

An improved real visual tracking system using particle filter

Abstract. This paper presents a real hybrid visual tracking system based on a special-color model of target with improving the performance of this designed visual tracking system using various linear and nonlinear estimators like Kalman filter and particle filter. Moreover, the whole system has been designed and implemented in the laboratory by fusing the tracking algorithm that was created utilizing python software with a moving camera sensor. In addition, the designed visual tracking system has been simple, low cost and achieved all stages of visual tracking process like target initialization, appearance modeling, movement estimation, and target positioning with a great success. Finally, the graphical analysis results of the designed system illustrated had a great illustration on the validity of utilizing particle filter was very efficient and clearer with maneuvering targets than that were used with Kalman filter.

Streszczenie. W niniejszym artykule przedstawiono hybrydowy system śledzenia wizualnego oparty na modelu celu w specjalnej kolorystyce z poprawą wydajności tego zaprojektowanego systemu śledzenia wizualnego przy użyciu różnych liniowych i nieliniowych estymatorów, takich jak filtr Kalmana i filtr cząsteczkowy. Co więcej, cały system został zaprojektowany i wdrożony w laboratorium poprzez połączenie algorytmu śledzenia, który został stworzony przy użyciu oprogramowania Pythona z ruchomym czujnikiem kamery. Ponadto zaprojektowany system śledzenia wizualnego był prosty, tani i osiągnął z dużym sukcesem wszystkie etapy procesu śledzenia wizualnego, takie jak inicjalizacja celu, modelowanie wyglądu, szacowanie ruchu i pozycjonowanie celu. Wreszcie, wyniki analizy graficznej zilustrowanego zaprojektowanego systemu doskonale ilustrują zasadność wykorzystania filtra cząstek, który był bardzo wydajny i wyraźniejszy w przypadku celów manewrujących niż ten, który był używany z filtrem Kalmana. (Ulepszony rzeczywisty system śledzenia wizualnego za pomocą filtra cząstek).

Keywords: Visual Tracking, Kalman Filter, Particle Filter, Camera Sensor, Special-color Model.

Słowa kluczowe: Śledzenie wizualne, filtr Kalmana, filtr cząstek stałych, czujnik kamery, specjalny model koloru.

Introduction

Visual tracking is one of the most important applications that have been used in recent years, due to the remarkable progress in the algorithms used in processing, the availability of high-resolution cameras, and their low cost [1]. Hence, visual tracking means, compute the trajectory of the object moving around a sight in the image plane [2]. In spite of this tremendous development in visual tracking systems, some challenges and problems arose, such as: noise in images, unorganized background, random complex target motion, object occlusions, non-rigid object, variation in the number of objects and change in illumination, etc. [3]. Therefore there must be radical solutions to not lose the efficiency of the visual tracking system. Thus, to achieve maximum efficiency for our proposed system, Target initialization, appearance modeling, motion estimation, and target positioning were taken into account before the design. Fig. 1 describes the taxonomy of visual tracking techniques.

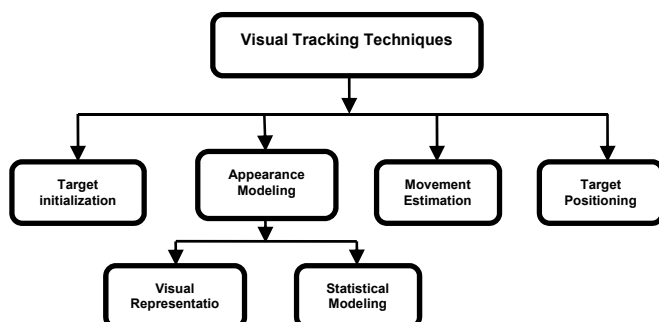


Fig.1. the visual tracking techniques.

A) Target Initialization

Target initialization is the initial step of visual tracking techniques by utilizing bounding or squares to locate the object accurately [4]. Hence, this process is a prerequisite for the detailed description of the target.

B) Appearance Modeling

The appearance model accurately describes the characteristics of the target, such as position and velocity [5]. So, various special features such as: special color-model, gradient, texture, shape, super-pixel, depth, motion, and optic flow are utilized to differentiate the target and background or different targets in the visual tracking system [6]. Hence, it can be divided into a visual representation and statistical modeling. And the Visual representation technique has been utilized in this paper by using the most popular method which is optical flow representation.

