A Comparative Study between SIFT- Particle and SURF-Particle Video Tracking Algorithms

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Abstract

Video tracking is one of the most active research topics recently. Tracking of objects and humans has a very wide set of applications such as teleconferencing, surveillance, and security. We propose a new tracker to enhance the tracking process by making use of SURF descriptor and Particle filter. SURF is one of the fastest descriptors which generates a set of interesting points which are invariant to various image deformations (scaling, rotation, illumination) and robust against occlusion conditions during tracking. Particle filter is one of the commonly used methods in video tracking to solve non-linear and non-Gaussian problems. Particle filter generates a random set of points called particles or samples for any target to be used for tracking through the process of the algorithm. But the fact that the initial particles are chosen randomly causes degradation in efficiency and reliability of the tracking process. It is possible to lose the tracked target at any frame if any change happened in the scene. Previous researches proposed an integration of Particle algorithm and scale invariant feature transform (SIFT) descriptor to overcome potential problems. SIFT is a predecessor of SURF and shares the same characteristics except that SURF is much faster. A comparative study was held between the traditional particle filter, SIFT-Particle tracker and the proposed tracker. The proposed SURF-Particle tracker proved to be more efficient, reliable and accurate than traditional particle filter and SIFT-Particle tracker. The idea of the proposed tracker is to use the discriminative interest points generated by the SURF descriptor as the initial particles/ samples to be fed into particle filter instead of choosing these particles randomly as done in traditional simple particle filter. Experimental results using the Actions as Space-Time Shapes Dataset of the Weizmann Institute of Science proved the correctness of the proposed idea and showed improved efficiency and accuracy resulted from using our proposed tracker over traditional simple particle filter and SIFT-Particle tracker. It also proved to be faster than SIFT-Particle.

Keywords: *Particle, SIFT, SURF, Video tracking*

1. Introduction

Visual object tracking is one of the active research topics in computer vision for its highly important applications such as teleconferencing, surveillance, security, human computer interaction, video compression and video editing, etc... Object tracking aims at locating the position of an object, especially humans and vehicles in frames continuously and reliably against dynamic scenes [1]. Object/human tracking faces a number of challenges including complex object motion, non-rigid nature of objects, illumination changes, cluttered background and partial or sever occlusions [2]. Previously, many algorithms were developed to overcome object tracking challenges including Kalman filter- based method for Gaussian and linear problems [3], particle filter- based approaches have been applied to non-Gaussian and non-linear problems [2, 4, 5], Multiple hypothesis tracking (MHT) [6, 7], active contour-based tracking [8, 9], kernel-based tracking [10, 11], optical flow-based tracking [12], and blob-based tracking [13, 14].

Previously established algorithms succeed to overcome many challenges, however they still face difficulties in handling sever occlusions and background clutters [1].Mean shift was proposed to handle occlusions and clutters [15,16]. Although mean shift succeeded in many circumstances, it still performs less efficiently against dramatic changes in color or intensity [17].

Particle filter is robust in object tracking against occlusions and complex human actions [18, 19].It is a numerical method to solve nonlinear and/or non-Gaussian Bayesian filtering problems. Particle filters-based algorithms employ color distribution to define objects [20, 21]; the distance between the color histogram of the target and those of the candidates in frames is evaluated using some kind of proximity metric such as Bhattacharya distance. Actually, color is not a sufficient discriminative feature as it may be unreliable against illumination change, viewpoint change over time etc… [2].

Multiple features such as edges, corners and silhouette can be integrated to improve trackers performance, but the fact they are application-dependent makes them less effective against scaling, rotation and translation [1]. Recently, the scale invariant feature transform (SIFT) is used to provide feature points that are invariant to scaling, rotation, illumination and viewpoint change [22]. Mean shift was integrated with SIFT in [1] to improve object tracking in real scenarios. Particle filter was combined with SIFT in [2, 23, 24] in order to achieve more robust and accurate results. SIFT provided a robust enhancement, however, it is relatively slow. Speeded up robust features (SURF) is a variant of SIFT that shares the same robustness and distinctiveness but with a much faster computing speed [25]. In this paper the proposed tracking algorithm is an effective integration of SURF features and particle tracking. SURF features are extracted from the target frame to generate the most discriminative interesting points which are then fed into particle filter to begin the tracking of particles process. This framework is supposed to enhance the tracking of objects/humans as the particle filter will use only the particles representing the most discriminative points/particles of target.

