MEAN SHIFT-BASED OBJECT TRACKING USING PROPER COLOR SPACE CHANNEL

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ABSTRACT

Color features show robustness against many variations such as translation, rotation, viewpoint change, partial occlusion, low resolution, pose variations, etc. Thus, they are considered effective cues for object representation and are widely employed for visual tracking. Mean shift algorithm is a robust non parametric technique that is used for estimating the gradient of a density function. It is employed widely as a fast and robust object tracker that can utilize any feature space such as the color space. In this article, we present a simple but rather effective enhancement to the mean shift algorithm to distinguish an object from its background by using a proper color space channel that is selected according to the region of interest.

Keywords: Color Space; Histogram; Mean Shift; Object Tracking.

1. Introduction

Color features are invariant to translation, rotation, partial occlusion, viewpoint change, pose variations, zooming, resolution, etc. They are also easily extracted. Therefore, color histograms are widely considered as effective cues for representing and identifying objects in the scene [1]. Object recognition and tracking can be accomplished through histogram comparison between the target model and its candidate (Cha [2] provide a comprehensive survey on distance/similarity measures that are used to compare two probability density functions represented by nominal type histograms).

Regarding to the powerful information provided by color spaces through color histograms to image and video processing, selecting the appropriate color space becomes a crucial decision that has to be made before using the color feature for a particular task such as object segmentation, detection, identification, or tracking. For example, an experimental evaluation study has been conducted by Paschos [3] to measure the performance of color texture analysis methods such as segmentation/classification through using different color spaces (RGB, HSV, L*a*b). The study has found that The HSV has the best performance in normal and noisy conditions. Another comparative evaluation survey has been provided by Vezhnevets et al. [4] about different skin color detection methods used in different color space. The study has shown that the goodness of the color space for skin modeling cannot be determined because different modeling methods react very differently on different color spaces. Shih and Liu [5] assess the performance of content-based face image retrieval in different color spaces using the PCA (Principal Component Analysis) algorithm. The comparative assessment is done by using 12 color spaces (RGB, rgb, HSV, HSI, YIQ, YUV, YCbCr, XYZ, L*a*b, L*u*v, U*V*W, and $I_1I_2I_3$) by evaluating 7 color configurations for every single color space. The experimental results show that some color configurations, such as YV in the YUV color space and YI in the YIQ color space, help in improving face retrieval performance.

Mean shift tracking is a robust non parametric technique for gradient estimation of a density function using a generalized kernel approach. It is considered a widely used tool for robust and fast object tracking that can use any feature space such as the color space. The mean shift algorithm was originally proposed by Fukunaga and Hostetler [6] for the pattern recognition problems of data clustering and intrinsic dimensionality determination. It was revived, after two decades, by Cheng [7] where he provided a general analysis of the algorithm calling to benefit from its many interesting and useful properties and stressing on its ability of seeking modes of real functions and its applications in clustering analysis and global optimization. The first use of the mean shift algorithm as a real-time tracker (face tracker) was provided by Bradski [8].The popularity of the algorithm became more evident in the computer vision society after its successful application to image segmentation and tracking by Comaniciu et al. [9, 10, 11].

In this paper, we provide a simple but rather effective enhancement to the mean shift algorithm to deal with the discrimination of an object from its background by trying to use the most appropriate color space channels according to the selected region of interest based on a simple evaluation criterion.

The paper is organized as follows. In section 2, we will review some variants of the mean-shift algorithm. In section 3, a simple review of the mean shift algorithm will be given and then our enhancement measure that is capable of selecting the appropriate color space channel will be introduced. In section 4, experimental results and comparisons will be shown and then a discussion about them will be introduced. In section 5, concluding remarks and future work will be provided.

2. Related work

Bradski [8] develops a real-time object tracking algorithm based on the mean shift algorithm (for the first time) to deal with dynamically changing probability density distributions. His algorithm is known as a continuously adaptive mean shift algorithm or simply “CAMSHIFT”. The CAMSHIFT algorithm uses a 1D color histogram sampled from the hue channel in the HSV color space to represent the probability density distribution of an object (after finding that his first choice of 2D color histogram sampled from red and green channels of the normalized rgb color space is much more sensitive to lighting changes). The algorithm has been applied for face tracking showing a four-degree of freedom (X, Y, Z location [heaving, swaying, surging] and head roll).

