A BLOBS DETECTION ALGORITHM BASED ON A SIMPLIFIED FORM OF THE FAST RADIAL SYMMETRY TRANSFORM

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ABSTRACT

Automatic blobs detection constitutes a basic but difficult problem. In this work a new fast blobs detection technique based on a scale-space representation of the original image, is proposed. The scale-space representation is constructed by using a new simplified form of the Fast Radial Symmetry Transform to precisely detect the essential blobs. From the experiments we have conducted, the proposed technique seems to outperform well known blobs detection methods such as the conventional FRST, Hough and SIFT based techniques, in both accuracy and detection rate. In addition, the proposed technique can be used for the automatic and perfect elimination of the well known Moiré effect which substantially degrades the quality of radiography (x-ray) images.

***Index Terms*—** Blobs Detection, Scale-Space representations, Fast Radial Symmetry Transform, Moiré Effect, Hough Transform, SIFT

1. INTRODUCTION

Interesting point extraction constitutes a major problem in many computer vision applications. The interesting points, called “blobs”, refer to the existence of visual structures with points in an image which are either brighter or darker than their surrounding [1]. Blobs can describe either the desirable features (e.g. eyes, particles, dots, cycles, etc.) or can be usually used as input for higher lever algorithms and methods such as image stitching, 3D reconstruction, aerial photography understanding and facade interpretation [2], to name a few. The advantage of the blobs stems from the fact that they can provide complementary information about regions that can’t be obtained from edge or corner detectors. To ensure the reliability of these interesting points, the blobs have to provide invariance under a variety of conditions. They should be robust in the presence of noise, blurring and illumination changes. Moreover, they should not be strongly affected in the presence of partial occlusions. Finally, it is desirable to be invariant to affine transformations.

Over the last decades many techniques have been proposed in the literature, trying to fulfill most of these requirements. However, most of them still present noticeable difficulties in achieving invariance of all the above mentioned parameters under several viewing conditions. By taking into account that all these requirements are quite general for almost all applications, concerning a specific application some of these are more significant than others. Thus, depending on the application, the specifications may differ significantly. The blob detection methods can be roughly divided into the following main categories:

1. Matched filters and template matching based methods [3]. These methods provide an enhanced robustness in the presence of noise but their complexity is heavily depended on the dimension of the used parameters space.

2. Watershed based methods [4], [5]. Watershed algorithm takes into consideration that the blobs usually consist of a homogeneous area and are surrounded by a boundary edge. The basic idea of these algorithms is that every image is assumed to be ”gray value mountains”. These methods simulate the process of rain falling onto the mountains, running down the mountain range and accumulating in valleys and basins. This process is terminated when all basins are filled and only the watersheds between the different basins remain. Despite the low complexity of these techniques, that permit their implementation in near real-time applications, they suffer from inherent noise sensitiveness which leads typically to over-segmented results. This problem can be overcame by incorporating information about the expected shape and size of the blobs.

3. Luminance-based methods using scale-space analysis. Scale-space [6], [7] is a formal theory for handling image structures at different scales, by representing an image as an one-parameter family of smoothed images. This representation, parameterized by the size of the smoothing kernel, used for suppressing fine-scale structures [7]. In this case, the complete scale-space representation is analyzed and the local extrema are extracted in order to select the appropriate scale. Lindeberg [1] proposed one of the first and most popular blob detectors, which is based on the Laplacian of the Gaussian (LoG). A similar approach uses differences of Gaussian kernels (DoG) [8], providing a close ap-

proximation to the scale-normalized LoG. The SURF descriptor [9], in order to detect interesting points, uses an integer approximation of the Determinant of Hessian (DoF) blob detector and is based on the sum of the Haar wavelet response around the point of interest. Christophe et al. [10] proposed a blob detector based on the wavelet transform modulus maxima. An affine invariant blob detection method that uses maximally stable extremal regions (MSER) is proposed by Matas et al. [11]. Mikolajczyk et al. [12] proposed an approach for detecting interest points, invariant to scale and affine transformations. They extended a multi-scale representation that uses Harris interest point detection to affine invariance, by estimating the affine shape of a point neighborhood.