The rest of this paper is organized as follows. Background of Particle filters theory; SIFT descriptor and SURF descriptor is presented in Section 2. In Section 3, the proposed framework is given. Experimental results are the described in Section 4. Finally conclusions and future work are given in Section 5.

2. Background

Particle filter is a Sequential Monte Carlo method for on-line learning within a Bayesian framework, generally applied to solve non-linear and non-Gaussian estimation problems. The first part of this section will present the particle filter theory.

Local invariant features are known to perform well in pattern recognition problems due to their robustness, distinctiveness and repeatability characteristics. The second part discusses the SURF descriptor in brief. The third part will explain the steps of SIFT briefly.

2.1 Particle Filtering

The basic idea of particle filter is that it estimates the posterior probability from a finite set of weighted samples/ particles [19]. Generally, particle filter is an iterative process that has three steps: Selection, Prediction and Measurement.

Let X_t , Z_t denote the state vector at time t and observation at time t respectively. Observations from time 1 to t is expressed as $Z_t = \{z_1, \ldots, z_t\}$. Suppose that at time t, each state has N weighted particles expressed as $\{s_t^{(i)}, w_t^{(i)}, i=1, \ldots, N\}$.

In Selection step, a new set of particles is chosen based on the highest posterior probability $p(x_{t-1}^{(i)} \mid z_{t-1})$ among the previous particle set at time t-1. Size of particle set (N) is constant.

In Prediction step, the prior probability $p(x_t|Z_{t-1})$ at time t is defined as:

$$p(x_t|Z_{t-1}) = \int p(x_t|x_{t-1})\, p(x_{t-1}|Z_{t-1}) dx_{t-1} \qquad (1)$$

Where $p(x_t|x_{t-1})$ is a state transition probability for t>0, and $p(x_{t-1}|Z_{t-1})$ is the posterior probability at time t-1.

Finally, In Measurement step, the posterior density $p(x_t|z_t)$ is calculated, the current particle is weighted using Eq. (1), and the likelihood probability $p(z_t|x_t)$ is calculated by applying observation z_t at time t.

The posterior p(xt|Zt) is defined in Bayesian form as:

$$p(x_t|Z_t) = \frac{p(z_t|x_t)\, p(x_t|Z_{t-1})}{p(z_t|Z_{t-1})} \qquad (2)$$

Where $p(z_t|Z_{t-1})$ is the normalizing constant expressed as:

$$p(z_t|Z_{t-1}) = \int p(z_t|x_t) p(x_t|Z_{t-1}) dx_t \qquad (3)$$

And the importance/normalized weights $w_t^{(i)}$:

$$w_t^{(i)} \alpha\, p(z_t|x_t^{(i)}=s_t^{(i)}) \,,\ \sum_{i=1}^{N} w_t^{(i)} = 1 \qquad (4)$$

Finally, the mean state $\hat{x}_t$ at time t is calculated by the average of the weighted particles as:

$$\hat{x}_t = E[x_t|Z_t] = \sum_{i=1}^{N} w_t^{(i)} s_t^{(i)} \qquad (5)$$

Particle filter has been proven to be effective; however, it suffers from many problems that recent research tried to solve. Particle filtering efficiency depends on the number of particles processed. The filter will fail if the number of particles is not sufficient. Increasing the number of particles to improve accuracy will be an expensive computational cost, as the algorithms will keep track of all the best particles simultaneously. Another problem of particle filter is sample degeneration, which means that the number of particles representing the posterior distribution will be very small, as after several iterations all particle weights are close to zero [2].

2.2 Speeded Up Robust Features (SURF)

Local invariant features are known to perform well in pattern recognition problems due to their robustness, distinctiveness and repeatability characteristics. A comparison and evaluation of different descriptors is presented in details in [26].

The task of finding correspondence between images of the same scene or object is essential in many computer vision applications. This can be achieved using three steps namely, detection, description and matching [25]. In detection step, interest points are selected from distinctive locations in an image such as corners and blobs. These interest points should be distinctive and repeatable, that's, they could be detected under different and even sever viewing conditions. In description step, the neighborhood of each interest point is represented by a feature vector. This process should be robust to noise, detection errors and geometric and photometric deformations. Finally, in matching step, feature vectors of different images are matched. This is usually done based on the distance between features vectors, e.g. Euclidean distance for example.