Collins [12] adapts Lindeberg’s theory of blob scale detection based on local maxima of differential scale-space filters to the problem of selecting kernel scale for the mean shift algorithm.

Allen et al. [13] evaluate the effectiveness of the CAMSHIFT algorithm for general object tracking by tracking multihued objects or objects where the hue channel alone cannot be used to discriminate between the objects and the surrounding background. They use a 3D HSV histogram for object representation, after finding that increasing the quantized feature spaces can enhance the tracking performance. They also weight the histogram with a simple monotonically decreasing kernel profile when the selected region contains pixels that belong to the background. In addition, they reduce the similarity between the object and the background by using a ratio histogram. Finally, they conclude from the results that the CAMSHIFT algorithm can be applied successfully but with inferior performance compared to the mean shift tracker.

Zhao *et al.* [14] use a simplified version of the color correlogram that was originally proposed in [20] as a new color histogram model to represent an object. By this new representation, they can incorporate spatial correlation of pairs of colors changes which is needed to obtain the orientation information. In addition, they extend the mean shift algorithm to a 3D domain to find both the target position and its orientation.

Babu et al. [15] combine two well-known trackers, SSD (sum of squared differences) tracker and the mean shift tracker, to track fast-moving objects. The two trackers complement each other by overcoming their respective disadvantages leading to better performance of the proposed tracker over the individual ones.

Li [16] presents an adaptive binning color model for the mean shift tracker by analyzing the object color based on a clustering algorithm, and then according to the result, the color space of the object is partitioned into subspaces by orthonormal transformation. Consequently, a color model is proposed considering both weighted number of pixels and intra-cluster distribution using ICA (Independent component analysis). Finally, the mean shift algorithm adopts the proposed color model which leads to better performance but at the cost of more computation.

Leichter et al. [17] suggest a simple method to use multiple reference histograms, obtained from different views of the target, for producing a single histogram that is more appropriate for tracking the target. Then, a convex hull of these histograms is used as the target model in order to enhance the performance of the mean shift tracker.

Exner et al. [18] present simple low-cost extensions to the CAMSHIFT for addressing the following issues. First, they accumulate multiple histograms to deal with object appearance changes (a reference histogram is pre-computed for each different appearance). Then, they support object identification for tracking multiple targets in cases of partial and full occlusion by making use of all possible reference histograms. Finally, they address the redetection of lost targets.

Mazinan et al. [19] suggest an improved convex kernel function to enhance the performance of the mean shift algorithm against partial occlusion. They also integrate the motion information of the desired sequence to the mean shift algorithm as another cue besides the color cue to overcome the background clutter and sudden light changes. In addition, they use a Kalman filter to solve the full occlusion assuming a constant speed.

3. Mean Shift-based Object Tracking

The analysis of the mean shift algorithm [9] is reviewed here for the sake of completeness. Given a set of n points in the d-dimensional space R^d; $\{x_i\}_{i=1\dots n}$, the multivariate kernel density estimate with kernel $K(x)$ and a bandwidth h (i.e. window radius) is given at the point x by the following formula:

$$\hat{f}(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \qquad (1)$$

To minimize the average global error between the estimate and the true density, the following multivariate Epanechnikov kernel is calculated as follows:

$$K_E(x) = \begin{cases} \frac{1}{2} c_d^{-1}(d+2)(1-\|x\|^2) & if\ \|x\| < 1 \\ 0 & otherwise \end{cases} \tag{2}$$

where c_d is the volume of the unit d-dimensional sphere.

Another commonly used kernel is the multivariate normal, given by:

$$K_N(x) = (2\pi)^{-d/2}\, e^{\left(-\frac{1}{2}\|x\|^2\right)} \tag{3}$$

The kernel profile, which is a radially symmetric kernel, is defined as a function $k : [0,\infty) \to R$ such that $K(x) = k(\|x\|^2)$. Therefore, we can define the equations (2) and (3) as follows:

$$k_E(x) = \begin{cases} \frac{1}{2} c_d^{-1}(d+2)(1-x) & if\ x < 1 \\ 0 & otherwise \end{cases} \tag{4}$$

$$k_N(x) = (2\pi)^{-d/2}\, e^{\left(-\frac{1}{2}x\right)} \tag{5}$$

Now, the density estimate in eq. (1) can be written in terms of the kernel profile notation as follows:

$$\hat{f}_K(x) = \frac{1}{nh^d} \sum_{i=1}^{n} k\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \tag{6}$$

By denoting that

$$g(x) = -\acute{k}(x) \tag{7}$$

And assuming that the derivative of k exists for all $x \in [0,\infty)$, except for a finite set of points. A kernel G can be defined as:

$$G(x) = Cg(\|x\|^2) \tag{8}$$

Where C represents a normalization constant.

