Robust Object Tracking using Log-Gabor Filters and Color Histogram

Oumaima Sliti, Chekib Gmati, Fouzi Benzarti and Hamid Amiri
Tunis El Manar University, National Engineering School of Tunis, Tunis, Tunisia

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Abstract: The performance of the tracking algorithm relies heavily on the target structural information accuracy. In this paper, we propose a robust object tracking method based on the log-Gabor texture and color histogram. Our hypothesis is that by adding log-Gabor filter to color features, and then embedded it in the mean shift framework, tracking performances will notably enhance. Compared with several methods of state-of-the-art mean shift trackers, our approach extracts the target information efficiently. Experimental results on various challenging videos show that the proposed method improves the tracking with fewer mean shift iterations.

1 INTRODUCTION

During the last two decades, real-time object tracking exists as a critical task in computer vision applications (Yilmaz, 2006). To overcome issues like non-rigid target structures, clutters and changing appearance patterns of the target, several algorithms have been established. The mean shift tracking algorithm has been quite popular lately by dint of its robustness and simplicity.

The target form is represented often as the color histogram, but it is inclined to fail especially when the target and its background have similar appearance. Therefore, the background-weighted histogram (BWH) has been proposed to decrease background intrusion in target representation (Comaniciu, 2003). Yet, after demonstrating that the BWH -based mean shift tracker and the conventional mean shift tracking method (Comaniciu, 2002) are equivalent, Ning et Zhang (Ning, 2012) proposed the corrected background-weighted histogram (CBWH). However, applying only color histograms in the mean shift algorithm has some deficiency (Yang, 2005). First, for the loss of the spatial information of the target, and second, for the confusion between the target and its background. Therefore, edge features (Haritaoglu, 2001) and Local Binary Pattern (LBP) texture (Ning, 2009) has been associated to the color histogram for a better target representation. Among these feature, the joint color-LBP texture histogram proposed by Ning (Ning, 2009), reaches the better tracking performance of the target. Indeed, the texture patterns, which offer the spatial structure of the target, are successful features to recognize and represent objects (Sonka, 2007). For three decades, the exploitation of features based on Gabor filters has been privileged, for their properties in image processing such as invariance to illumination and scale (Fischer, 2007) and (Kong, 2009).

In this paper, a robust mean shift tracker is proposed. We chose a bank of log-Gabor filter to model the target texture and then combined it with color to form an effective target representation. Compared with several state-of-art variants of mean shift tracker, this algorithm proves to be efficient in exploiting the target structural information and thus it reaches higher tracking performance with fewer mean shift iterations.

Section 2 briefly describes the mean shift algorithm. Section 3 discusses the theoretical background of the features used in this framework. Yet, experimental results are presented and discussed in section 4. Finally, section 5 concludes the paper.

2 CONVENTIONAL MEAN SHIFT ALGORITHM

2.1 Target Representation

In the mean shift algorithm, the target model is

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usually represented by its PDF (Comaniciu, 2003).
Target Model: In the beginning, let us define the target model representation:
The pixel locations of the target model, centred at 0 are denoted by $\{x_i^*\}_{i=1\ldots n}$. We consider the function $b: R^2 \to \{1 \ldots m\}$ which associates to each pixel location x_i^* its indicator $b(x_i^*)$ in the histogram bin. The target model $\hat{q}$ is computed as:

$$\begin{cases} \hat{q} = \{\hat{q}_u\}_{u=1..m} \\ \hat{q}_u = C\sum_{i=1}^{n} k(\|x_i^*\|^2)\delta[b(x_i^*) - u] \end{cases} \quad (1)$$

