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A Study of α β Tracker with Some New Algorithms for Selecting α and β Parameters

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ABSTRACT

This paper deals with target tracking using α β Tracker. Some of the theoretical properties of this classical tracker are discussed and the problem of selecting the suitable α and β parameters is studied. Two well known classical methods of estimating α and β parameters are veiwed and another three new algorithms of estimating these parameters are suggested. Some simulation experiements are performed in the cases of white noise and color noise to check the accuracy of the classical as well as the new ones. The performance of our new suggested algorithms seems to be very well.

1. INTRODUCTION

The α β tracker is a very simple filter still used in many tactical military systems although it has been used firstly in tracking radar at the early of 1960’s. This tracker has an excellent performance for tracking non-maneuvering targets. Because of its simplicity, it is often considered as a candidate filter (Bhagavan and Polge [1974] and West and Blair [2001]).

α β tracker is one of the type fading memory filters with fixed gain and it can be implemented recursively. i.e., data received in the past are included in the present estimates (Hanna [1989]). This tracker is one step ahead predictor of position that uses the current error in order to predict the next position.

Sklansky, in his seminal paper, analyzed the behavior of an α β tracker (Sklansky [1957]). His analysis of the range of values of the smoothing parameters α and β which resulted in a stable filter constrained the parameters to lie within a stability triangle. He also derived closed form equations to relate the smoothing parameters for critically damped transient response and the ability of the filter to smooth white noise. Following his work, Benedict and Brodner [1962] used calculus of variation to solve for an optimal filter which minimizes a cost function which is a weighted function of the noise smoothing and the transient (maneuver following) response bringing a constraint to the optimal filter. Schooler [1975], discussed the inaccuracies of α β tracker and modeled them; then he provided an optimal α β tracker for the systems with modeled inaccuracies. Lefferts [1981] studied the correlation regions assumed of independent and Gaussian distributed error. He used a dynamically varing correlation region to yield improved tracking performance.

In 1990's there were many studies and researches related to α β tracker and further improvement was obtained, (see for example Yosko and Kalata [1992], Aubree et al. [1995], Llinas et al. [1998] and West and Blair [2001]). Anyway, tracking through α β tracker still is an attractive area, which needs rich analysis and improvement.

The usefulness of α β tracker as compared to others with superior performance lies mainly in the ease of implementation and limited computational requirements. This means that it may be needed as a result of computational limitations if the sampling interval is short, or if many targets must be engaged (Leffertds [1981] and Hanna [1989]). α β tracker provides a good performance for non-maneuvering, constant velocity targets. It has the ability to deal with a maneuvering target if it is modeled as a constant – velocity system with random maneuvering.

However, α β tracker is just one step ahead position predictor; this restricts the ability to predict the target path through next n steps of times. It has fixed coefficient parameters, so its gain is not adaptively hanged it has little capability to track severely maneuvering targets (Bhagvan and Ploge [1974] and Lefferts [1998]).

It is well known that it is not possible to select smoothing parameters on line which are optimal in all cases, so it is frequently necessary to use several sets of smoothing parameters to achieve a practical system. The α β tracker however, is obtained by neglecting the acceleration term in the equation of motion, the manner that affects dealing with maneuvering targets. This work therefor, is trying to minimize the problem by selecting suitable values of α and β parameters, on line with minimum error.

2. α β TRACKER

The form α β tracker equations can be drived from Newton's laws of motion. Consider the motion of point mass with constant acceleration. It is well known that this motion is described by integrating the Newton's First Law.

Let *x(t)* denotes the position of a point mass at time t, then the equation of motion can be reduced to (Llinas et al. [1998]) :

$$x(t) = x(0) + v(0)t + \tfrac{1}{2}at^2 \quad , \qquad (1)$$

where *x(0)* is the initial position, *v(0)* is the initial velocity and a is the acceleration which is assumed here to be constant independent of time. Now, if the acceleration is negligible then the equation (1) can be written as:

$$x(t) = x(0) + v(0)t \quad . \qquad (2)$$

Assuming that we have measurements at discrete time points; say $t = 1,2,..$. Substituting the initial conditions $x_{(0)}$ and *v(0)* by the smoothed position x_s and the smoothed velocity v_s; respectively, then the following equation of one-step-ahead prediction is obtained (Llinas et al. [1998]) :

$$x_p(t+1) = x_s(t) + Tv_s(t) \quad ;t = 1,2,.. \quad , \qquad (3)$$

where $x_p(t+1)$ is the 1st-step ahead predicted position at time t,
$x_s(t)$ is the smoothed position at time t,
$v_s(t)$ is the smoothed velocity at time t,
T is the sampling time interval.