Then, by taking the estimate of the density gradient as the gradient of the density estimate, we get the following

$$\begin{aligned} \nabla f_K(x) \equiv \nabla \hat{f}_K(x) &= \frac{2}{nh^{d+2}} \sum_{i=1}^{n} (x-x_i)\, \acute{k}\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \\ &= \frac{2}{nh^{d+2}} \sum_{i=1}^{n} (x_i-x) g\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \\ &= \frac{2}{nh^{d+2}} \left[\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)\right] \left[\frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x\right] \end{aligned} \tag{9}$$

Where $\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)$ is assumed to be nonzero.

The last bracket of eq. (9) represents the sample mean shift vector, i.e.

$$M_{h,G}(x) \equiv \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x \qquad (10)$$

And the density estimate, computed with kernel *G*, at *x* is

$$\hat{f}_G(x) \equiv \frac{C}{nh^d} \sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \qquad (11)$$

Now, from equations (9), (10), (11), the estimate of the density gradient becomes

$$\hat{\nabla} f_K(x) = \frac{2/C}{h^2} \hat{f}_G(x) M_{h,G}(x) \qquad (12)$$

Then, the sample mean shift becomes

$$M_{h,G}(x) = \frac{Ch^2}{2} \frac{\hat{\nabla} f_K(x)}{\hat{f}_G(x)} \qquad (13)$$

The last equation shows that the sample mean shift vector with kernel *G* is an estimate of the normalized density gradient obtained with kernel *K*.

The mean shift algorithm is then specified as to recursively compute the mean shift vector $M_{h,G}(x)$ and translates the center of kernel G by this vector. So, the successive locations of kernel *G*, denoted as $\{y_j\}_{j=1,2,\dots}$, are computed as follows:

$$y_{j+1} = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{y_j-x_i}{h}\right\|^2\right)}, \quad j = 1,2, \dots. \qquad (14)$$

Then, the density estimates computed with kernel *K* in the points given by eq. (14) are:

$$\hat{f}_K = \{\hat{f}_K(j)\}_{j=1,2\dots} \equiv \{\hat{f}_K(y_j)\}_{j=1,2\dots} \qquad (15)$$

If the kernel *K* has a convex and a monotonic decreasing profile, then the equations (14) and (15) are convergent.

3.1. Mean shift as a tracker

We will consider here, the Bradski implementation [8] which can be summarized as follows:

1- Choose the size and the initial location of the region of interest (ROI).

2- Calculate the histogram of the ROI

3- Calculate the color probability distribution image through histogram back-projection

4- Compute the mean location in the selected ROI as follows:

$$M_{00} = \sum_x \sum_y I(x,y), \qquad M_{10} = \sum_x \sum_y xI(x,y), \qquad M_{01} = \sum_x \sum_y yI(x,y) \qquad (16)$$

where M_{00}, M_{10}, M_{01} are the zeroth and first spatial moments.

$$x_c = \frac{M_{10}}{M_{00}}, \quad y_c = \frac{M_{01}}{M_{00}} \tag{17}$$

5- Center the selected ROI at the mean location computed in step 4

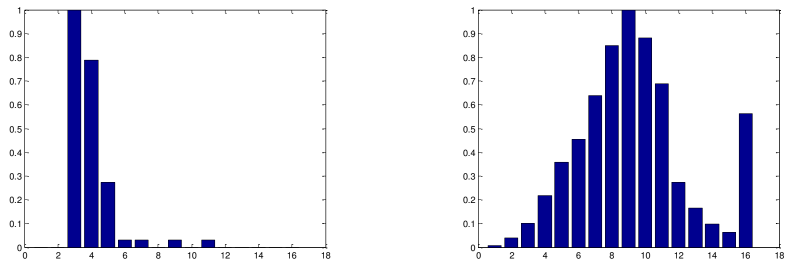
6- Repeat steps 4 and 5 until convergence or until the mean location moves less than a predefined threshold.