Note that $\hat{q}_u$ is the probabilities of feature $u = 1..m$ in the target model $\hat{q}$, δ present the Kronecker delta function, m is the number of feature spaces, and $k(x)$ is an isotropic kernel, which attribute smaller weights to pixels distant from the centre. The kernel $k(x)$ has a monotonic and convex decreasing profile, and it is presented as a function $k: [0, \infty) \to \mathbb{R}$ and $k(x) = k\|x\|^2$ (Comaniciu, 2003).
By imposing $\sum_{u=1}^{m} \hat{q}_u = 1$, the normalization constant C is defined as:

$$C = 1/\sum_{i=1}^{n} k(\|x_i^*\|^2) \quad (2)$$

Target Candidates: First, let us consider $\{x_i\}_{i=1\ldots n_h}$ as the pixel locations of the target candidate which is centered on the location y in the current frame. The target candidate model corresponding to the candidate region is computed by

$$\begin{cases} \hat{p} = \{\hat{p}_u(y)\}_{u=1..m} \\ \hat{p}_u(y) = C_h\sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta[b(x_i) - u] \end{cases} \quad (3)$$

The scale of the target candidate (i.e., the number of pixels) is determined by the constant h which plays the same role as the bandwidth (radius) in the case of kernel density estimation.
Similar to the target model, and by imposing the condition $\sum_{u=1}^{m} \hat{p}_u = 1$, we obtain the normalization constant

$$C_h = 1/\sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \quad (4)$$

The correspondence between the two normalized histograms of the target model $\hat{q}$ and the candidate model $\hat{p}(y)$ is calculated by a metric based on the Bhattacharyya coefficient:

$$\rho[\hat{p}(y), \hat{q}] = \sum_{u=1}^{m} \sqrt{\hat{p}_u(y_0)\hat{q}_u} \quad (5)$$

From where, the distance between $\hat{p}(y)$ and $\hat{q}$ is calculated by:

$$d[\hat{p}(y), \hat{q}] = \sqrt{1 - \rho[\hat{p}(y), \hat{q}]} \quad (6)$$

2.2 Mean shift tracking

Beginning by y_0 location in the previous frame, the iterative process is initialized. To minimize the distance (6) between $\hat{p}(y)$ and $\hat{q}$ we should maximize the Bhattacharyya coefficient. Taylor expansion is used around $\hat{p}_u(y_0)$, from where the linear approximation of the Bhattacharyya coefficient (5) is calculated by:

$$\rho[\hat{p}(y), \hat{q}] \approx \frac{1}{2}\sum_{u=1}^{m} \sqrt{\hat{p}_u(y_0)\hat{q}_u} + \frac{1}{2}C_h\sum_{i=1}^{n_h} \omega_i k\left(\left\|\frac{y-x_i}{h}\right\|^2\right) \quad (7)$$

Where

$$\omega_i = \sum_{u=1}^{m} \sqrt{\frac{\hat{q}_u}{\hat{p}_u(y_0)}}\delta[b(x_i^*) - u] \quad (8)$$

The first term in (7) is independent of y, thus, in order to minimize the distance in (6), the second term in (7) would be maximized. The estimated target moves, in the iterative process, from y to a new position y_1, is computed by:

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i\omega_i g\left(\left\|\frac{y-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n_h} \omega_i g\left(\left\|\frac{y-x_i}{h}\right\|^2\right)} \quad (9)$$

$g(x) = -k'(x)$, we suppose that the derivative of $k(x)$ exists for all $x\epsilon\,[0, \infty)$ (Comaniciu, 2003). Choosing the kernel g with the Epanechnikov profile, (9) would be reduced to:

$$y_1 = \frac{\sum_{i=1}^{n_h} x_i\omega_i g}{\sum_{i=1}^{n_h} \omega_i g} \quad (10)$$

Using (10), the mean shift locates, in the new frame, the most analogous region to the object.

3 PROPOSED METHOD

3.1 Log-Gabor Filter

For texture analysis, Gabor filters (Fischer, 2007) are often used for its efficiency of acquiring simultaneous localization of frequency and spatial information. However, the maximum bandwidth captured by those filters is approximately one octave. Whenever the bandwidth is larger, the DC component is directly obtained from the Gabor spectrum. This could be overcome by using the log-Gabor function proposed by Field (Field, 1987) which has two important characteristics to note. First, by definition, log-Gabor function has no DC component, which improves the contrast between the target and its background. Second, the transfer

function of the log-Gabor filter allows us to obtain large spectral information. Besides, log-Gabor function's bandwidth could vary from one to three octaves. Thus, the features used become more informative, effective and reliable (Zhitao, 2002). Those proprieties preserve true texture structures of the target. In this paper we adopted the new design of log-Gabor wavelets proposed in (Fischer, 2007). Log-Gabor filter have a Gaussian transfer function, viewed on the logarithmic frequency scale. It can be divided in polar coordinate system, into two components:

1-the radial filter which the frequency response is obtained by:

$$G_r(r) = exp\left(-\frac{[log(r/f_0)]^2}{2\cdot\sigma_r^2}\right) \quad (11)$$

2-the angular filter's frequency response is defined as:

$$G_\theta(\theta) = exp\left(-\frac{(\theta-\theta_0)^2}{2\cdot\sigma_\theta^2}\right) \quad (12)$$

By multiplying these two components, the overall log-Gabor transfer function is obtained:

$$G(r,\theta) = G_r(r)\cdot G_\theta(\theta) \quad (13)$$

where (r,θ), are the log-polar coordinates, f_0 and θ_0 present respectively the center frequency and the orientation angle of the filter, σ_r is the scale bandwidth and σ_θ represents the angular bandwidth. Often, a problem appears in the first scales, because G_r Eq. (11) would have significant amplitude beyond the Nyquist frequency ($\rho \geq log2(\frac{n}{2})$). Indeed, cut off sharply the filter response beyond the Nyquist frequency, distorts the filter form in the spatial domain (which could cause the appearance of side lobes or ringing). That's why, high frequencies are not covered in many implementations, and a part of the spectrum is frequently discarded, e.g. in (Ro, 2001). In order to overcome this problem, Nestares and al. included a non-oriented high-pass filter (Nestares, 1998). Thus, to prevent the loss of information of the target, we adopted the Gaussian high-pass oriented filters proposed by Fischer, which have a smooth shape without extra side lobes (Fischer, 2007).

3.2 Target Representation with Joint Color-log-Gabor Texture Histogram

The object and its background texture are frequently different, from where came the idea to joint log-Gabor texture to color feature for tracking.

To construct the filter bank, we used four different scales to insure the variation of radial frequency r and six orientations θ. In the feature extraction process, every frame in the video (i.e. in the space domain) would be transformed to the frequency domain by applying the Discrete Fourier transform (DFT) (Moisan, 2011). Thus, each pixel represents a particular frequency contained in the real domain image. To extract local frequency information, the image is convolved with banks of quadrature pairs of log-Gabor wavelets, and we reaches the best empirical results by using value of $\sigma_r = \sigma_\theta = 0.65$. While in the frequency domain, we can multiply the image with the filter. Then, the multiplied image is converted back to the space domain, by applying the inverse discrete Fourier transform.

Employing discrete Fourier transform (DFT), regular or inverse, offers an output of complex numbers, which is not a problem for the convolutions described above. But, the mean shift tracker is not designed to work with complex numbers, so it is a problem when using the filtered images for tracking, thus, the idea proposed in this section is to use a feature encoding (Sanderson, 2000) and (Daugman, 2002).

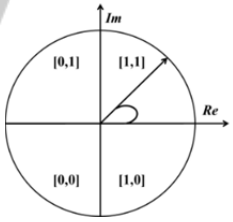


Figure 1: The process of phase quadrant demodulation.

Implementation (Feature Encoding): First, the 2D image (frame) is broken up into its number of rows. Each row (i.e. a 1D signal), would be convolved with 1D Gabor wavelets. Actually, the angular direction is taken instead of the radial one, corresponding to the columns of the 2D image, as the maximum independence occurs in the angular direction. According to the technique of the phase-quadrant demodulation, each phase of the output of the filtering process will be coded on two bits. The output of phase quantization is a grey code, so that when going from one quadrant to another, only 1 bit changes, this will limit the errors if the phase is calculated to the boundary between adjacent quadrants. The feature encoding process is presented in Figure 1. Finally, the encoding process generates a bitwise template containing a number of bits of information. The number of bits in the texture

template will be:

$$(angular\ resolution \times radial\ resolution) \times 2 \times number\ of\ filters\ used.$$