Herbert Bay et. al., [25] introduced the local invariant interest points' detector-descriptor (SURF). SURF is invariant to common image transformations, rotation, scale change, illumination change and small change in viewpoint.

SURF uses integral images (summed area tables), which are intermediate representations for the image and contain the sum of gray scale pixel values of image, to reduce computation time. The detector is based on Hessian matrix to make use of its good performance in computation time and accuracy.

Given a point x= (x, y) in an image I, H(x, σ) is the Hessian matrix in x at scale σ defined as:

$H(x, \sigma) = \begin{bmatrix} l_{xx}(x,\sigma) & l_{xy}(x,\sigma) \\ l_{xy}(x,\sigma) & l_{yy}(x,\sigma) \end{bmatrix}$, Where $l_{xx}(x,\sigma)$, $l_{xy}(x,\sigma)$ and $l_{yy}(x,\sigma)$ represent the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with image I in point x.

The descriptor makes use of Haar-wavelet responses within the interest point neighborhood. SURF descriptor works as follows: firstly, identify a reproducible orientation based on information from a circular region around the point of interest. Then, it builds a square region aligned to the selected orientation and extracts its SURF descriptor.

A. Orientation assignment: Firstly, Haar-wavelet responses in x and y direction are calculated in a circular neighborhood of radius 6s around the interest point, s is the scale that the interest point was detected at. The Haar-wavelet responses are represented as vectors. Then, all responses within a sliding orientation window covering an angle of 60 degree are summed. Both horizontal and vertical responses in the window are summed yielding a new vector. The longest such vector is the dominant vector.

B. Description: This step includes constructing a square region which is centered around the interest point, and oriented along the selected orientation. Then, the interest region is split into 4x4 square sub-regions with 5 x 5 regularly spaced sample points inside. Haar wavelet responses d_x and d_y are calculated, where d_x, d_y are the Haar wavelet response in horizontal and vertical directions respectively. These responses are then weighted with a Gaussian kernel centered at the interest point to increase the robustness towards deformations and localization errors. The responses d_x, d_y over each sub-region are summed up separately forming a first set of entries to the feature vector. To get information about the polarity of intensity changes, sum of the absolute values of the responses $|d_x|$,

$|d_y|$ is extracted.

The intensity structure for each sub-region is described by

$$V = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|).$$

Finally, the vector is normalized into a unit length to achieve invariance to contrast.

2.3 Scale- Invariant Feature Transform (SIFT)

SIFT algorithm developed by Lowe [22] is used to describe the features of an object in an invariant way that the same object can still be recognized regardless of variations in scale, rotation and affine transformations. SIFT is widely used in computer vision applications such as visual tracking of objects. The SIFT algorithm has four major stages: Scale-space extrema detection, Keypoint localization, Orientation assignment and Keypoint descriptor.

(1) ***Scale-space extrema detection***: after constructing a scale space from the original image to be used for extracting the keypoints and their descriptors, a search over all scales and locations of the image is performed to identify the potential interest points. These candidate interest points that are invariant to scale and orientation are found using difference-of-Gaussian (DOG) function.

(2) ***Keypoint localization***: in this stage, each candidate interest point is tested against some measures of stability after building a detailed model at that point to determine its location and scale. Unstable interest points are discarded and only stable ones are retained for further using in formulating the descriptor.

(3) ***Orientation assignment***: each keypoint location is assigned one or more orientations based on local image gradients directions, thus making the formulated descriptor invariant to rotation.

(4) ***Keypoint descriptor***: the local image descriptor is built for each keypoint using the local image gradients that are measured at the selected scale in the support region around each point. These are transformed into representations that allows for levels of distortion in shape and illumination change.

3. SURF-Particle Tracker

In the proposed framework, tracking is performed by temporal tracking of a target in all subsequent frames in a video. A block diagram of the proposed framework is presented in Figure 1.

Initially, the user specifies the target object at the reference frame. Then, the proposed framework extracts SURF features for the target object. SURF extracted features represent the target in a discriminative, scale invariant, rotation invariant, illumination invariant and view point invariant set of points called interest points. The idea is to partially use these interest points to enhance the traditional particle filter tracker.