3.2. The proposed enhancement

Our enhancement to the mean shift tracker is to choose the appropriate color space channel that is able to better discriminate the object from its background. This method could be much more effective than other methods in distinguishing the object from the background, and hence enhancing the tracker robustness against failures as seen in the results. This enhancement goes as follows:

1- Find the index (indices) of the maximum bin(s) value(s) "the dominant bin(s)" in the histogram of the selected ROI.

2- Calculate the histogram of a predetermined searchable area around the ROI.



(a) (b)

Fig.1. Examples of the histograms when using the value channel for sequence no.1 a) ROI histogram, b) searchable-area histogram

3- Find the bin value of the searchable-area histogram that corresponds to the index given in step 1.

4- Divide the bin value given in step 3 by the sum of the histogram calculated in step 2 in order to know its representation percentage in the searchable-area.

5- If the output of step 4 is a vector (In case there are two or more equal dominant bins), then sum it to produce a scalar.

6- Calculate the probability distribution of the selected ROI by back-projecting its histogram.

7- Calculate the discrimination value of selected ROI by dividing the sum of its probability distribution calculated in step 6 by its area.

8- Divide the scalar calculated in step 5 by the discrimination value calculated in 7 and store the result as a similarity measure for later comparison.

9- Repeat this algorithm for the all thirteen color space channels.

10- The color space channel with the minimum similarity measure is chosen to work with the mean shift tracker.

4. Experimental Results and Discussion

In this paper, we used five sequences from the PETS (Performance Evaluation of Tracking and Surveillance) public datasets (PETS 2000 and PETS 2004) to investigate the robustness of our new tracker. We have tracked distant and very distant objects using noisy and low resolution cameras. In all sequences, we have used the same region of interest to deal with all examined color channels, and thus we have ensured a fair evaluation. We have investigated the potency of four color spaces plus the gray channel in dealing with the tracking process. These color spaces are RGB, HSV, YIQ, and YCbCr. Table no. 1 shows the resolution of the used sequences.

In Fig. 2, different probability distribution images are shown for different color space channels where the tracking of a person's head begins in sequence no. 1. From this figure, we have a strong clue about how the selection of the appropriate channel can be very effective in pursuing the tracking process. For example, Fig.3 shows us the success of the tracking process when using the value channel of the HSV color space where the similarity measure between the ROI and its background is 3.5, while it has a catastrophic failure when using the hue channel as shown in Fig. 4 where the similarity measure is 18.2. Tracking the person's torso is successful when switching to the saturation channel in the HSV color space as shown in Fig. 5. It also fails greatly when using the hue channel as shown in Fig. 6 or when using a 3D RGB color histogram as shown in Fig. 7.

For sequence no. 2, the tracking process is successful when using the value channel of the HSV color space as shown in Fig. 8. For sequence no. 3 shown in Fig. 9, the tracking is successful when using the hue channel. But it is also successful for the value and saturation channels in the HSV color space and the luminance channel in the YIQ color space.

For sequence no. 4 tracking a person's torso shows the successful application of the value channel in the HSV color space (see Fig. 10). It also succeeds when using the luminance channel in the YIQ color space, but it fails when using the hue channel as shown in Fig. 11.

Different frames of sequence no. 5 are shown in figures 12, 13, 14, and 15. Here the best channel to perform the tracking process of a white truck is the luminance channel in the YIQ color space and the value and saturation channels in the HSV color space. While using the standard CAMSHIFT fails greatly. The tracking also fails when using a 3D HSV or a 3D RGB.

We can conclude from the above, that the appropriate selection of color space channels plays a very crucial role in the tracking process. Therefore, we deemed the success of our modified tracker to its appropriate selection of the used color space channel, which in turn is done according to the selected region of interest.