The innovation, or prediction error, at time t is denoted by $e(t)$ and defined as the difference between the measured position $x_m(t)$ and the predicted position $x_p(t)$.
I.e.:

$$e(t) = x_m(t) - x_p(t) \quad ;t = 1,2,.. \qquad (4)$$

Assuming the ratio of the difference between the smoothed position and the predicted position to the innovation is a constant, say α acting as a smoothing parameter of the position and computed as:
Hence, the smoothed position can be obtained from the following equation:

$$\alpha = \frac{x_s(t) - x_p(t)}{x_m(t) - x_p(t)} \quad . \qquad (5)$$

$$x_s(t) = x_p(t) + \alpha\left[x_m(t) - x_p(t)\right] \quad ;t = 1,2,.. \quad , \qquad (6)$$

Also similarly, the smoothed velocity can be obtained by using the well known physical law : velocity = distance / time , and letting :

$$\beta = \frac{v_s(t) - v_s(t-1)}{[\ x_m(t) - x_p(t)\ ]/T} \qquad (7)$$

Then the smoothed velocity equation is given by:

$$v_s(t) = v_s(t-1) + \beta/T\left[x_m(t) - x_p(t)\right] \quad ;t = 1,2,.. \qquad (8)$$

3. INITIALIZING THE α β TRACKER

α β tracker is a recursive filter as the prediction equation (3) is in recursive form, this means that it needs to be initialized. Two measured target positions are required to determine the initial smoothed velocity, causing the target position prediction begins at the third time step. The measured position is considered to be the initial predicted target position till the second time step. The initial smoothed velocity is calculated as (Llinas et al. [1998]):

$$v_s(2) = \frac{x_m(2) - x_m(1)}{T} \quad . \qquad (9)$$

The first predicted position is then calculated as:

$$x_p(3) = x_m(2) + T v_s(2) \quad . \qquad (10)$$

Figure (1) illustrates the track initialization. It is clear that the initial innovation is zero and the smoothing parameters have no influence of the initial prediction.

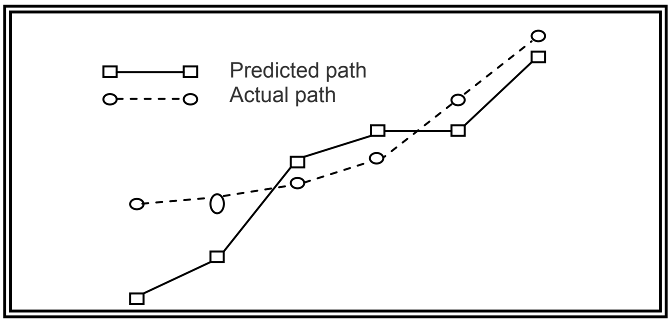

Figure (1): Track Initilization.

4. STABILITY ANALYSIS

The regions of stability at different transient response characteristics of α β tracker can be specified in the α β space. Writing equations (3), (6) and (8) in the z-domain and substituting x_s and v_s into the prediction equation (3) yielding the transfer function of the α β tracker in the z-domain *G(z)* as follow (Llinas et al. [1998]) :

$$G(z) = \frac{\alpha(z-1) + \beta z}{z^2 + (\alpha + \beta - 2)z + (1-\alpha)} \quad , \qquad (11)$$

which can be used to determine the region of stability of the α β tracker. Stability requires that roots of the characteristic polynomial lie within the unit circle in the z-domain. The characteristic polynomial is given by the denominator of equation (11). To prove that the roots lie within the unit circle, one can transform equation (11) into the w-domain, mapping the unit circle of the z-domain to the left half plane of the w-domain and applying one of the known stability criteria in continuos domain. Another approach is to check the stability directly in the z-domain using Jury's Stability Test.

The Jury's Stability Test can be used to analyze the stability of the system without explicitly solving for the poles of the system. Therefore, it is used to determine the bounds on the parameters which result a stable transfer function in the z-domain.

Llinas et al. [1998] showed the stability region of the α β tracker is defined by the following three constraints:

$$(i) \qquad 0 < \alpha < 2 \quad , \tag{12}$$
$$(ii) \qquad \beta > 0 \quad and \tag{13}$$
$$(iii) \qquad 2\alpha + \beta < 4 \quad . \tag{14}$$

The characteristic polynomial is:

$$z^2 + (\alpha + \beta - 2)z + (1 - \alpha) = 0 \tag{15}$$

and the roots of this characteristic equation are:

$$z_1 = \frac{-(\alpha + \beta - 2) + \sqrt{(\alpha + \beta - 2)^2 - 4(1 - \alpha)}}{2} \quad , \tag{16}$$
$$z_2 = \frac{-(\alpha + \beta - 2) - \sqrt{(\alpha + \beta - 2)^2 - 4(1 - \alpha)}}{2} \quad . \tag{17}$$

Critical damping is obtained when $z_1 = z_2$ i.e. when

$$(\alpha + \beta - 2)^2 - 4(1 - \alpha) = 0 \tag{18}$$

i.e. when

$$\alpha + \beta - 2 = \pm 2\sqrt{1 - \alpha} \tag{19}$$

i.e. when

$$\beta = 2 - \alpha \pm 2\sqrt{1 - \alpha} \quad . \tag{20}$$

Equation (20) is valid for all $\alpha \leq 1$ and the system is oscillating if the poles in equation (11) contains a non-zero imaginary part.