Interest points resulting from the previous step represent the samples/particles to be fed into the particle filter. Instead of choosing the initial points (particles) randomly as done in simple particle filter. The SURF points are used to make use of their advantages.

Finally, particle filter starts its tracking process and localize target object in subsequent frames.

The proposed framework improves the object tracking process by making use of SURF features which are known to be invariant to rotation, scaling change, illumination change and viewpoint change. SURF has an advantage of recovering occlusions as well. Also, Particles of particle filter are not chosen randomly, instead, they are the interest points resulted from SURF, hence, increasing reliability and efficiency of the tracking process. The proposed framework also tries to solve sample degeneration problem.

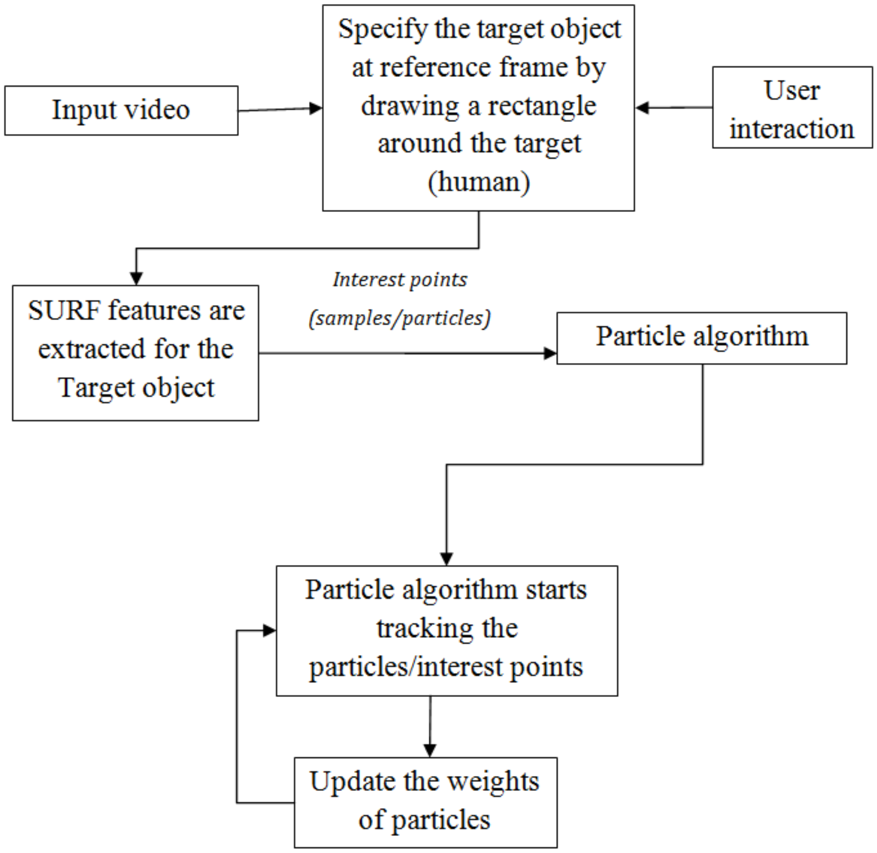

Figure 1. Block Diagram of the Proposed Framework

SURF- Particle Algorithm

1. Specify the target at the reference frame in the input video.
2. Extract the SURF features of the selected target.
3. Justify the interest points resulting from step 2 to suit the particle filter input (samples/ particles).
4. Feed the list of points resulting from step three into the particle algorithm.
5. Start tracking.
6. In each iteration of the particle algorithm, do the following steps until reaching the stopping condition:
    - 6.1. Find the tracked target in the specified frame by drawing circles representing the predicted particles of target in that frame.
    - 6.2. Update weights of particles.
    - 6.3. Go to step 6.

7. Check the stopping condition (reaching the end of the input video) and stop if reached.

4. Experimental Results

The proposed SURF-Particle tracker was tested using Actions as Space-Time Shapes Dataset of the Weizmann Institute of Science [27]. This dataset regards human actions such as walking, running, jumping, bending, one-hand waving, two-hand waving, skipping and others as three-dimensional shapes induced by the silhouettes in the space-time volume.