Table 1.
resolutions of the used sequences

Sq. no.	Sequence belong to the public dataset	Resolution	Tracked Object
1	PETS 2004	384*288	Human
2	PETS 2004	384*288	Human
3	PETS 2004	384*288	Human
4	PETS 2001	320*240	Human
5	PETS 2001	320*240	Truck

5. Conclusions and Future Work

As we have said earlier, color features are invariant to translation, rotation, partial occlusion, viewpoint change, pose variations, zooming, and resolution. Therefore, color histograms are considered very effective cues for representing different objects in the scene. Making use of the powerful information provided by color spaces is a very important issue. Thus, we have investigated how selection of the appropriate color space channels becomes a crucial decision that has to be made before using the color feature for a particular task such as object tracking. We have used the mean shift algorithm as a tracker because it is considered a robust, fast, and widely used tool for object tracking that can use any feature space such as the color space. We have demonstrated, by many examples, how choosing the appropriate color space channel can save the tracker from failure by providing a simple measure to the mean shift algorithm to deal with the discrimination of an object from the background. We have done so according to the selected region of interest. Although we have dealt with tracking distant and very distant objects using noisy and low resolution cameras, but our new tracker proves effectiveness and robustness against these conditions. For future work, we will investigate some other sequences such as those given by a moving camera or where there is a lot of traffic, etc, by adding, among other things, the switching ability between different channels for the same selected region of interest as a further enhancement to the mean shift algorithm to deal with the dynamically changing background.