Llinas et al. [1998] have shown that when $\alpha > 1$, then the roots of the equation (15) are never negative so the above approach can not be applied. Hence, the final stability boundaries are:

$$0 < \alpha \leq 1 \quad and \tag{21}$$
$$\beta = 4 - 2\alpha \quad . \tag{22}$$

Figure (2) shows the stability region of α β tracker.

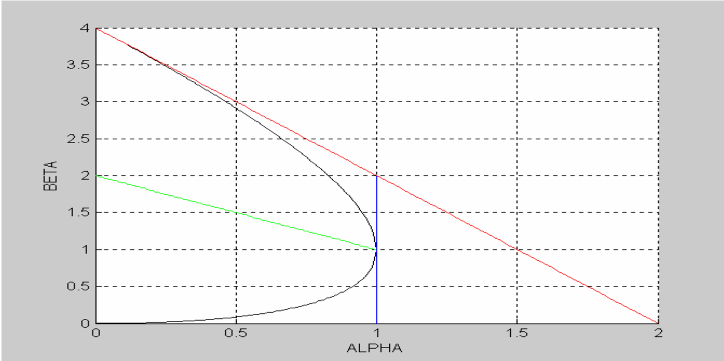

Figure (2): Stability Region of α β Tracker.

5. CHOICE OF α AND β PARAMETERS

In this section we describe the standard methods of selecting α and β parameters. Also, three new methods are suggested.

5.1 CLASSICAL METHODS

The classical α β tracker is designed originally to minimize the mean square error in the filtered position and velocity. The problem with α β tracker is that its design implies a compromise between good noise smoothing, i.e. required small α and β, and good maneuver following capability, i.e. required large α and β values (Hanna [1989]). One of the well known estimates of α and β parameters are (Llinas et al. [1998]) :

$$0 < \tilde{\alpha} \leq 1 \qquad (23a)$$

$$\tilde{\beta} = \tilde{\alpha}^2 / (2 - \tilde{\alpha}) \qquad (23b)$$

Now, the main objective here is to use the possibility to change α and β parameters during confirmed tracking. Thus, the unknown target maneuvers must influence the α and β parameters by increasing swiftness or stability according as the target is accelerating or not (West and Blair [2001]). Hence, the other criterion for selecting the α and β parameters is based on the best linear track fitted to the radar data in a least squares sense. This is leading to use the evolutive parameters which are given as (Skolink [1981] and West and Blair [2001]):

$$\hat{\alpha} = \frac{2(2n-1)}{n(n+1)} , \qquad (24a)$$

$$\hat{\beta} = \frac{6}{n(n+1)} , \qquad (24b)$$

where n is the sequence number of the target measurements and $n > 2$.

5.2 NEW SUGGESTED METHODS

In the last subsection, we have considered two classical methods for estimating α and β parameters. The first method (M1), based on selecting a given value of the parameter α from the interval *(0, 1)*, usually near zero; say $\alpha=0.05$ or $\alpha=0.01$, and then the corresponding value of β is obtained from the equation (23b). The second method, (M2) based on calculating the estimated values of α and β as functions of the available number of measurements n.

We describe now three suggested methods for estimating α and β. The first suggested method, method 3 (M3) is based on the two estimates of β obtained by the previous two methods. A linear combination of two estimated β from the equations (23b) and (24b) can be considered as alternative estimate and denoted by β_{LC} .This suggested estimate is defined as :

$$\beta_{LC} = w\tilde{\beta} + (1-w)\hat{\beta} \quad , \qquad (25)$$

where w is a given weight such that $0 \le w \le 1$. The choice of w can be based on optimization strategies such as the minimization of the mean square error or the minimization of the mean absolute error.