Optical flow is demonstrated by dense field displacement vectors of each pixel in the image and utilized to locate moving targets with a high accuracy in video frames .So, optical flow is suitable for multi-moving targets analysis in complex scenes with a dynamic background. Furthermore, it gives a two-dimensional vector field called motion field that illustrates velocities and directions of each pixel in consecutive image sequences with time and is present by the following equation [7-8].

$$(1) \quad I_i(x_i + \Delta x, y_i + \Delta y, t + \Delta t) = I_i(x_i, y_i, t)$$

Since $I_i(x_i, y_i, t)$ is the intensity of the pixel at a point (x_i, y_i) at a given time t .

C) Movement Estimation

Movement estimation is based on motion vectors which utilized to represent the transformation through adjacent two-dimension at image frames in a video sequence and it can be calculated by pixel-based techniques or direct technique, and feature-based techniques or indirect technique. So, direct techniques motion parameters are estimated directly by computing the contribution of each pixel that results in optimal usage of the available information and image alignment. But, in indirect techniques, various features are utilized to match between features in various frames [9-10]. Movement for targets is considered a dynamic state estimation, so it can be

modeled in any visual tracking system by various estimators such as Kalman filter and particle filter [11-13]. Yet, there are some restrictions that determine the type of filter used, such as: the amount, type of noise, and the linearity of the proposed system. Also, the efficiency of the visual tracking system based on the type of filter used, and in this research paper many types of filters such as the Kalman filter and particle filter were used in the proposed system. Thus, the following algorithm illustrates the main procedures of the particle filter as example in the proposed visual tracking system.

Table.1. General Particle filter algorithm for tracking.

General Particle Filter Algorithm for Tracking.
1: Initialize particles with a random location.
2: while True do.
3: Update particles based on robot movement.
4: Observe Camera sensor measurements.
5: Assign weight to each particle by comparing with sensor data.
6: Resample particles based on weight
7: Estimate location from particle locations and weights
8: end while

Fig. 2 present the basic steps block diagram of particle filter for visual tracking system:

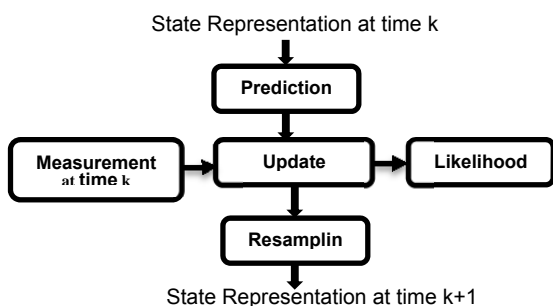


Fig.2. The basic steps block diagram of particle filter.

From the previous block diagram the basic equations of particle filter [14-19]. So, visual tracking system can be presented as the following:

D) State representation or initialization

A number of particles are utilized to describe the property density function (pdf) of the state values instead of using the 2nd order statistical description so; the (pdf) is presented by the fowling equation:

$$(2) \quad p(x) = \int_{i=1}^n w_i K(x - x_i)$$

Since w_i the weight of i^{th} particle and $K(\cdot)$ the basis function. And if $K(x)$ assumed to be the Dirac's delta, the particles representation of $p(x)$ and equal weights will be:

$$(3) \quad p(x) = \frac{1}{n} \int_{i=1}^n \delta(x - x_i)$$

So, from the previous equations and equations (2) and (3) we can write the equation of the state presentation:

$$(4) \quad p(x_{k+1}/y_{0,\dots} y_k) = \int_{i=1}^n w_{k,i} \delta(x_{k+1} - \bar{x}_{k,i})$$

From the previous equation the equation of prediction $p(x_{k+1}/y_{0,\dots} y_k)$ and update equation $p(x_{k+1}/y_{0,\dots} y_{k+1})$.

E) Prediction

$$(5) \quad (x_{k+1}/y_{0,\dots} y_k) = \int p(x_{k+1}/x_k) p(x_k/y_{0,\dots} y_k) dx_k$$

$$(6) \quad p(x_{k+1}/y_{0,\dots} y_k) = \sum_{i=1}^n w_{k,i} p(x_{k+1}/\bar{x}_{k,i})$$

After sampling $\{\hat{x}_{k,i}\}$ the equation of prediction will be:

$$(7) \quad p(x_{k+1}/y_{0,\dots} y_k) = \sum_{i=1}^n \frac{1}{n} \delta(x_{k+1} - \hat{x}_{k,i})$$

F) Update

$$(8) \quad p(x_{k+1}/y_{0,\dots} y_{k+1}) = \int_{i=1}^n \frac{1}{n} \delta(x_{k+1} - \bar{x}_{k+1,i})$$

By using the resampling step, the degeneracy problem can be removed which occurred when a few of the particles will have a significant weight, and all the other particles will have very small weights and be obtained by estimating the effective sample size by the fowling equation:

$$(9) \quad N_{eff} = \frac{1}{\int_{i=1}^n (w_k^i)^2}$$

G) Target Positioning

This stage is considered the final and important stage in the visual tracking system and depends entirely on all the previous stages, especially the type of filter or estimator that was used in the system because it predict with future position of the target [20].