Original Video Frame


A person's head is selected


Gray Channel

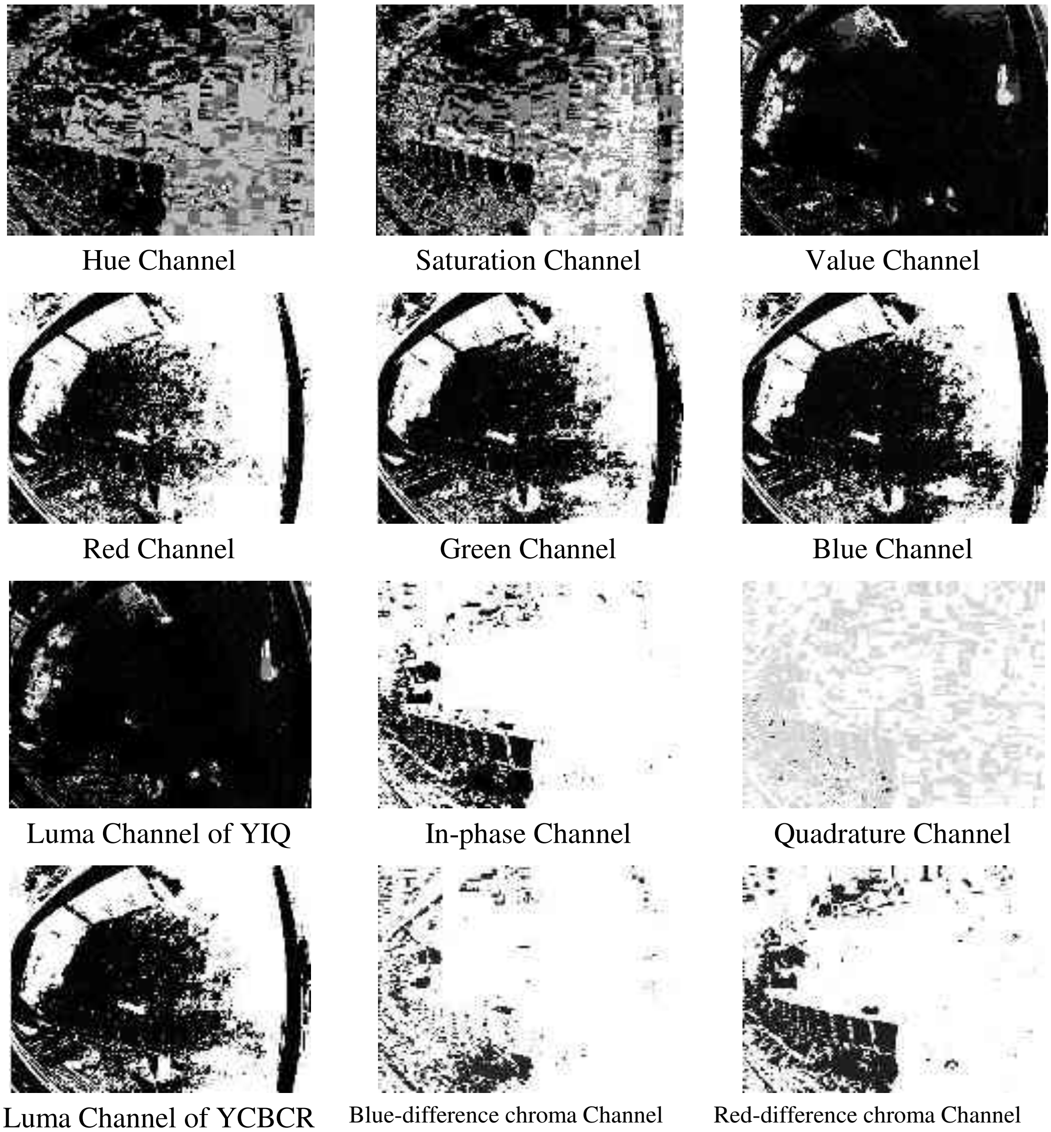


Fig. 2. Probability distribution images produced by various color space channels for the first frame of sequence no.1 where tracking a head of a walking person begins


Frame 20


Frame 40


Frame 60


Frame 80


Frame 100


Frame 112

Fig. 3. tracking a person's head in sequence no.1 using our method in different frames (the best channels here to perform tracking are the value channel in the HSV color space and the luma channel in the YIQ color pace)


Frame 2


Frame 4


Frame 6


Frame 8


Frame 10


Frame 12

Fig. 4. tracking a person's head in sequence no.1 using the mean shift operating on the hue channel in different frames

Frame 5 Frame 30 Frame 60

Frame 80 Frame 100 Frame 120

Fig. 5. tracking a person's torso in sequence no.1 using our method in different frames (the best channel here to perform tracking is the saturation channel in HSV color space)

Frame 1 Frame 3 Frame 5

Frame 7 Frame 9 Frame 11

Fig. 6. tracking a person's torso in sequence no.1 using the mean shift operating on the hue channel in different frames

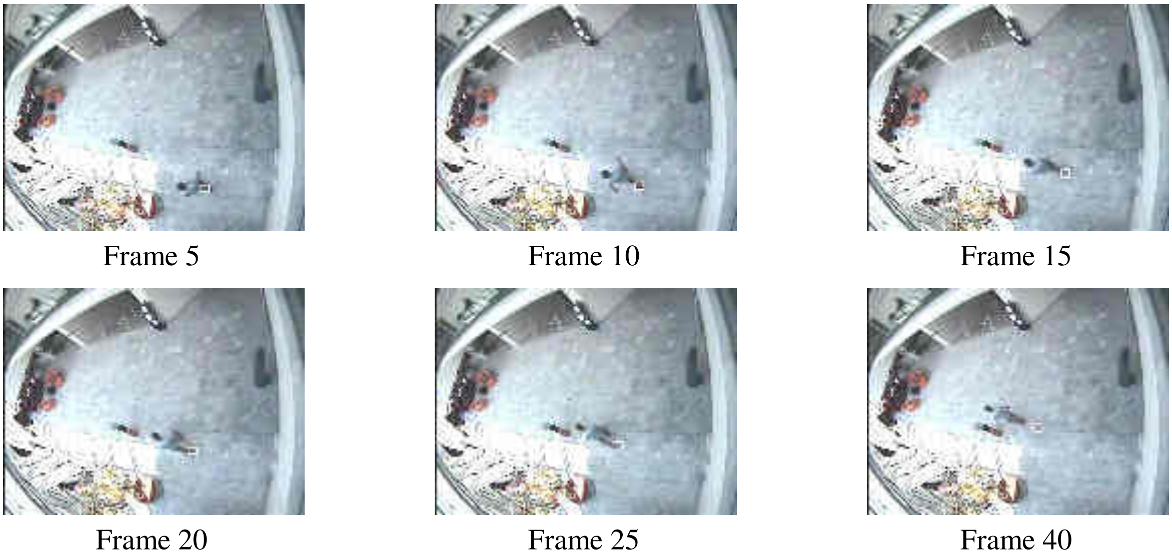


Fig. 7. tracking a person's torso in sequence no.1 using the mean shift algorithm operating on the red, green, and blue channels of the RGB color space in different frames