In our test we made a comparison between the simple (traditional) particle filter, SIFT-Particle tracker and the SURF-Particle tracker that is proposed. As mentioned in previous sections of this paper that traditional particle filter chooses the initial samples or particles randomly. On the other hand the SURF-Particle tracker that we propose chooses particles or samples using the SURF descriptor that is responsible for generating the most discriminative interest points of the target. State of the art SIFT-Particle trackers were implemented in many ways. We tested the SIFT-Particle tracker that has the same methodology of the proposed SURF-Particle tracker in which particle filter is fed with interest points generated by SIFT descriptor.

In our implementation of the SURF-Particle tracker, frames are chosen to cover motion of human throughout the video. At the reference frame the SURF interest points are extracted. The interest points are considered the samples or particles of the particle filter. The particle filter in turn uses the interest points to find the object of interest (human in our case) in subsequent frames. Particle filter generates a list of points in the form of X, Y coordinates. This list represents points covering the area of the tracked human. We draw circles using these points; each circle's center represents the coordinate of one point in the resulting list. Circles represent the predicted position of target using particle filter algorithm. We repeated that for extracting SIFT features then feeding them into particle filter in the same way.

Figure 2, Figure 3 and Figure 4 present a test example of a walking person that is tracked throughout one of the videos provided in the dataset for the action walking. The target (human in this case) was tracked through the frames numbered 4, 19, 34, 59, 74 and 83. Figure 2 shows the results of tracking using the traditional simple particle filter which choose the particles randomly. Figure 3 presents the result of SIFT-Particle tracker. Figure 4 shows the results of tracking using the proposed SURF-Particle tracker.

In Figure 4, we notice that most of the circles are drawn exactly over the target while in Figure 2 most of the circles are positioned out of the target which means less accuracy compared with our proposed tracker. Although results in Figure 3 are better than results of traditional particle filter, SURF-Particle tracker results are much better than both.

Evaluation of running time showed that the SURF-Particle tracker consumes more time than simple particle filter as shown in Figure 5. On the other hand, SURF-Particle tracker consumes time less than SIFT-Particle tracker. Time is evaluated in seconds, the figure shows that the three methods particle, SIFT-Tracker and SURF-Particle consume very small amount of time (Less than one second).The figure indicates the following:

(1) Particle is the fastest with lowest efficiency.

(2) SIFT-Particle consumes the longest time with efficiency better than traditional particle algorithm and less than SURF.

(3) SURF-Particle provides the highest efficiency with time less than what SIFT-Particle consumed.