The remainder of the paper is organized as follows. In Section 2 the proposed technique is introduced. In Section 3 the results we obtained from the application into several images of the proposed method are presented. In addition, the performance of the proposed technique is compared against three other well-known techniques. Moreover, its use for the perfect elimination of the Moiré effect which substantially degrades the quality of radiography images is presented. Finally, Section 4 contains our conclusions.

2. PROPOSED TECHNIQUE

Symmetry constitutes one of the primary properties of the blobs. Conventional FRST, proposed by Loy and Zelinsky [13], is a low complexity voting procedure that highlights circular shapes. It determines the contribution each pixel makes to the symmetry of pixels around it, rather than considering the contribution of a local neighborhood to a central pixel. The proposed blob detection method is based on a simplified form of the conventional FRST. This simplified form is used to form a multi-scale representation of the original image. By searching the local extrema of this representation, the detection of the dominant blobs and their radii is achieved.

The description of the basic steps of the proposed technique is presented in the following paragraphs.

2.1. Simplified Form of FRST

In our approach, only the Magnitude component of the conventional FRST is used. In addition, the proposed scheme differs from the conventional one in highlighting the circular symmetry of shapes of a specific radius contained in the candidate image, instead of accumulating the results from a set of different radii. More specifically, consider that the radius r is given. Then, for each pixel $\mathbf{p}$ the positive and negative affected pixels $\mathbf{p}_{\pm}(r)$ are obtained by translating the original pixel along the normalized gradient direction, at distance equal to $\pm r$, that is:

$$\mathbf{p}_{\pm}(r) = \mathbf{p} \pm \mathit{round}\Big(\frac{\nabla I(\mathbf{p})}{||\nabla I(\mathbf{p})||_2} r\Big), \quad (1)$$

where $||\mathbf{x}||_2$ denotes the l_2 norm of vector $\mathbf{x}$ and round(x) indicates the closest integer to number x. The "Magnitude Projection Image" (MPI) is constructed by adding and subtracting the magnitude of the gradient at the specific pixel, to the position of the positively and negatively affected pixels respectively, as follows:

$$M_r \equiv M(\mathbf{p}_{\pm}(r)) = M(\mathbf{p}_{\pm}(r)) \pm ||\nabla I(\mathbf{p})||_2. \quad (2)$$

Finally, in order to smooth out the MPI, it is convolved with a Gaussian kernel, i.e.:

$$L_r = M_r * G_{\sigma_r} \quad (3)$$

with " $*$ " denoting the convolutional operator and the standard deviation σ_r of the Gaussian kernel of size $M \times M$ being controlling the smoothing of the MPI. In all experiments the parameter σ_r and the kernel's size M was set to $r/4$ and $\mathit{round}(6\sigma_r + 1)$ respectively.

2.2. Multi-Scale Representation

The scale-space representation was proposed by Lindeberg in [1], and was implemented as an image pyramid. According to this approach, the images are repeatedly smoothed by a Gaussian kernel and sub-sampled in order to successively create the higher levels of the pyramid. In spite of this, in the proposed technique the simplified form of FRST is applied in parallel, but with different radius, to the original image. Therefore, the proposed scale-space representation is constructed by increasing the radius as we are proceeding to the upper levels of the representation, instead of iteratively reducing the image size as shown in Fig. 1.