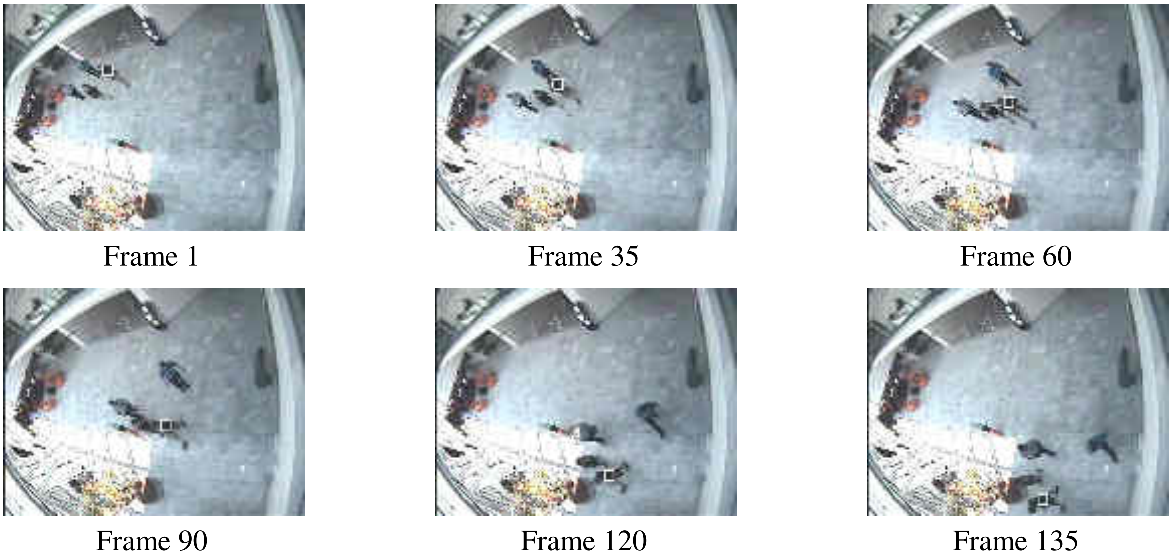


Fig. 8. tracking the torso of person no. 2 in sequence no.2 using our method in different frames (the best channels here to perform tracking are the value channel in the HSV color space and the luma channel in the YIQ color pace)

Frame 1 Frame 80 Frame 160

Frame 260 Frame 440 Frame 590

Fig. 9. tracking the torso of person no. 3 in sequence no.3 using our method in different frames (the best channels here to perform tracking are the hue, value, and saturation channels in the HSV color space and the luma channel in the YIQ color pace)

Frame 1 Frame 60 Frame 150

Frame 180 Frame 210 Frame 250

Fig. 10. tracking a person's torso in sequence no.4 using our method in different frames (the best channels to perform tracking are the value channel in the HSV color space and the luma channel in the YIQ color pace)


Frame 2


Frame 10


Frame 20


Frame 30


Frame 50


Frame 80

Fig. 11. tracking a person's torso in sequence no.4 using the mean shift operating on the hue channel of the HSV color space in different frames


Frame 1


Frame 5


Frame 10


Frame 15


Frame 20


Frame 25

Fig. 12. tracking a white car in sequence no.5 using our method in different frames (the best channels here to perform tracking are the luma channel in the YIQ color pace and the value and saturation channels in the HSV color space)