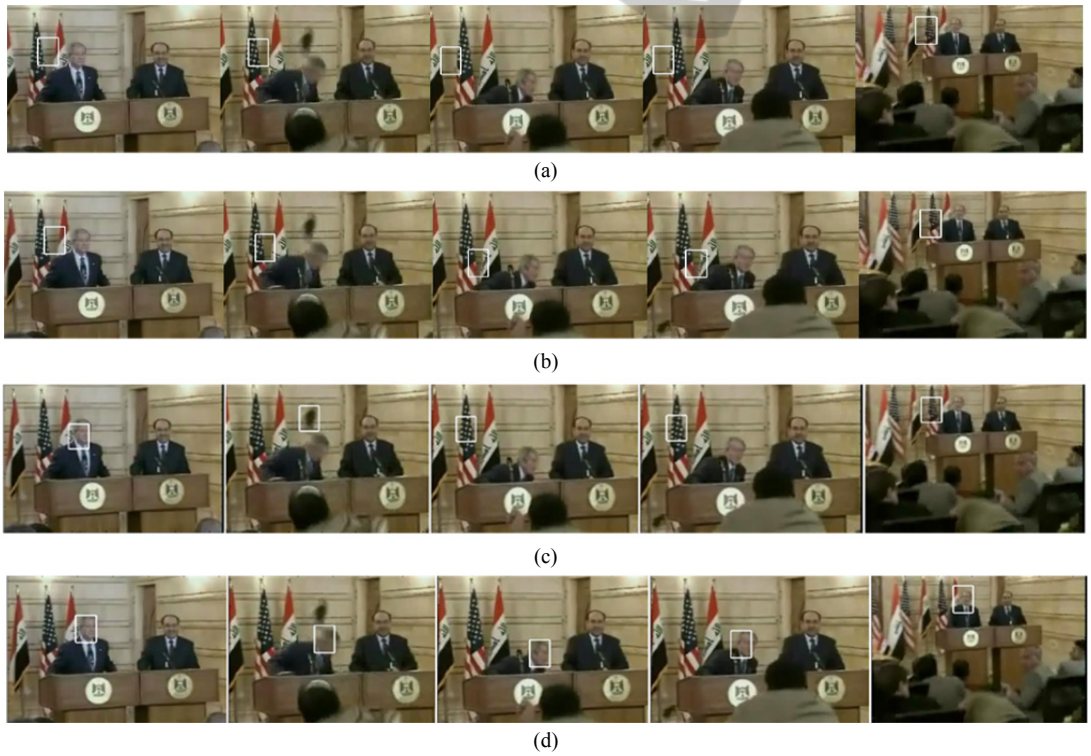
Afterwards, we use the generated bitwise template with the RGB channels to jointly describe the target model using (1), then embed it into the mean shift tracking framework. In order to acquire the texture and color distribution of the target region $\hat{q}_u$, we use (1) where $u = 8 \times 8 \times 8 \times T$. The first three dimensions (i.e. 8 ×8 ×8) illustrate the quantized bins of color channels, and the fourth dimension (i.e. T) is the bin of the log-Gabor texture patterns in the generated template. As well, the target candidate model $\hat{p}(y)$ is calculated by (3).

4 EXPERIMENTAL RESULTS AND DISCUSSION

In this section, representative and extensive experiments are performed to testify and illustrate the proposed joint log-Gabor texture-color model based mean shift tracking algorithm.

It will be compared with several state-of-art variants of mean shift tracker, we denote by M1 the background-weighted histogram (BWH) method, M2 the corrected background-weighted histogram (CBWH) method, M3 the joint color and LBP texture method and by M4 our proposed method.