The statistical properties of β_{LC} , like unbiasness and consistency, can be studied if the statistical properties of $\tilde{\beta}$ and $\hat{\beta}$ are known. If both $\tilde{\beta}$ and $\hat{\beta}$ are unbiased estimates of β, such that

$$E(\tilde{\beta}) = E(\hat{\beta}) = E(\beta)$$

and $E(\ .\ )$ is the expectation operator. Then, it is easy shown that β_{LC} is also unbiased estimate of β, i.e.,

$$\begin{aligned} E(\beta_{LC}) &= E[w\tilde{\beta} \quad + \quad (1-w)\beta] \\ &= wE(\tilde{\beta}) + (1-w)E(\hat{\beta}) \\ &= w\beta + (1-w)\beta \\ &= \beta \quad . \end{aligned}$$

On the other hand, when we take the variance operator of both sides of (25), and assuming that $\tilde{\beta}$ and $\hat{\beta}$ are independent, then

$$\text{var}(\beta_{LC}) = w^2\,\text{var}(\tilde{\beta}) + (1-w)^2\,\text{var}(\hat{\beta})$$

Hence, if $\tilde{\beta}$ and $\hat{\beta}$ are consistent estimates of β, then

$$\text{var}(\tilde{\beta}), \text{var}(\hat{\beta}) \to 0 \quad \text{as} \quad n \to \infty$$

Therefore,

$$\text{var}(\beta_{LC}) \to 0 \quad \text{as} \quad n \to \infty$$

and β_{LC} will be also consistent estimate of β.

To avoid the arbitrary choice of α, and also to obtain good maneuver following capability, we can use the estimate (24a) for α, which is denoted by $\hat{\alpha}$.

The summary of the above discussion can be observed in the following algorithm.

ALGORITHM (1) : α β Tracking by Linear Combination Method M3.

Step 1: Fix the value of α at α_0 .
Step 2: Calculate the value of $\bar{\beta}$ and $\hat{\beta}$ from equations (23b) and (24b), respectively.
Step 3: Search for optimal weight w, to obtain the optimal value of β_{LC}.

The second suggested method (M4) is called the adjusted α β tracker. In this method, we suppose that there is a moving window which moves through the measurements during α β tracker computations. Through the moving of the window, the optimal values of *α* parameter is found for the measurements inside the window with respect to the window innovation. The diagram in Figure (3) describes the adjusted α β tracker.

Again, the value of corresponding *β* is obtained from equation (23b). The adjusted *α* and *β* parameters are then employed for the next stage of tracking. To decrease the computation time, the parallel approach maybe used in manner of calculating optimal *α* and *β* parameters for a given window in parallel way during α β tracker computations. However, the parallelism will be used clearly in the next suggested method.
The summary of M4 can be observed in the following algorithm.

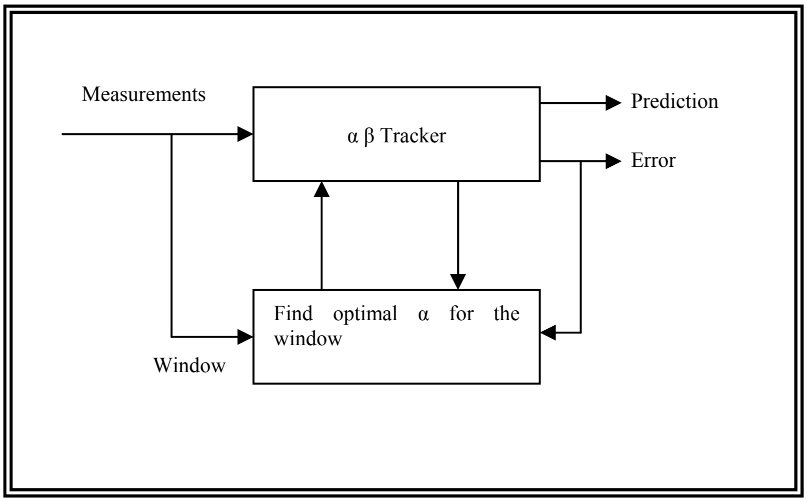

Figure (3): α β Tracking with Adjusting through Window.

ALGORITHM (2) : α β Tracking with adjusting through a window Method M4

Step 1: Fix the values of α and β at α0 and β0 respectively.
Step 2: Track by α β tracker.
Step 3: While tracking, search for optimal α and β for a given window.
Step 4: Adjust α and β parameters by those in step 3.
Step 5: Go to step 2.

The third suggested method (M5) is based on Parallel Processing principles. It is well known that Parallel Processing is a computer trend for improving processing speed by

doing more than one function at the same time. This is depending on Parallel Computers or Parallel Processors (Wagih [1999]). The method M5 is called Parallel α β tracking, and it supposes that there are K α β trackers each one is a fixed gain tracker but with different *α* and *β* parameters. Tracking will be done through all those trackers in parallel manner and the prediction with lowest innovation will be considered as the best prediction in the mean square (or mean absolute) error sense (see Figure (4)). The number of the trackers is constrained by hardware availability. Hence, as the number of the trackers increases, the prediction will be more accurate and vice versa. On the other hand, if the tracking lies between two neighbor trackers for long time, we can increase the trackers between them. However, if the time interval between two measurements (sampling rate) is not too small, M5 can be simulated in the sequential mode easily.
The summary of M5 can be observed in the following algorithm.