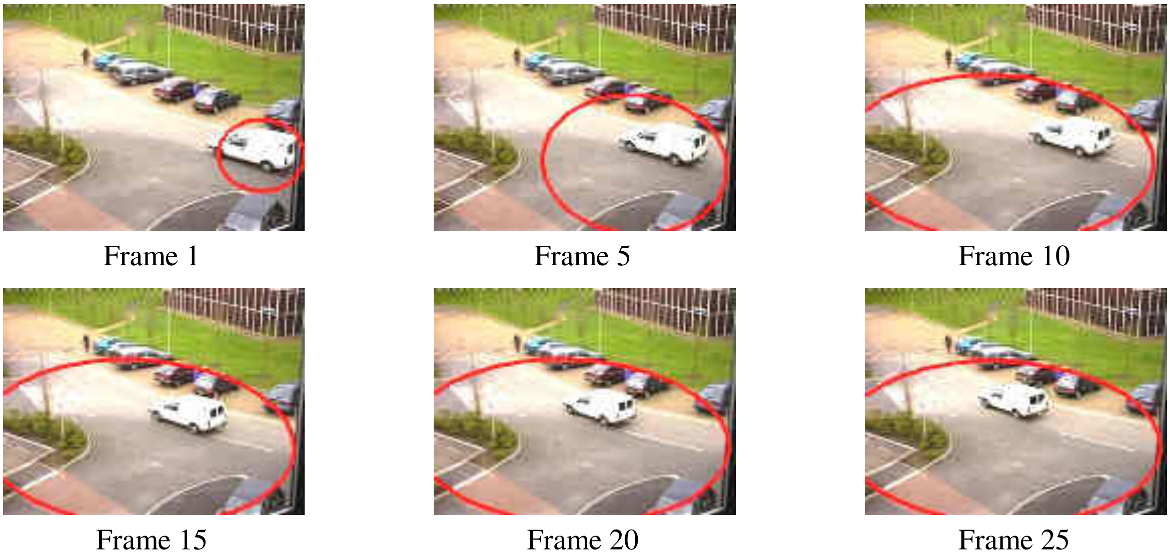


Fig. 13. tracking a white car in sequence no.5 using the standard camshift ‘that uses the hue channel’ in different frames

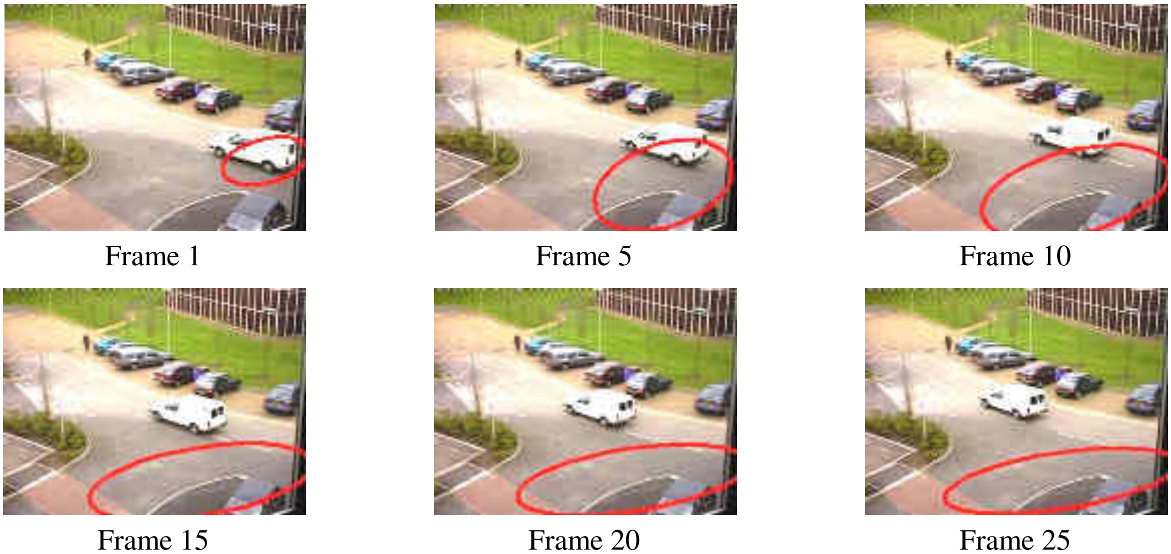


Fig. 14. tracking a white car in sequence no.5 using camshift with a 3D HSV histogram in different frames

Frame 1

Frame 5

Frame 10

Frame 15

Frame 20

Frame 25

Fig. 15. tracking a white car in sequence no.5. using camshift with a 3D RGB histogram in different frames

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تتبع الأهداف عن طريق الإزاحة المتوسطة باستخدام الصبغة اللونية المناسبة

الملخص العربى

اللون يعد من الخصائص الهامة التي يمكن من خلالها تمثيل الأشياء (الأهداف)، وذلك لقدرتها في التغلب على الكثير من العقبات مثل الانتقال والدوران و الاختفاء الجزئي وتغير وضع الهدف و انخفاض دقة التصوير ... الخ. ولهذه الأسباب يستخدم اللون بكثرة في عملية التتبع البصري. يعد خوارزم الإزاحة المتوسطة أسلوبا متينا لتقدير ميل دالة الكثافة ولذا فهو يستخدم بكثرة كمتتبع سريع ومتين بإمكانه استخدام الكثير من الخصائص من ضمنها خاصية اللون. فى هذه المقالة سنقدم أسلوبا جديدا لجعل هذا الخوارزم قادرا على تمييز الهدف من الخلفية الخاصة به عن طريق استخدام الصبغة اللونية المناسبة.