Problem Formulation and Modeling

The proposed visual target tracking system has been designed in the laboratory and it is simple and inexpensive in the main parts that used in its design. So, it consists of the following basic components: a moving low price (USB) camera with a set of actuators to control its movement while tracking the target, a low price data transmission cable, and a laptop. First, we connect the moving camera with the laptop by the cable which is used to transfer the data from camera to laptop, and in this case, the camera is considered as a sensor used for detecting the moving target and it is surrounding area. Then by running the Python program, it divides the selected target image by the camera into a set of frames and detects the special color -model only by utilizing the color-based detection technique. That adapted the upper and lower boundaries of the special color model of the target. Then, the target boundaries are computed according to hue, saturation, and value color representation theory. So, the target image appears only and all unwanted in the background disappears, but as a result of this process, frames data are divided into foreground and background. Foreground data identify moving targets and this process is repeated in each nth frame, then the target is detected. After that fig .3 illustrated the process of converting the image of the target from (RGB) to (HSV), to ease of executing the process on (HSV) images, and a group of series filters called kernel filters are applied to enhance and restore the target image from noise because some frames are corrupted while performing the process in background subtraction detection technique on the first frame. Also, this algorithm increases the depth of the target signal, draws a square around the target signal, divides the length and width into two, and determines the center of the square. Secondly, the true path of the target is drawn immediately when it moves using Matlab. At last, a set of linear and nonlinear estimators like Kalman filter and particle filter are utilized to predict the location of the target. Fig. 4 presented the block diagram of the proposed visual tracking system that consists of a low price, simple and reliable USB web camera used as a sensor, USB hub used to transfer data of target from the sensor to laptop, and the associated software program which included an algorithms

used to track a moving target with python software based on target features like a special-color model. Furthermore, a weighted gain filter is utilized in the algorithm to reduce noise in order to enhance the image performance. Also, noise in the image pixels is eliminated by utilizing the morphological transformation filter in python a. Then, foreground object pixel is multiplied by a designed factor to compensate the target signal and fig. 5 presented the flow chart of the proposed method.

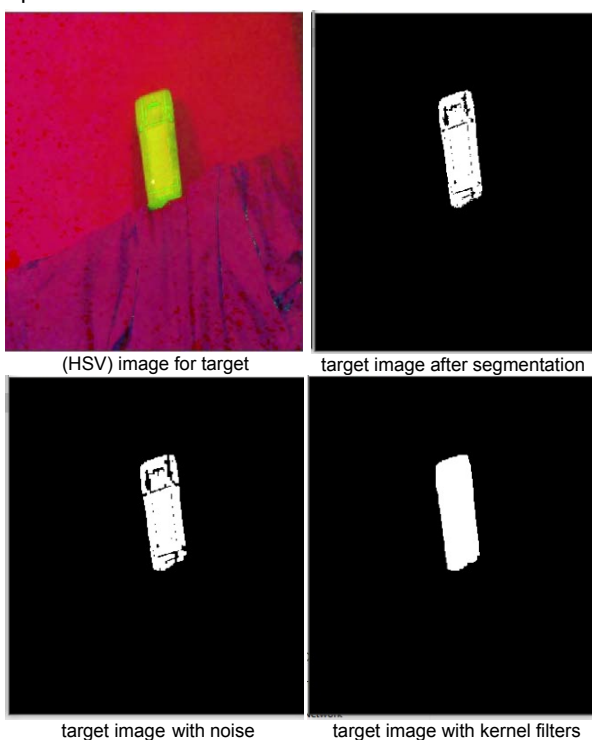


Fig.3.The target image process.

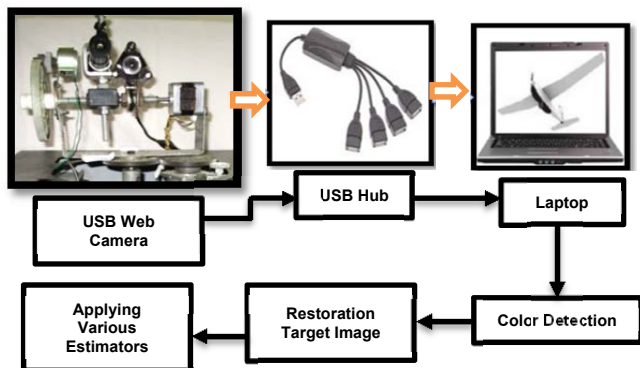


Fig.4.The block diagram of the proposed system.