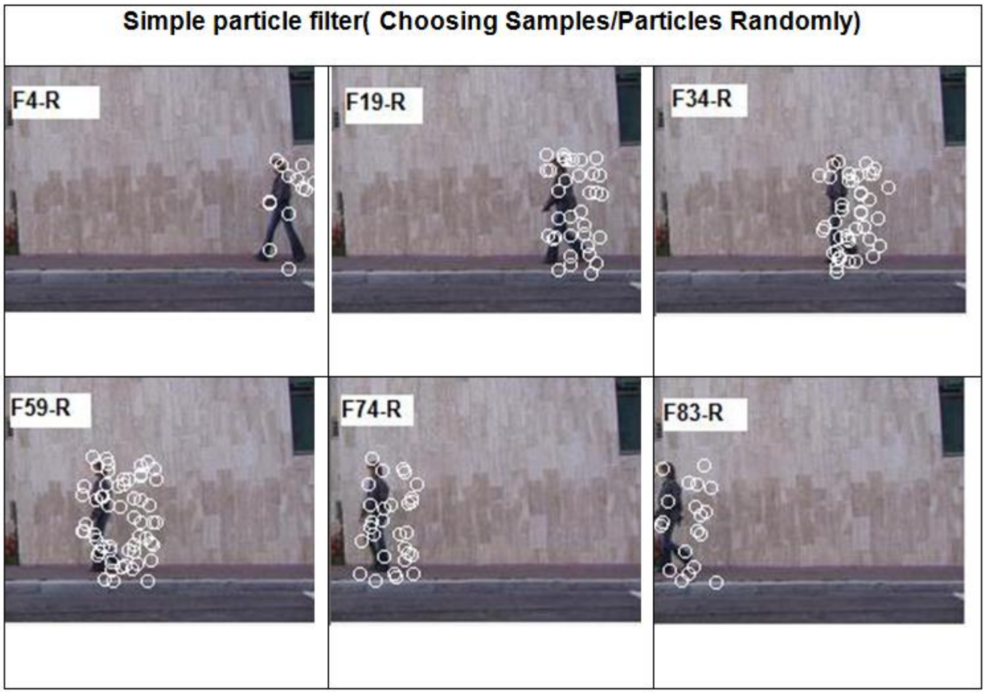

Figure 2. Simple Particle Filter Tracking

Figure 3. SIFT-Particle Tracking

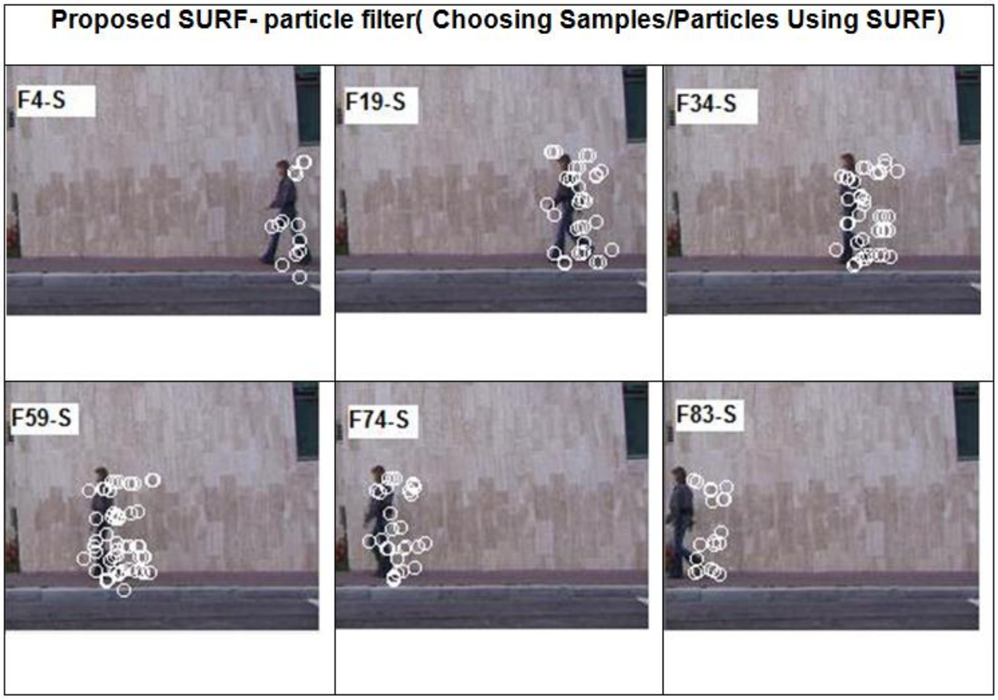

Figure 4. Proposed SURF-Particle Tracking

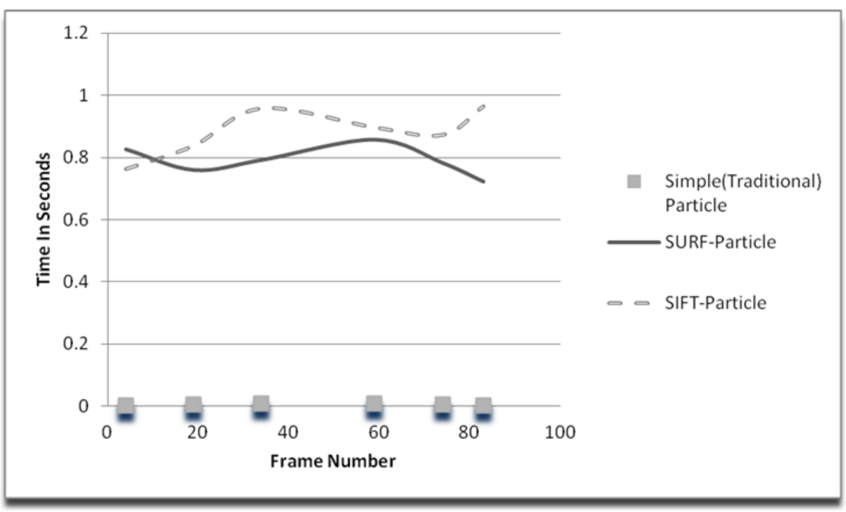

Figure 5. Running Time Comparison

Accuracy comparison between the three types of trackers (particle, SIFT-Particle, SURF-particle) is held and presented in Figure 6.