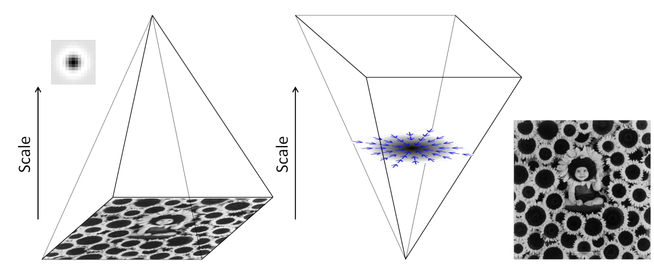

Fig. 1. Instead of iteratively reducing the image size, the use of the modified FRST allows us the up-scaling of the transform at constant complexity

The basic idea behind of this specific use of the FRST is the formation of a multi-scale representation of the candidate image that can be used to solve the blobs detection problem. To this end, let us define the following set of radii:

$$\mathbb{S}_r = \big\{r_{\min},\ r_{\min} + s_r,\ \cdots,\ r_{\max}\big\},\ r \in \mathbb{Z}, \quad (4)$$

where $r_{\min}$ and $r_{\max}$ are estimations of the smallest and largest size of the blobs under consideration and s_r the used step. Then, for each member of $\mathbb{S}_r$ set, we can compute the corresponding MPI, thus forming a scale-space representation of the original image. Note that the aforementioned use of the simplified FRST ensures a constant complexity for each scale layer, thus making the proposed algorithm computationally efficient (Fig. 1). Furthermore, there is no need of down-sampling the image thus preventing the aliasing. Finally, this representation preserves the high-frequency components that could get lost and limit the scale invariance in the down-sampled images. Concluding, the scale-space representation, give us the possibility to solve the blobs detection problem by searching for local extrema through the scale dimension, as we are going to see in the next paragraph.

2.3. Local Extrema Detection

As it is common, the candidate blobs result from the detection of the local extrema in the formed scale-space representation. Specifically, the local maxima correspond to the dark blobs and the local minima to the bright. In order to detect them from the scale-space representation, we define window of size $K \times K$ sample points with its center the candidate extremum. Each candidate point is compared to its $K^2 - 1$ neighbors, in the current scale's level and K^2 neighbors in each one of its neighbors scale levels. It is selected only if it is a maximum (or minimum) in this cube. The parameter K affects the minimum distance between two blob centers and is set equal to r. To eliminate the false detections due to noise, a threshold T to the Magnitude Projection Image is introduced. This threshold controls the sensitivity of the proposed method to the detection of the blobs. In all experiments we have conducted, this parameter was taking values in the range $0.1-0.2$. The sampling frequency of the scale domain depends on the expected variations between the blob radii. An increment of the sampling frequency leads to more accurate results but also increases the computational complexity of the technique.
An outline of the proposed algorithm follows.

Input: Image I, Set $\mathbb{S}_r$ and Threshold T
Compute the gradient of the input grayscale image I
for $r = r_{\min} : s_r : r_{\max}$ **do**
  Compute $\mathbf{p}_{\pm}(r)$ using Eq. (1)
  Construct the MPI $M_r(\mathbf{p}_{\pm}(r))$ using Eq. (2)
  Use Eq. (3) to smooth out MPI
end
for $r = r_{\min} + s_r : s_r : r_{\max} - s_r$ **do**
  Find the local maxima of the MPI, if they are bigger than T and are maxima in three $K \times K$ consecutive regions
end
Output: The selected centers and radii of the blobs

Algorithm 1: Outline of the proposed algorithm

Concluding, the proposed technique indicates high accuracy in detecting blobs and its computational cost is very low and comparable with the computational cost needed by the state of the art techniques [9].

3. EXPERIMENTAL RESULTS

In this section, in order to evaluate the performance of the proposed technique and highlight its invariance to several geometric and photometric deformations, we have conducted a number of experiments, and its performance is compared against well known blobs detection techniques such as the conventional FRST [13], the Hough [14] and SIFT based [15] techniques. On the other hand, in order to point out its possibilities in estimating parameters that are closely related to the size of blobs thus solving well known and sub-optimally solved problems, we use the proposed technique for removing the well known Moiré Effect [16], [17] from an x-ray image.