Results and Discussion

The experiment has been carried on real image sequences of the target to evaluate the performance of the proposed system and there are several performance

measures used to determine the efficiency of the proposed visual tracking system like center location error, bounding box overlaps, tracking length, failure rate, area under the lost-track-ratio curve, but the most common of these metrics used is the comparison between the true path of the target and the estimated path using different estimators. Hence, in this paper, when the proposed visual tracking system was designed, the simplicity of design, low cost, and high robustness were taken into consideration. So, the graphical analysis is used to summarize the results to differentiate between the true path of the target and the predicted path using several kinds of linear and nonlinear estimators such as Kalman filter and particle filter.

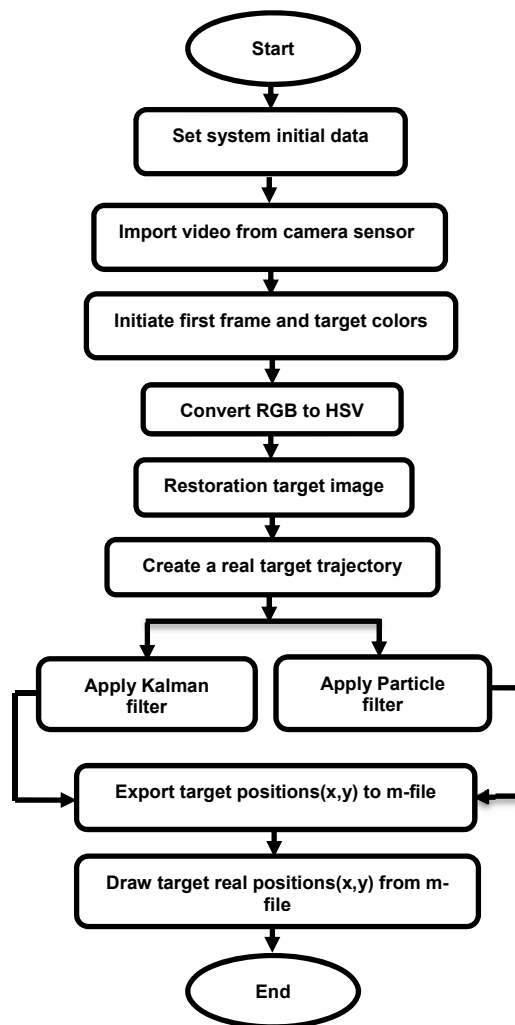


Fig.5.The flow chart of the proposed method.

Therefore, the previous experiment was carried out in two phases. The first phase, using a target that maneuvers along the path at a constant speed with changing time in azimuth (x) and elevation (y).second phase using a target that maneuvers along the path but changes its speed continuously with the change of time in azimuth (x) and elevation (y). Then, when the information of the target is obtained from the camera used as a sensor, and by fusing this information with Python software, the true path of the target was drawn utilizing MatLab in azimuth (x) and elevation (y). So, fig. 6 presented a target that maneuvers along the path with the constant speed with changing times in azimuth (x) and elevation (y).

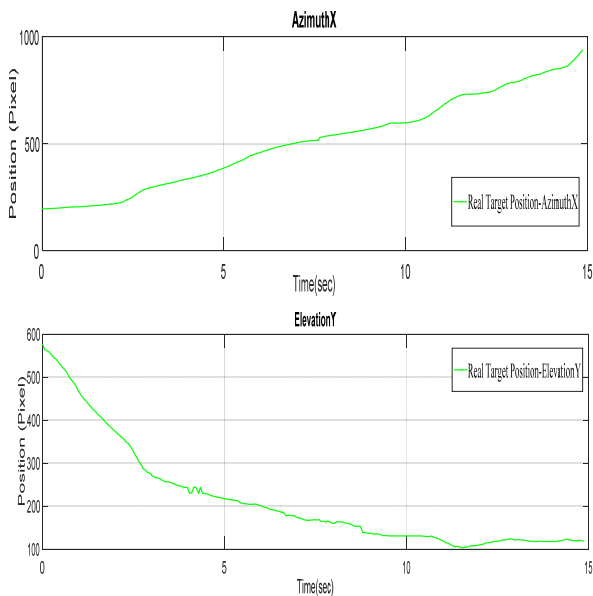


Fig.6. Real target path in azimuth (x) and elevation (y).

