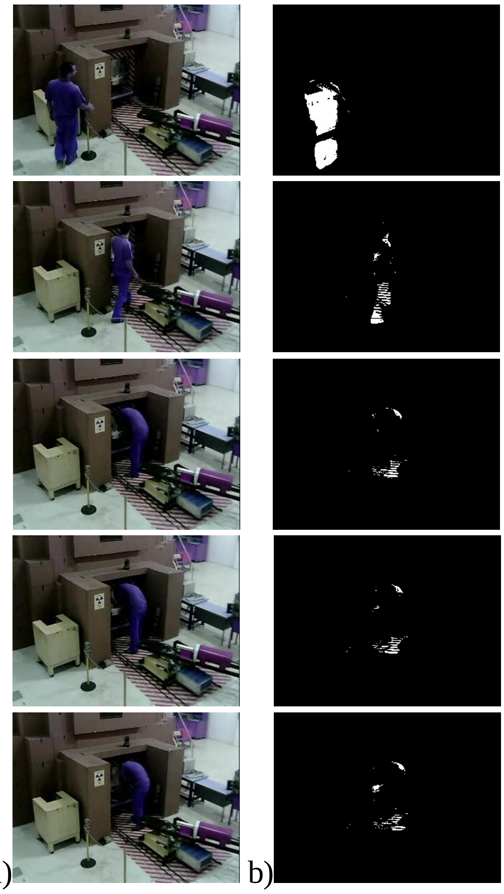
4- Bounding box:

Bounding box post-processing was performed over the (filtered) segmented foreground, to estimate its position through its limits or its geometric center, and the later was used for dose estimate, in a first approach.

7. RESULTS

7.1. Two-Frame Difference with Static Background

Figure 2 shows a sequence of video frames where the leftmost column shows the original frames, and the rightmost column shows the foreground after binarization. One can notice the resulting low background noise due to a higher threshold choice, but that also caused more disconnected body parts.

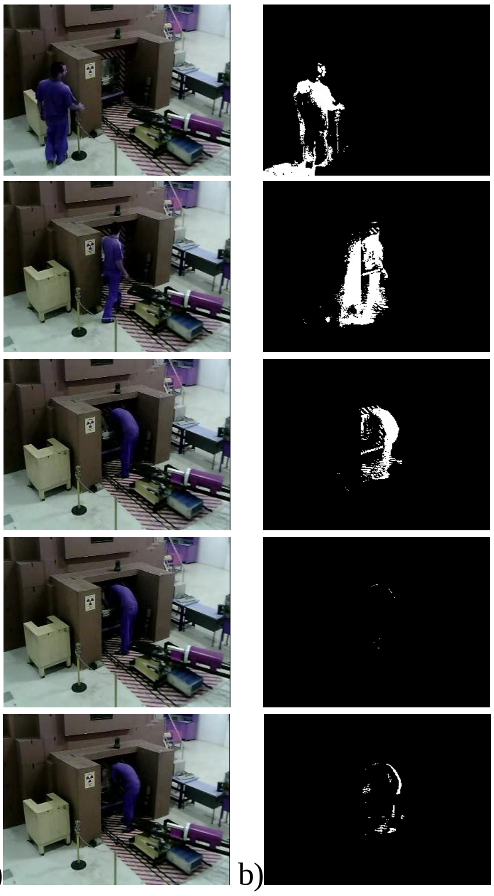


a) b)

Figure 2. Background subtraction by frame difference, without background updating; a): original frames; b) binarized foreground.

7.2. Two-Frame Difference with Background Update

Figure 3 shows results by presenting the original frames in the leftmost column, with the foreground after binarization in the rightmost column. One can notice the subtracted foreground of a quasi-static user is almost lost in the last frames, even applying a lower threshold.



a) b)

Figure 3. Background subtraction by frame difference, with background updating; a): original frames; b) binarized foreground.

7.3. Background-Foreground Separation by BSS

Figure 4 shows the mixtures used and the estimated signals corresponding to the foreground and to the background. Figures 4a and 4b show the mixtures used for ICA estimation, where Figure 4a contains a background-only frame, and Figure 4b a frame with the foreground (full body), according to the approach reported in [32]. Figures 4c and 4d show the estimated independent signals, where Figure 4c shows the signal corresponding to the estimated foreground, and Figure 4d the signal corresponding to the estimated background. One can notice that signal separation is not perfect, because of the presence of background texture in the foreground, and a ñghostò in the background.

Figure 5 shows results for the BSS/ICA for the same original framesô sequence used in Figures 2 and 3. There, the leftmost column shows the original frames, while the rightmost column shows the foreground after binarization.

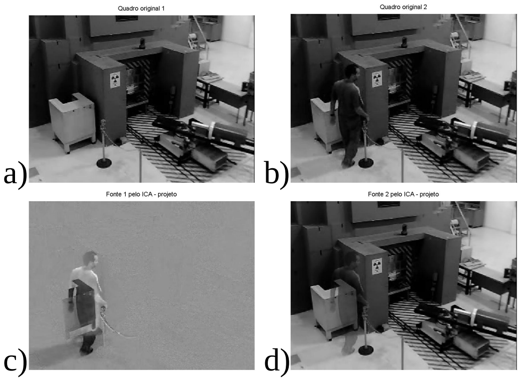


Figure 4. Signals estimation by ICA; a) and b) mixtures used for estimation, c) and d) estimated signals.