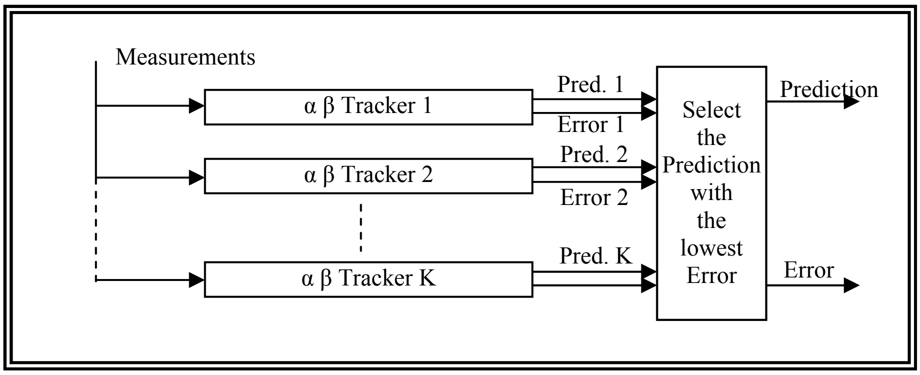

Figure (4): Parallel α β Tracking.

ALGORITHM (3) : Parallel α β Tracking Method M5.

Step 1: Prepare the K α β trackers with different α's and β's parameters.
Step 2: Track with all K α β trackers.
Step 3: At each time step, consider the prediction value with the lowest absolute error as optimal one.

6. SIMULATION EXPERIMENTS

In this section we try to check the performance of the trackers discussed in the last section through simulation approach. Ten sets of simulated radar data were generated, half of them were corrupted by Gaussian white noise and the others were corrupted by Gaussian colored noise. Each set of the data was treated by each five methods M1, M2, M3, M4 and M5.

To specify the major of optimality, we need to measure the distance between the true position and the predicted position by each method. Usually, the Root Mean Square Error (RMSE) is used in this context which is obtained as:

$$RMSE = \sqrt{\frac{sum(actual \;\; position - predicted \;\; position)^2}{no. \;\; of \;\; measured \;\; data}} \quad . \qquad (26)$$

Figures (5) and (6) show comparisons between actual, measured and predicted track using α β tracker by the five methods of selecting α and β parameters and for white and colored noised corrupting; respectively. Figures (7) and (8) as Tables (1) and (2) show the *RMSE* of these results in each case, again for white and colored noise corrupting; respectively. A quick look at these two tables indicates the efficiency of the suggested methods. It is clear that method M5 gives very lower *RMSE* than other methods.