Fig. 7 illustrated the predicted or the computed target path using kalman filter (red dot line) in azimuth (x) and elevation (y) and target true path (green solid line) vs time. And fig.8 illustrated the predicted target path using particle filter (blue solid line) in azimuth (x) and elevation (y) and target true path (green solid line) vs time.

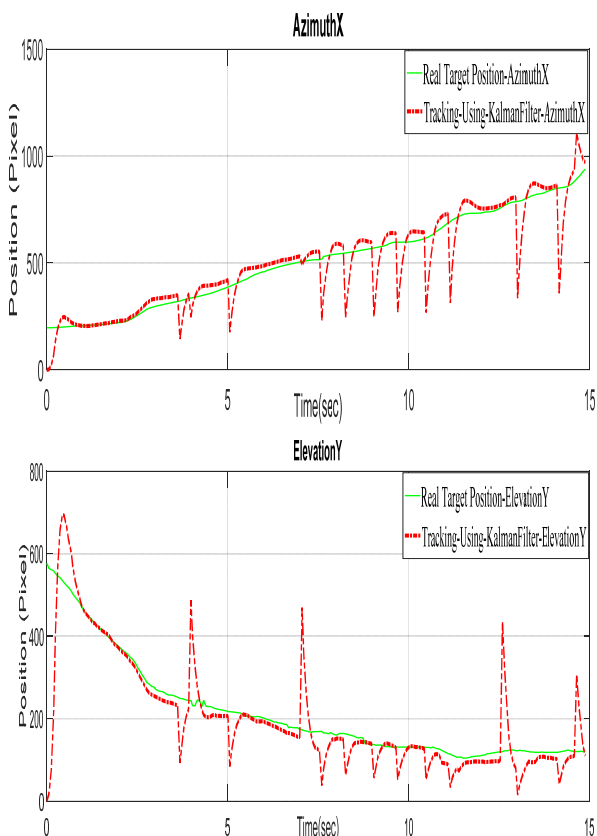


Fig.7.The real target path vs predicted path using Kalman filter in azimuth (x) and elevation (y).

Fig. 9 illustrated the differentiation between the predicted or the computed target path using particle filter (blue solid line), using Kalman filter (red dot line), with target true path (green solid line) in azimuth (x) and elevation (y)

vs time. Where, it is visible from the visual examination only that the predicted target path that is utilizing particle filter is closer to the real path of the target than the predicted target path using Kalman filter.

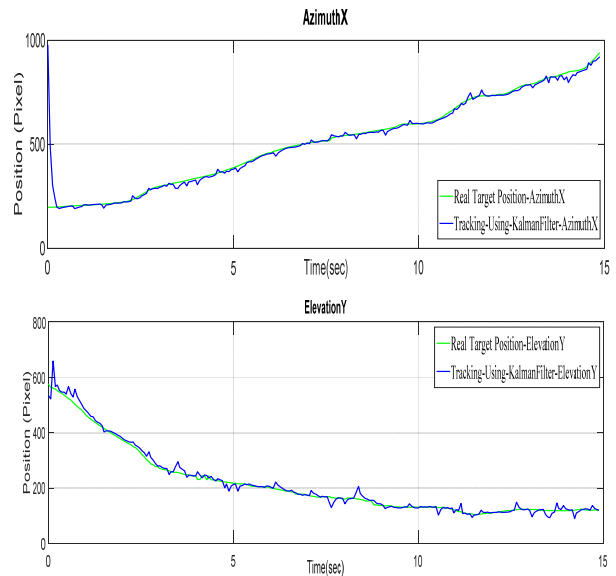


Fig.8. The real target path vs predicted path using particle filter in azimuth (x) and elevation (y).