In this paper, we just present some experimental results of different challenging public video sequences. The color of the target and its surrounding area could have the same color, the objects being tracked could change in shape and size due to the camera motion. These four algorithms are implemented in MATLAB R2013a interface and run on a PC with Intel® Core™2 Duo 2.1GHz CPU and 2 GB RAM, and tested on complexes sequences. The first experiment is on a video sequence of shoe_attack (Figure 2) with 115 frames of spatial resolution 360×480. In this video, we will track a region of size 42×28, and compare the target locating accuracies by the four target representations M1, M2, M3 and M4. Since no motion model has been affected, and despite the alter of decrease and increase of image intensity due to the camera's flashes (frame 52), the tracker adapted greatly to the non-stationary character of the head's movements which alternates abruptly with its fast reaction. The joint log-Gabor texture with the color feature proves to be robust to partial occlusion (frame 80), clutter,



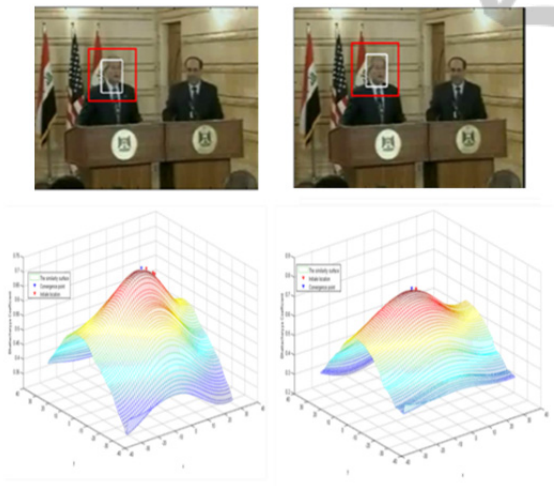
(a) (b) (c) (d)

Figure 3: Tracking results of shoe_attaque sequence by the target representation models (a) M1, (b) M2, (c) M3 and (d) M4. Frame 52, 80, 90, 94 and 115 are displayed.

distractors (frame 90), and camera motion (frame 115). In fact, the log-Gabor feature is actually responsive not only to the target itself, but also to the texture of the background. Consequently, the target is localized by tracking the non-background part of the filtered frames which have a positive impact on tracking performance.

To demonstrate the robustness of our approach, Figure 3 presents the surface computed by the Bhattacharyya coefficient for the 81× 81 pixels rectangle marked in Figure 3, frame 29.

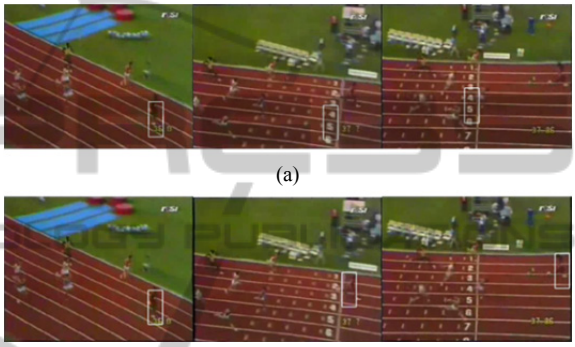
The target model has been compared with the target candidates of the first frame obtained by sweeping in frame 29 the rectangular region inside the bigger one. The iteration numbers of mean shift tracking with M1, M2, M3 and M4, in the frame number 29 are 6, 4, 4 and 2 respectively. While most of the tracking approaches based on only color (Comaniciu, 2003) and (Ning, 2012) and LBP texture (Ning, 2009), must proceed an exhaustive search in the rectangle to find the maximum of similarity, our proposed algorithm converged in lower number of iterations because it suppresses the backgrounds feature.



Frame 29_M3 Frame 29_M4

Figure 3: The similarity surface (values of the Bhattacharyya coefficient) of the two methods corresponding to the rectangle marked in frame 29_ (M3 and M4) in the shoe_attack sequence. The red triangles in the similarity surface represents the initial point, the blue triangle represent the final position. We can see that M4 converges much faster than M3.

The second experiment is on a video sequence of a sprint with 173 frames of spatial resolution 360×480. In this movie, we will track a region of size 82×33, describing the sprinter with heavy occlusions and whose dress color is the same as its background. So, the methods based only on color histogram M1 and M2 drift away and fail to track the target. To save space, Figure.3 presents only tracking results of the M3 and M4. During the sequence, the target form is often fuzzy, nevertheless the methods M3 and M4 based on texture joint color histogram can still locate the target. For this video we had a partial occlusion due to background color, thus, we used a bank of different log-Gabor filters constructed with six different scales and eight different orientations. It can be experimentally observed that the proposed approach can still locate the target when heavy occlusion appears starting with frame 156.