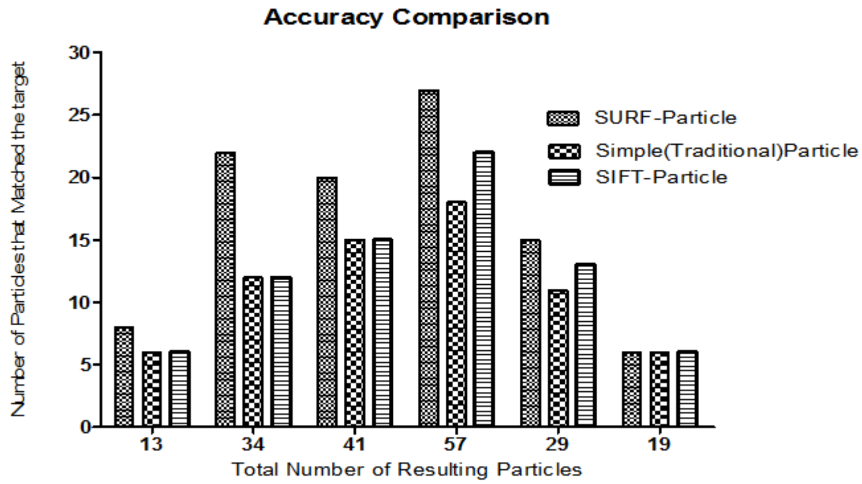

Figure 6. Accuracy Comparison

Accuracy is estimated by evaluating the percentage of matching points on the tracked target. The number of points that are positioned exactly on the target is divided on the total number of points resulting from the tracker. For example, when the total number of points resulting of the tracking process is 57 point, we find that the traditional particle filter produces about 18 points only positioned exactly on the target.

Then, accuracy in the case of simple traditional particle filter=18/57=32%.

On the other hand, SIFT-Particle positions about 22 points exactly over the target, then accuracy= 22/57=39%.

And our proposed SURF-Particle tracker produces about 27 points exactly positioned on the target. Then, accuracy =27/57=47.5%.

So, the proposed SURF-Tracker has proved to be more accurate and reliable than simple particle filter and SIFT-Particle tracker.

5. Conclusions and Future Work

Experimental result proved that SURF- Tracker is more efficient in tracking than traditional particle filter and SIFT-Particle tracker. It increased the accuracy percentage which means more reliability in detecting and tracking targets. The proposed tracker makes use of SURF which is one of the most fast descriptors which generates a set of interesting points which are invariant to various image deformations (scaling, rotation, illumination) and robust against occlusion conditions during tracking.

In our future work, we will test using complex video scenarios with more hard conditions like occlusions. Trying to track humans while they are partially or completely occluded is not easy, but using a fast and discriminative descriptor like SURF, is supposed to solve the problem, and that is what we work on in our future work plan. We will test our framework against variations of SURF such as upright-SURF (U-SURF), proved to be faster than SURF at the expense of reliability and performance, and enhance the performance of the framework. There are variations of particle filters that tried to solve different problems such as sample degeneration; we will integrate them in our framework until we reach a real time and reliable framework.