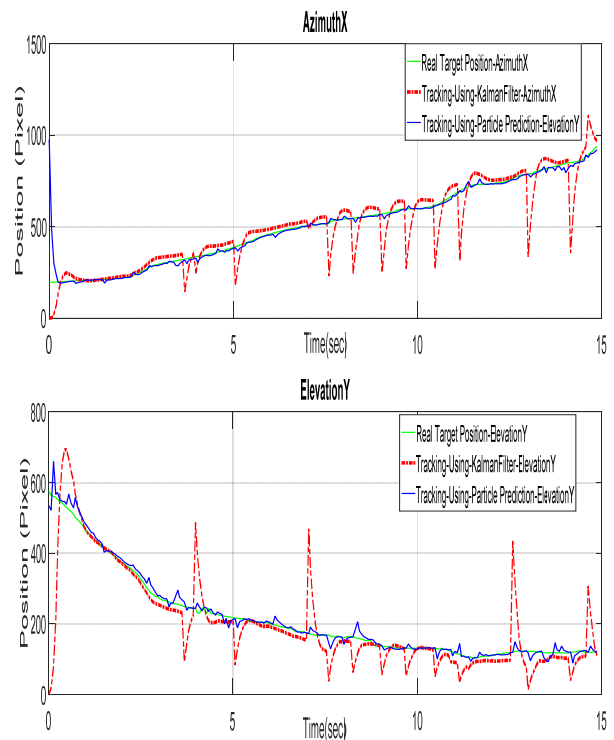


Fig.9. Differentiation between various predicted target paths using particle filter, kalman filter and true path in azimuth (x) and elevation (y) vs time.

Fig. 10 presented a target that maneuvers along the path, but changes its speed continuously with the change of time in azimuth (x) and elevation (y).

Fig.11 illustrated the predicted target path using kalman filter (red dot line) in azimuth (x) and elevation (y) and target true path (green solid line) vs time. And fig. 12 illustrated the differentiation between the predicted or computed target path using particle filter (blue solid line) in azimuth (x) and elevation (y) with target true path (green solid line) vs time.

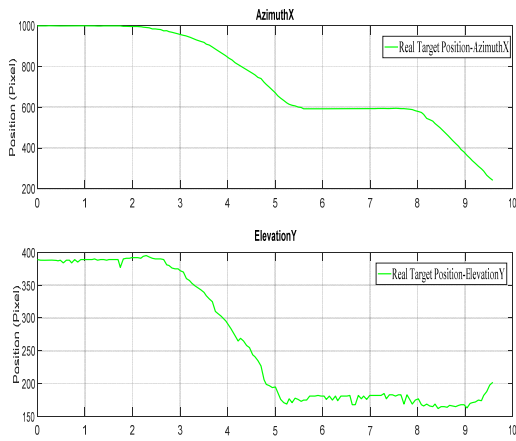


Fig.10. Real target path in azimuth (x) and elevation (y).

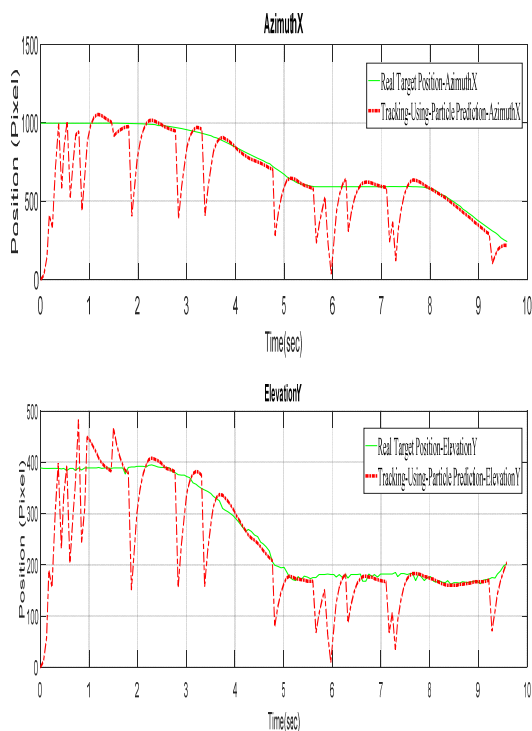


Fig.11.The real target path predicted path using Kalman filter in azimuth (x) and elevation (y).

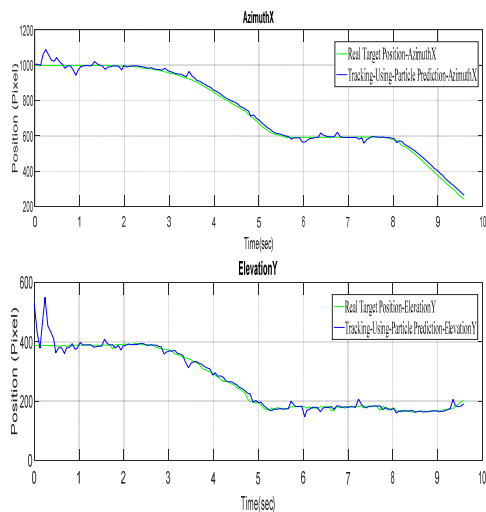


Fig.12. The real target path vs predicted path using particle filter in azimuth (x) and elevation (y).