(a)

(b)

Figure 4: Tracking results of sprint sequence by the target representation models (a) M3 and (b) M4. Frame 116, 156 and 171 are displayed.

The second experiment is on a racing sequence (Figure 5) of about 155 frames, the driver's head was used as target model of size 30 ×40. The tracker was tested for the intense blurring (frame 17) caused by a shadow, scale changes due to the camera motion (frames 49 and 81), and the dramatic changes in appearance (frame130). However, neither M1 nor M3 can locate the target object while both M2 and M4 can still track the target accurately. The forth row of Table 1 gives the total numbers of iterations of the four methods, and it indicates that the proposed approach has the fewer number of iterations then M2, which prove that M4 performs better than the other trackers. The number of mean shift iterations necessary for each frame with the four methods is shown in Figure 6.

The peaks correspond to occlusion and the fast move of the driver's head caused by the high speed of the racing care. The M1 have few number of iteration, M3 need a tough search especially when no model has been affected to his head, but, our proposed algorithm succeeds to locate the target with less iteration. In addition, the intense blurring present in last frames due to the camera motion,

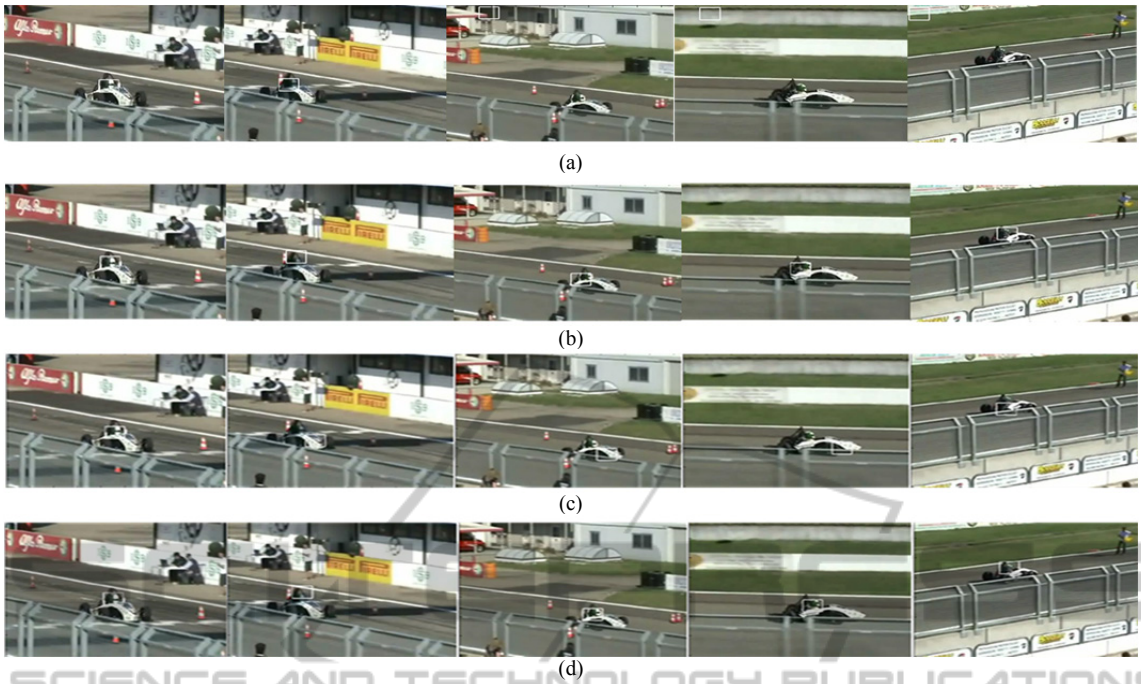


Figure 5: Tracking results of racing sequence by the target representation models (a) M1, (b) M2, (c) M3 and (d) M4. Frame 9, 17, 49, 81 and 130 are displayed.