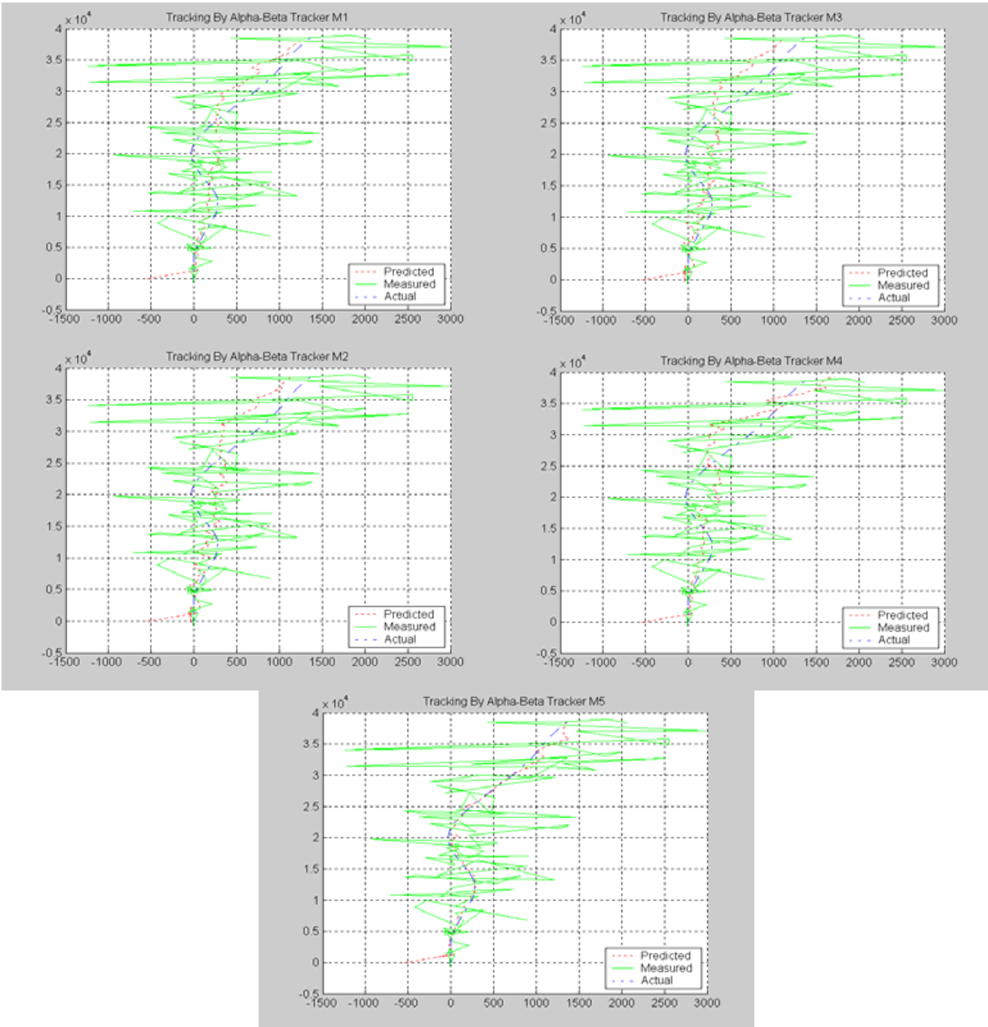

Figure (5): Tracking simulated measurements corrupted by white noise.