Fig.13 illustrated the differentiation between the predicted or the computed target path using particle filter (blue solid line), using Kalman filter (red dot line), with target true path (green solid line) in azimuth (x) and elevation (y) vs time. Where, it is visible from the visual examination only that the predicted target path utilizing particle filter is closer to the real path of the target than the predicted target path using Kalman filter.

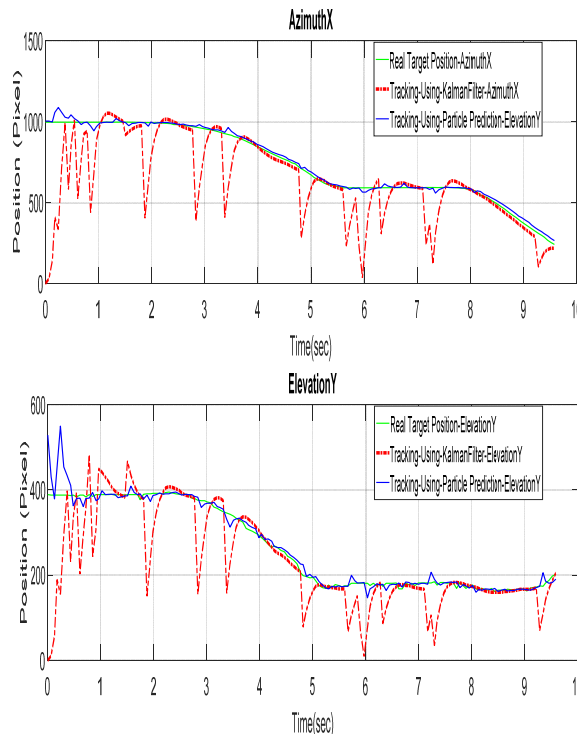


Fig.13. Differentiation between various predicted target paths using particle filter, kalman filter and true path in azimuth (x) and elevation (y) vs time.

From the previous graphical analysis, the proposed visual tracking system has presented more accurate tracking using a standard particle filter depends on the special color model, than the Kalman filter because the proposed visual tracking system is a nonlinear system with Gaussian noise and the Kalman filter is limited to a linear system with Gaussian noise. Moreover, using a large number of particles can sufficiently cover the region of work with a high observation likelihood when the camera is moving. But, this large number of particles leads to the degeneracy problem, so resampling step in particle filter is utilized to reduce particles by adopting a better proposal density for existing particles and a better prior density of appearing target. Finally, the previous proposed visual tracking system demonstrated many advantages, like low manufacturing cost, ease of programming, high durability, and high efficiency in detecting and tracking fixed and moving targets. Furthermore, it can be applied in several areas, for example, but not limited to Posture estimation, Robotics, Education, Sports, Cinematography, and Marketing.

Table 2 presents the deviation, of the predicted or computed target path using particle filter and, using Kalman filter in azimuth (x) and elevation (y) from the real paths of the target that maneuvers along the path at a constant speed with changing time in azimuth (x) and elevation (y). Also, the target that maneuvers along the path but, its speed changes continuously with the change of time in azimuth (x) and elevation (y).

Tab.2. The amount of deviation of the predicted target path using particle filter and, using Kalman filter.

The Experiment Phases	The Kind of Estimator	The Amount of Deviation
The target that maneuvers along the path at a constant speed with changing time	particle filter	4%
	Kalman filter	11%
The target that maneuvers along the path but, its speed changes continuously with the change of time	particle filter	6%
	Kalman filter	14%

Conclusion

This paper presented an efficient, low-cost, easy-to-manufacture, and high-robust model for a visual tracking system based on the special color model used to track moving or static targets because special color contains richer information than the general color histogram since it incorporates the spatial distribution of pixels in addition to color. Moreover, a group of different algorithms has been fused with each other using the Python programming language to work with the proposed system. Firstly, one of these algorithms detects the target and creates a set of sequence video frames for the target using the camera that is used as a sensor, and then subtracts the background from the image using a color-based detection method. Secondly, the next algorithm converts the image of the target to be tracked from (RGB) to (HSV) to ease of executing the process on (HSV) images and performs the restoration and enhancement of the target image after the previous operation using a group of series filters called kernel filters to remove the noise from the image of the target. Thirdly, the final algorithm utilized various types of linear and nonlinear estimators to predict the new position of the target and drawn the predicted paths by using Matlab then differentiate it with the true path of the target and presented the closest path to the true path. Finally, the proposed visual tracking system graphical analysis results illustrated the effectiveness of the particle filter in visual tracking than kalman filter.