3.1. Experiments

3.1.1. Experiment 1

The goal of this experiment is to point out the invariance of the proposed technique to variations of the scale, luminance and shape as well as to the presence of partial occlusions. To this end, we have applied the proposed technique on several images and the obtained results are shown in Fig. 2. In the same figure for comparison, the obtained results from the application of the well known Hough transform are shown. As it is evident from this figure, the proposed method is able to detect precisely the blobs even in the cases they were not perfectly cyclic. However, this is not the case for the Hough transform, whose performance is strongly affected from the circularity of the blobs.

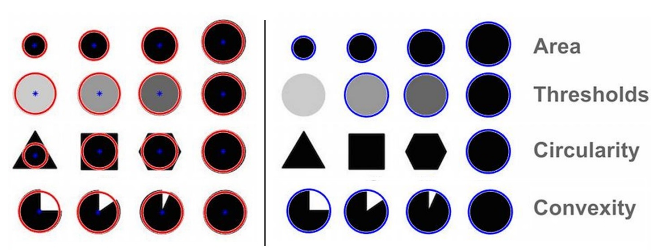

Fig. 2. Blobs detection results obtained from the application of the proposed method (red) and the Hough transform (blue) to the shapes shown in the image ($r_{\min} = 12$, $s_r = 4$ and $r_{\max} = 40$ pixels)

3.1.2. Experiment 2

In this experiment we are going to test the proposed method in detecting blobs invariably to their scale. To this end, the proposed technique is applied to the left image shown in Fig. 3 where there is a large number of artificial blobs of different sizes. As it is clear from the results shown in the right image of Fig. 3, the proposed technique precisely detects all the existing blobs. In addition, the proposed technique is ap-

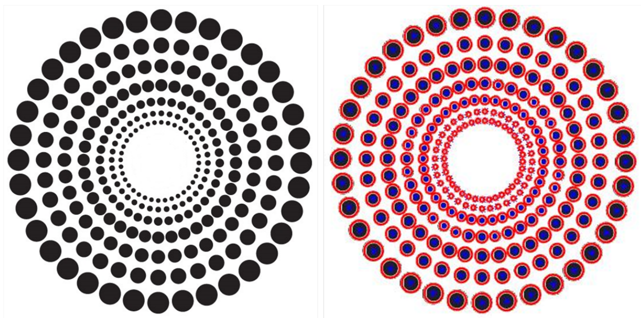

Fig. 3. Invariance of the proposed method to scale variations ($r_{\min} = 2$, $s_r = 4$ and $r_{\max} = 25$ pixels)

plied to the left image shown in Fig. 4 containing physical, with some of them partially occluded, blobs with shape and scale variations. The obtained results are shown in the right image of Fig. 4 and as it is evident all the dominant blobs are successfully detected.

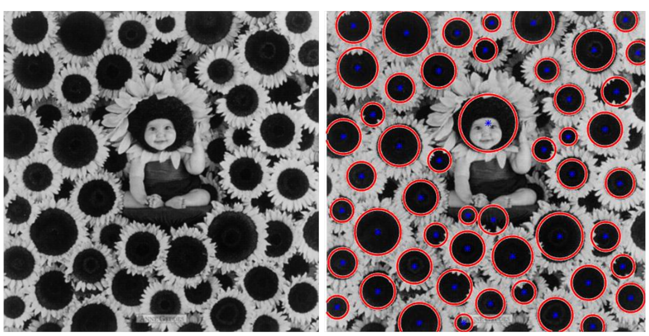

Fig. 4. Detection of the dominant blobs ($r_{\min} = 8$, $s_r = 4$ and $r_{\max} = 45$ pixels)

3.1.3. *Experiment 3*

In this last experiment we are going to apply the proposed method in a more difficult blobs detection problem. More specifically, we apply the method in an image that contains 95 brights blobs (golf balls) with many of them being partially occluded. Their detection is performed by searching for local minima in the Magnitude Projection Image. As we can see in Fig.5 (a) all 95 balls have been detected even in the cases they were partially occluded and thus, clearly, their distinction constitutes an extremely difficult problem. For comparison reasons in the same figure, the results obtained from the application of well known blobs detection techniques based on the conventional FRST, the SIFT and the Hough transform respectively, are also shown. As it is clear, the proposed method outperforms its rivals both in accuracy and detection rate. Specifically, the conventional FRST (Fig. 5 (b)) detects 91 balls, the Hough transform based method (Fig. 5 (c)), detects 92 blobs while the SIFT based one (Fig. 5 (d)) 79 out of 95. This is because, as we can easily see, some blobs are identified as one blob, and some others are not detected at all.