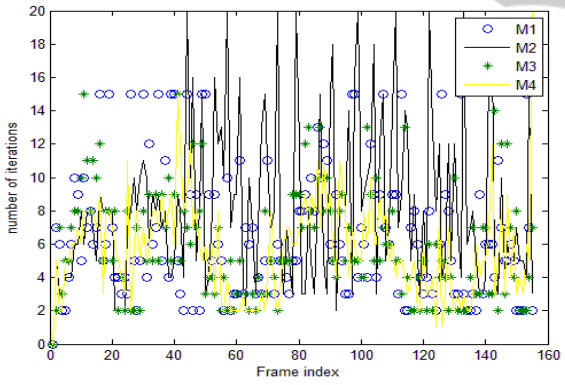


Figure 6: The number of mean shift iterations function of the frame index for the racing sequence.

does not influence the tracker performance for M4 (frame between 100 and 155) unless it failed to locate the target for M1and M3, while M2 locate the target but with an exhaustive search showed in the last and largest peak. In all these cases, M4 prove to be robust to the relative large movement between two consecutive frames which puts more of a burden on the mean shift procedure. In the tennis_table sequence of 300 frames, we will track the player's movements which alternate between slow and fast action and compare the target locating accuracies by the four target representations.

In this video the tracking is made more challenging by the quality of the sequence due to the camera motion and image compression artefacts. As shown in figure 7, in this scene the target appearance is slightly similar to its background. Figures 7(a)–7(b)–7(c) and 7(b) present the mean shift tracking results by the four target representation. Because the initial target region contains much of the background, the accuracy of the target location of mean shift tracking with M3 loses the object after frame 10 due to the change of the background caused by the camera motion. To save space, we show the experimental results only for first 43 frames. However, our proposed model M4 and the two methods based on color histogram M1 and M2, extract the main target features while suppressing the background features so that the target location is much more robust than that by M3 model. For each frame of this sequence, the minimum value of the distance of Bhattacharya (7), i.e., the distance between the target model and the target candidate, is shown in Figure 8.

The compression noise, and the fast movement of the player elevates the residual distance value from 0 (perfect match) to an about 0.35. Significant deviations from this value correspond to occlusions generated by the background where other persons exist and the player's moves (large changes in the representation). For example, the distance 0.5 peak corresponds to the partial occlusion in frame 278.