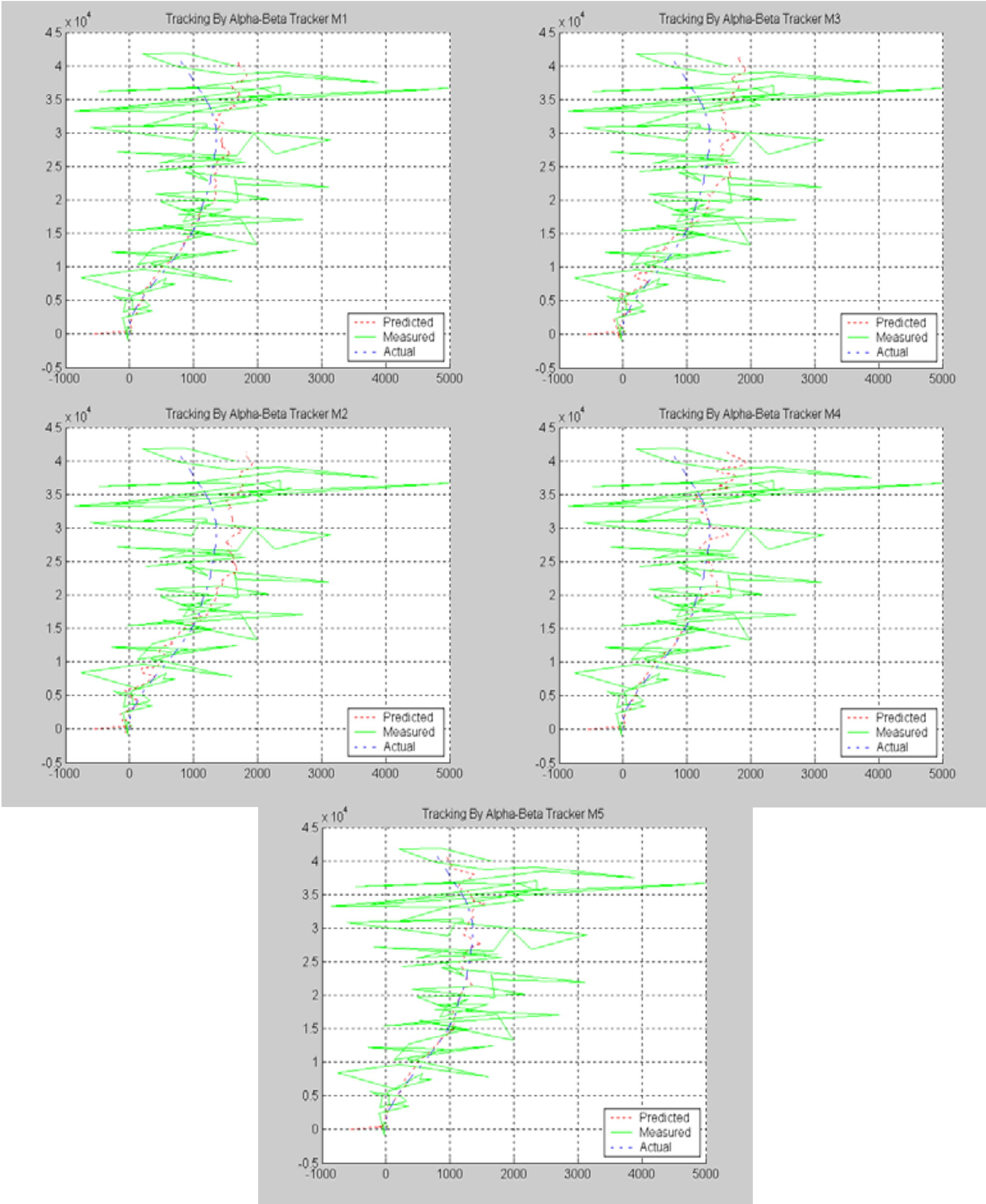

Figure (6): Tracking simulated measurements corrupted by color noise.

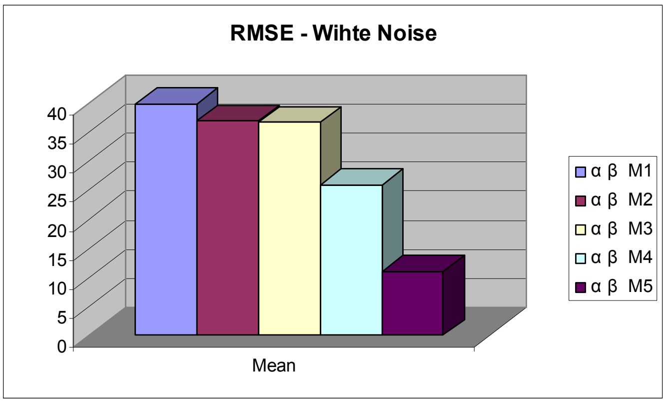

Figure (7): RMSE of the 5 methods – White Noise

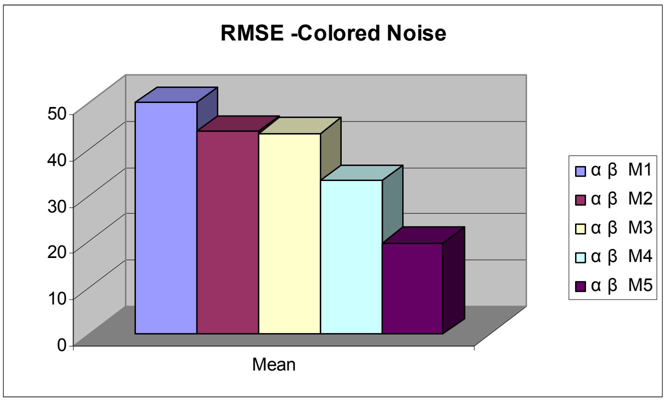

Figure (8): RMSE of the 5 methods – Colored Noise

Table (1): RMSE of tracking white noised simulated data by 5 methods of α β trackers.

Experiment	Coordinates	M1	M2	M3	M4	M5
1	X	28.4589	26.6355	26.6802	25.3460	10.4094
	Y	291.7924	63.6673	66.8815	265.2983	17.7988
2	X	45.8634	47.2913	46.9485	26.1398	11.0342
	Y	299.7238	55.5100	59.1243	268.2146	18.2989
3	X	34.2435	29.6414	29.7098	31.4221	10.1660
	Y	296.4985	60.3253	63.7537	268.3542	17.0756
4	X	40.6228	27.5558	26.8202	23.5749	11.5605
	Y	299.8339	75.4845	78.4928	278.6082	19.1451
5	X	50.5104	53.6469	53.1669	22.7810	11.9972
	Y	307.2010	61.0965	64.9569	278.5191	19.2215

Table (2): RMSE of tracking colored noised simulated data by 5 methods of α β trackers.

Experiment	Coordinates	M1	M2	M3	M4	M5
1	X	43.7560	44.4713	44.0580	25.6035	17.0891
	Y	292.9631	78.7142	79.2807	273.4808	21.6512
2	X	77.0170	51.1982	50.0406	44.6987	17.2379
	Y	277.4844	84.7149	84.5255	259.9784	22.3588
3	X	43.2933	30.5868	29.9748	33.5310	17.4046
	Y	295.8656	102.6156	102.3371	284.3615	21.0918
4	X	36.7597	39.6073	39.6211	36.5744	18.2052
	Y	306.6647	79.9087	80.7844	285.2135	23.2990
5	X	49.1139	53.1412	52.7067	25.1383	16.5149
	Y	300.8425	85.0407	85.7739	283.3336	21.0630

7. DISCUSSIONS AND CONCLUSIONS

In this paper we studied the classical α β tracker and focused our attention on the problem of selecting the α and β parameters. Five methods of selecting these two parameters were considered, two of them are classical, and the others are suggested by the authors of this paper. These five methods are tested through simulation technique and based on realizations of white and colored noise. The simulation exercise is applied on five different experiments.