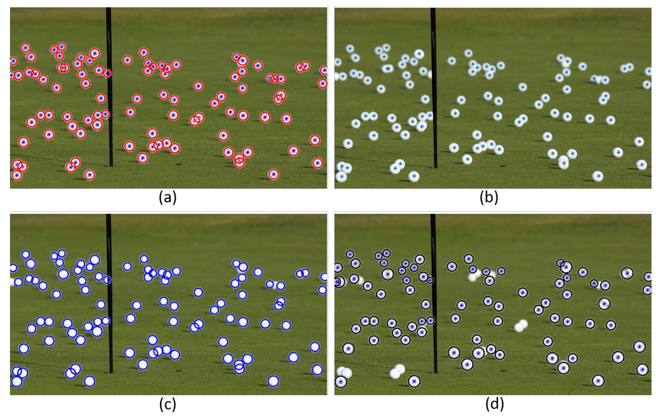

Fig. 5. Bright blobs detection with the results of the proposed method (a) to be more accurate than that of conventional FRST (b), Hough transform (c) and SIFT (d) based techniques ($r_{\min} = 5$, $s_r = 1$ and $r_{\max} = 11$ pixels)

3.2. Moiré Effect's Removal as a Blobs Detection Problem

In this paragraph we are going to apply our method for the elimination of the well known Moiré effect which is frequently appeared in x-ray images. The Moiré effect can occur in the x-ray spectrum when two (2) Bucky grids are superimposed. This effect degrades the quality of the image and, as it is more than clear, it is crucial to be removed without affecting the original image. This pattern is noticeable in the frequency domain as a number of unexpected dots, whose removal implies both the detection of their center and radius. So far, several methods have been proposed in the literature [16], [17]. Most of them are using filters (Gaussian, median, notch) to remove this undesirable effect. However, the precise localization of the noisy regions remains a challenging problem. For this purpose, the proposed method can be used to precisely detect them. In this experiment, the x-ray image shown in Fig. 6, with obvious Moiré effect is used. The steps followed for the image denoising are shown in Fig. 6. The detected blobs correspond to the undesired frequencies and must be removed. A notch filter, which is a band-stop filter with narrow stop-band, is appropriate for this purpose. It's application to the frequency domain of the original image

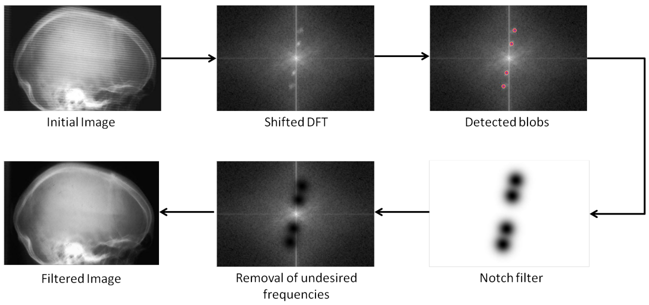

Fig. 6. Detection of undesired blobs in the frequency domain of a noisy image and their removal for image restoration

with its centers in the detected blob centers results in a noise free image without any noticeable loss in details.

4. CONCLUSIONS

In this paper a blobs detection method based on a simplified version of the fast radial symmetry transform was presented. Its performance was evaluated from its application on several images and was compared against the conventional FRST, Hough and SIFT based blobs detection techniques. In all experiments the proposed method outperformed its rivals in both accuracy and detection rate. Moreover, its reduced computational complexity permits its use in real-time applications. In addition, the proposed technique was also successfully used for the automatic and perfect elimination of the well known Moiré Effect that degrades the quality of x-ray images.

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