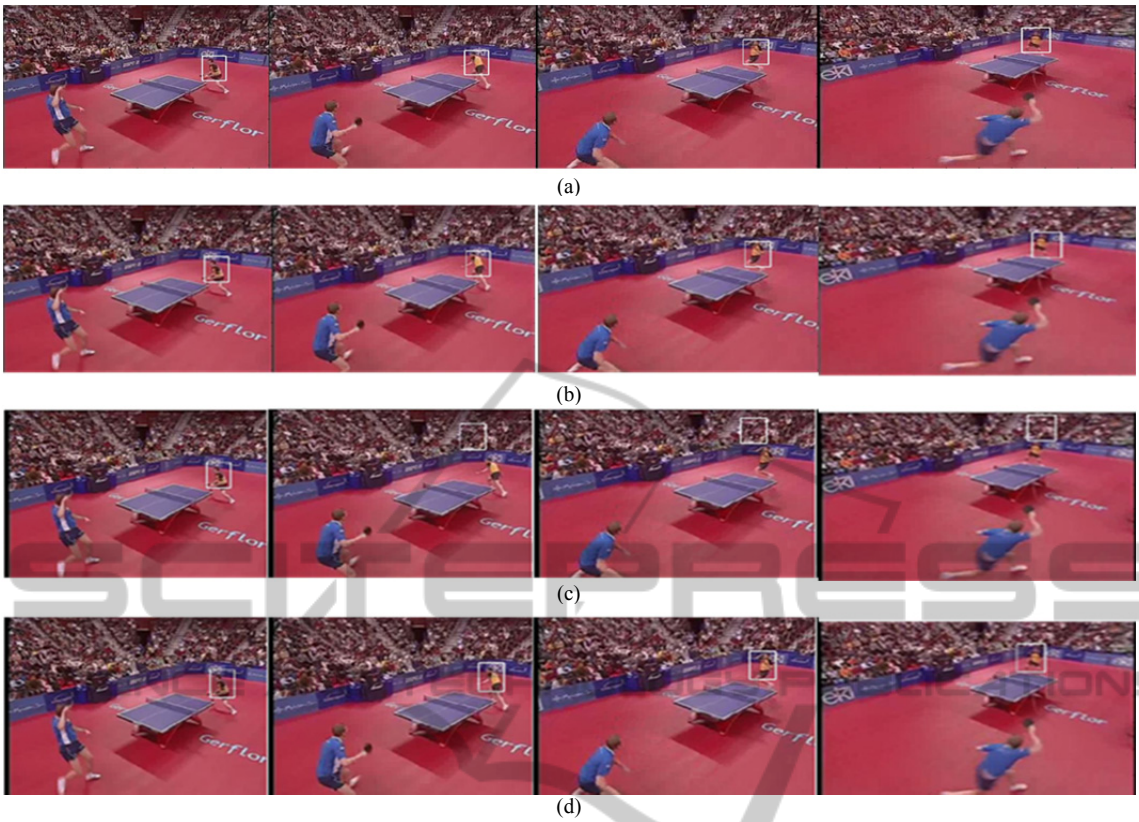


Figure 7: Tracking results of Tennis_table sequence by the target representation models (a) M1, (b) M2, (c) M3 and (d) M4 Frame 3, 14, 24, and 43 are displayed.

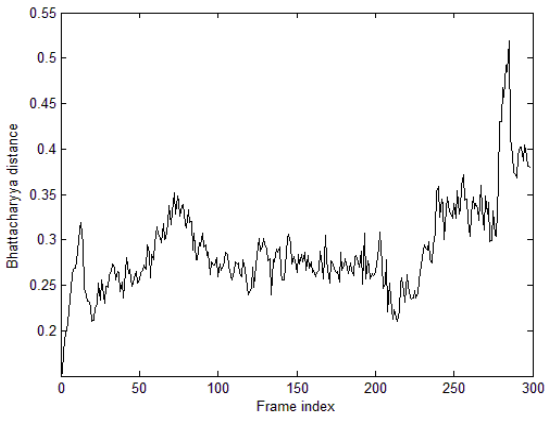


Figure 8: The minimum value of Bhattachayya distance function of the frame index for the Tennis_table sequence. The mean distance of Bhattacharyya is 0.2894 per frame.

At the end of the sequence, the person being tracked gets out of the scene, which produces a complete occlusion. Our proposed method proves to be robust not only because it succeed to localize the target, but also it tracks the key feature points of candidate region with less number of iterations (refer to Table 1), though it needs additional computation to calculate the log-Gabor banc of filter. In our approach we used four scales and six orientations,

Table 1: The number of mean shift iterations by the two methods.

Video sequence	Frames	Target Represen-tations	Mean shift iteration	
			Total number	Average number
Shoe_attack	115	M1	402	3.49
		M2	438	3.8
		M3	386	3,35
		M4	427	3,71
Sprint	173	M3	1039	9,03
		M4	869	7,55
Racing	155	M1	838	5,4
		M2	1278	8,24
		M3	1034	6,67
		M4	919	5,92
Tennis_table	44	M1*	195	4,43
		M2	183	4,15
		M3	202	4,59
		M4	181	4,11

* Since the target is lost after frame 44 for M1, we only use the first 44 frame in the calculation for M1.

but, in complexes scenes, sometimes we increase these numbers in order to make sure that the feature contains accurate information about the object. Thus, we adjust the log-Gabor filter parameters ourselves to find the best settings that different log-Gabor filters makes us think about speeding up the program, so, we aim to implement it in C/C++ which guaranty a significant speedup, making real time processing possible.

5 CONCLUSION

In this paper we presented a new filter based approach for video tracking of arbitrary objects. Log-Gabor feature is a powerful tool to measure the spatial structure of local image texture which has been modelled by a bank of log-Gabor wavelets. In order to improve the robustness of target representation and reduce the computational cost, we proposed a joint color and log-Gabor texture based mean shift tracking algorithm. Our proposed method use only one target representation and localize the new object and background appearances in every frame. The system deals with different objects and settings and is robust to perspective transformations, rotations, heavy occlusion and lightening conditions.

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