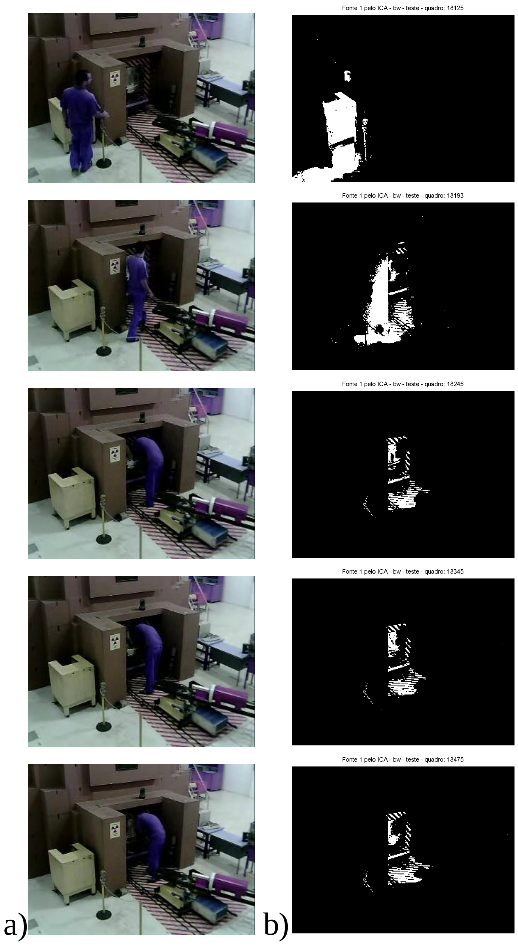


Figure 5. Background subtraction by BSS/ICA; a) original frames; b) binarized foreground.

7.4. Further Processing

This Section shows the effects of further processing in segmented foregrounds. First, Figure 6 shows a foreground segmented by BSS/ICA, as an example, binarized with different threshold levels. Figure 6a shows binarization applying a threshold level equal to 0.61, which results in reduced background noise, but also with the risks to eliminate some body parts, such as head and arms. Figure 6b shows binarization with an intermediary threshold level equal to 0.45, while a threshold level equal to 0.43 was applied in Figure 6c. These two threshold levels did not cut the head, but resulted in higher background noise levels, especially the later one. Therefore the 0.45 threshold level was kept for design.

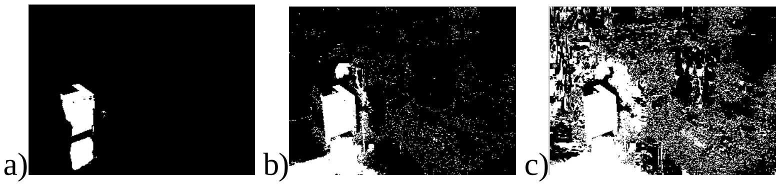


Figure 6. Effect of different binarization threshold level; a) level equal to 0.61; b) level equal to 0.45; c) level equal to 0.43.

Figure 7a shows the result of background noise filtering by using the opening morphological operation, for which the structuring element was a disk with radius equal to 5. The threshold used was 0.45. Figure 7b shows the result of body parts reconnection by using the closing morphological operation; the structuring element was also a disk, but the radius was equal to 16. These choices were made after a number of trials. In the later case, for body parts reconnection, the radius was chosen so as to result in a reasonably neck thickness: not so thin, nor so large comparatively to headôs dimension.

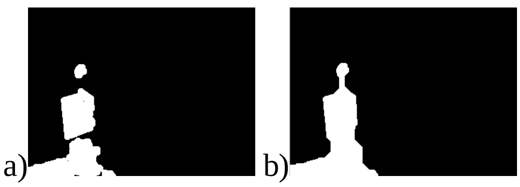


Figure 7. a) Background noise filtering by opening morphological operation with a 5-pixel disk; b) Body parts reconnection by closing morphological operation with a 16-pixel disk.

8. CONCLUSIONS

These results demonstrate the viability of using any of the two segmentation methods tested: (i) by frame differencing, or (ii) by BSS/ICA. The former one, despite its fast execution (especially with static background), has presented some issues related to neglecting or not objects to the background; still humans must not be considered as background, while objects modified in the scene that are not important to the dose estimation must be considered as background (they are not humans). An intermediate solution has to be evaluated, to overcome this problem. Other relevant questions are: how much frequently must the background be updated? In which form background has to be updated to achieve good results? The later methodology (BSS/ICA), in turn, is also a fast method, and overcomes the problem of considering standing still humans as background.

Mathematical morphology has proved to be a good approach for both filtering background noise and reconnecting body parts. Further evaluation has to be performed to account for structuring element dimensioning. Also, further work has to be done relatively to automatic human body detection in the scene, and foreground tracking. Even though, the bounding box approach may suffice in a first implementation.

In future works, we intend to extend all these tasks to 3D tracking, and to integrate them to the virtual simulations already in course in IEN.

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