References

[1] H. Zhou, Y. Yuan and C. Shi, "Object tracking using SIFT features and mean shift", Computer vision and image understanding, vol. 113, no. 3, **(2009)**, pp. 345–352.
[2] B. Feng, B. Zeng and J. Qiu, "Tracking object by combining particle filters and SIFT features", in: IEEE Fifth International Conference on Image and Graphics, **(2009)** September 20-23, pp. 527-532.
[3] G. Welch and G. Bishop, "SCAAT: incremental tracking with incomplete information", SIGGRAPH, New York, NY, USA, **(1997)**, pp. 333-344.
[4] M. Isard and A. Blake, "CONDENSATION—conditional density propagation for visual tracking", International Journal of Computer Vision, vol. 29, no. 1, **(1998),** pp. 5–28.
[5] K. Choo and D. J. Fleet, "People tracking using hybrid Monte Carlo filtering", in: Eighth IEEE International Conference, Computer Vision, vol. 2, **(2001)**, pp. 321-328.
[6] I. J. Cox and S. L. Hingorani, "An efficient implementation and evaluation of Reid's multiple hypothesis tracking algorithm for visual tracking", in: ICPR94 **(1994)**, pp. A: 437-442.
[7] D. Reid, "An algorithm for tracking multiple targets", IEEE Transactions on Automatic Control, vol. 24, no. 6, **(1979)** December, pp. 843-854.
[8] A. Yilmaz, X. Li and M. Shah, "Contour-based object tracking with occlusion handling in video acquired Using mobile cameras", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 26, **(2004)**, pp. 1531-1536.
[9] M. Kass, A. Witkin and D. Terzopoulos, "Snakes: Active contour models", in: Proceedings of the 1st International Conference on Computer Vision, **(1987)**, pp. 259-268.
[10] D. Comaniciu, V. Ramesh and P. Meer, "Kernel-based object tracking", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, **(2003)**, pp. 564- 577.
[11] A. D. Jepson, D. J. Fleet and T. F. El-Maraghi, "Robust online appearance models for visual tracking", Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 25, no. 10, **(2003)**, pp. 1296-1311.
[12] B. D. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision", in: IJCAI81 **(1981)**, pp. 674-679.
[13] R. T. Collins, "Mean-shift blob tracking through scale space", in: IEEE Conference on Computer Vision and Pattern Recognition, vol. 2, **(2003)**, pp. 234-240.
[14] M. Khansari, H. R. Rabiee, M. Asadi and M. Ghanbari, "Occlusion handling for object tracking in crowded video scenes based on the undecimated wavelet features", in: IEEE/ACS International Conference on Computer Systems and Applications, **(2007)**, pp. 692-699.
[15] D. Comaniciu, V. Ramesh and P. Meer, "Real-time tracking of non-rigid objects using mean shift", vol. 2, **(2000)**, pp. 142-149.
[16] Y. Cai, N. de Freitas and J. J. Little, "Robust visual tracking for multiple targets", ECCV06, **(2006)**.
[17] D. A. Ross, J. Lim and Ming-Hsuan Yang, "Adaptive probabilistic visual tracking with incremental subspace update", ECCV (2), **(2004)**, pp. 470-482.
[18] J. Graham, "Target tracking with Lucas-Kanade optical flow and particle filters through affine transforms and occlusion", The University of Texas at Arlington, **(2010)**, 112 pages; AAT 1488362.
[19] I. -C. Chang and S. -Y. Lin, "3D human motion tracking based on a progressive particle filter", Pattern Recognition, **(2010)** May 7.
[20] P. Pérez, C. Hue, J. Vermaak and M. Gangnet, "Color-based probabilistic tracking", in: European Conference on Computer Vision, ECCV, **(2002)**.
[21] H. Sugano and R. Miyamoto, "a real time object recognition system on cell broadband engine", in: 2nd Pacific Rim Symposium on Image and Video Technology, PSIVT 2007, vol. 4872 LNCS **(2007)** December 17 - 19, 2007, pp. 932-943.
[22] D. Lowe, "Distinctive image features from scale-invariant keypoints", in: International Journal of Computer Vision, vol. 60, **(2004)**, pp. 91-110.
[23] S. Fazli, H. M. Pour and H. Bouzari, "Particle filter based object tracking with SIFT and color feature", in: Second International Conference, Machine Vision, ICMV '09, **(2009)**, pp. 89-93.
[24] T. Gao, Z. -g. Liu, W. -c. Gao and J. Zhang, "Moving Vehicle Tracking Based on SIFT Active Particle Choosing", Lecture Notes in Computer Science, Advances in Neuro-Information Processing, vol. 5507, **(2009)**, pp. 695-702.
[25] H. Bay, T. Tuytelaars and L. Van Gool, "SURF: Speeded Up Robust Features", in: 9th European Conference on Computer Vision, **(2006)** May 7-13.
[26] K. Mikolajczyk and C. Schmid, "A performance evaluation of local descriptors", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 10, **(2005)** October, pp. 1615-1630.
[27] Actions as Space-Time Shapes Dataset of the Weizmann Institute of Science, http://www.wisdom.weizmann.ac.il/~vision/SpaceTimeActions.html, **(2011)** October 28.

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