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REFERENCES

- Sun Y, Meng MQH. Multiple moving objects tracking for automated visual surveillance. In: 2015 IEEE international conference on information and automation. 2015; IEEE. pp. 1617–1621.
- Chincholkar AA, Bhojar MSA, Dagwar MSN. Moving object tracking and detection in videos using MATLAB: a review. Int J Adv Res Comput Electron. 2014;1(5):2348–5523.
- Kang B, Liang D, Yang Z. Robust visual tracking via global context regularized locality-constrained linear coding. Optik. 2019;183:232–40.
- Chaki J, Dey N, Shi F, Sherratt RS. Pattern mining approaches used in sensor-based biometric recognition: a review. IEEE Sens J. 2019; 19(10):3569–80.
- Fan L, Wang Z, Cail B, Tao C, Zhang Z, Wang Y et al. A survey on multiple object tracking algorithm. In: 2016 IEEE international conference on information and automation (ICIA). IEEE; 2016. pp. 1855–1862.
- Liu S, Feng Y. Real-time fast moving object tracking in severely degraded videos captured by unmanned aerial vehicle. Int J Adv Rob Syst. 2018; 15(1):1729881418759108.
- J. Hariyono, V. Hoang, and K. Jo, "Moving Object Localization Using Optical Flow for Pedestrian Detection from a Moving Vehicle," Scientific World Journal, Vol. 2014, Article ID 196415, 2014.
- Akpinar S, Alpaslan FN. Video action recognition using an optical flow based representation. In: Proceedings of the international conference on image processing, computer vision, and pattern recognition (IPCV) (p. 1). The Steering Committee of the World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp). 2014.
- Acharjee S, Ray R, Chakraborty S, Nath S, Dey N. Watermarking in motion vector for security enhancement of medical videos. In: 2014 International conference on control, instrumentation, communication and computational technologies (ICCICCT). IEEE; 2014. pp. 532–537.
- Acharjee S, Pal G, Redha T, Chakraborty S, Chaudhuri SS, Dey N. Motion vector estimation using parallel processing. In: International Conference on Circuits, Communication, Control and Computing. IEEE; 2014. pp. 231–236.
- Dou J, Qin Q, Tu Z. Robust visual tracking based on generative and discriminative model collaboration. Multimed Tools Appl. 2017; 76(14):15839–66.
- Chang, Dah-Chung, and Meng-Wei Fang. "Bearing-Only Maneuvering Mobile Tracking With Nonlinear Filtering Algorithms in Wireless Sensor Networks." Systems Journal, IEEE Transactions on 8, no. 1 (2014): 160-170.
- N. Mosto, M. Elhabiby, and N. El-Sheimy, "Indoor localization and mapping using camera and inertial measurement unit (imu)," in Position, Location and Navigation Symposium-PLANS 2014, 2014 IEEE/ION. IEEE, 2014, pp. 1329-1335.
- Dou J, Qin Q, Tu Z. Robust visual tracking based on generative and discriminative model collaboration. Multimed Tools Appl. 2017; 76(14):15839–66.
- Kristan M, Matas J, Leonardis A, Felsberg M, Cehovin L, Fernandez G, et al. The visual object tracking vot2015 challenge results. In: Proceedings of the IEEE international conference on computer vision workshops. 2015. pp. 1–23.
- Čehovin L, Leonardis A, Kristan M. Visual object tracking performance measures revisited. IEEE Trans Image Process. 2016; 25(3):1261–74.
- M. D. Jenkins, P. Barrie, T. Buggy, and G. Morison, "Selective sampling importance resampling particle filter tracking with multibag subspace restoration," IEEE Trans. Cybern., vol. 48, no. 1, pp. 264–276, Jan. 2018.
- Xiao, R. Stolkin, M. Oussalah, and A. Leonardis, "Continuously adaptive data fusion and model relearning for particle filter tracking with multiple features," IEEE Sensors J., vol. 16, no. 8, pp. 2639–2649, Apr. 2016.
- P. Li, D. Wang, L. Wang, and H. Lu, "Deep visual tracking: Review and experimental comparison," Pattern Recognit., vol. 76, pp. 323–338, Apr. 2018.
- Fiaz M, Mahmood A, Jung SK. Tracking noisy targets: a review of recent object tracking approaches. arXiv preprint arXiv :1802.03098 . 2018.