We start our discussion by considering the two classical methods M1 and M2, as the base for the purpose of comparison. Table (3) shows the averages of the differences between the *RMSE* obtained from each of the classical methods and each of the suggested new methods and when the noise is white. Table (4) shows these averages but when the noise is colored. It is quite obvious that these averages are positive in all cases except when we compare M4 with M2 in the Y-coordinate. In fact, a statistical paired t-test is applied on these differences and indicated a very highly significance difference in *RMSE* obtained for these comparisons. Hence, we may conclude that our suggested algorithms are significantly differing than the classical ones in the positive direction.

In order to see the respective efficiency of the suggested algorithms with respect to the classical ones, we fix method M1 as the base. Then, we compute the percentage of change of RMSE of each of M3, M4, and M5 (RMSEMi $;i = 3,4,5$) with respect to that of M1 ($RMSE_{M1}$), which is defined as

$$PC_{i.1} = \frac{(RMSE_{M1} - RMSE_{Mi})}{RMSE_{M1}} * 100\% \quad ; \quad i = 3,4,5 \quad . \qquad (27)$$

Table (3): The averages of the difference RMSE of Table (1).

Relative to	Coordinates	M3	M4	M5
M1	X	4.7713	14.0870	28.9063
	Y	232.2810	27.3819	280.7019
M2	X	0.3343	11.8137	25.9207
	Y	3.5122	-208.4113	44.9087

Table (4): The averages of the difference RMSE of Table (2).

Relative to	Coordinates	M3	M4	M5
M1	X	9.4102	16.8788	32.6976
	Y	208.2237	17.4905	272.8713
M2	X	0.5262	11.8695	26.5106
	Y	0.5287	-191.0747	64.3061

Tables (5) and (6) show the obtained values of $PC_{i.1}$ and when the noise is white and colored; respectively. Obviously, algorithms M4 and M5 give high and positive $PC_{i.1}$ values, e.g., 10.9382 means that *RMSE* of M4 is 10.9382 % lower with respect to M1.

From the previous tables we may draw a main conclusion that algorithm M5 is the best, then M4, and then M3.

Table (5): The percentage (%) of change of RMSE with respect to M1 - white noise.

Experiment	Coordinates	M3	M4	M5
1	X	6.2501	10.9382	63.4230
	Y	77.0790	9.0798	93.9002
2	X	-2.3659	43.0050	75.9412
	Y	80.2737	10.5127	93.8947
3	X	13.2396	8.2392	70.3126
	Y	78.4978	9.4922	94.2409
4	X	33.9775	41.9663	71.5418
	Y	73.8212	99.0708	93.6148
5	X	-5.2593	54.8984	76.2481
	Y	78.8552	9.4433	93.7430

Table (6): The percentage (%) of change of RMSE with respect to M1 - Colored noise.

Experiment	Coordinates	M3	M4	M5
1	X	-0.6902	41.4857	60.9446
	Y	72.9383	6.6500	92.6098
2	X	35.0266	41.9626	77.6181
	Y	69.5368	6.3088	91.9423
3	X	30.7634	22.5492	59.7984
	Y	65.4109	3.8882	92.8712
4	X	-7.7841	0.5041	50.4751
	Y	73.6571	6.9950	92.4025
5	X	-7.3152	48.8163	66.3743
	Y	71.4888	5.8199	92.9987

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Appendix: List of Symbols.

x	Target position coordinate.	V	Target velocity.
a	Target acceleration.	T	Time instant.
x_p	Target predicted position.	x_s	Target smoothed position.
v_s	Target smoothed velocity.	T	Time period between two scans.
e	Prediction error.	x_m	Target measured position.
α	Position smooth parameter.	B	Velocity smooth parameter.
z	Z-transform coefficient .	G	Transfer function.
w	Weight parameter in method 3.	N	Number of measurements.
K	Number of $\alpha\beta$ trackers in method 5.	$RMSE$	Root Mean Square Error.
$\tilde{\alpha}$	Estimated α by method 1.	$\tilde{\beta}$	Estimated β by method 1.
$\hat{\alpha}$	Estimated α by method 2.	$\hat{\beta}$	Estimated β by method 2.
β_{LC}	Estimated β by method linear combination of methods 1 and 2.		

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دراسة المعقب الفا بيتا باستخدام بعض الخورزميات الجديدة لاختيار المعلمتين ألف وبيتا

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ملخص

تدرس هذه المقالة مسالة تعقب الهدف و ذلك بواسطة معقب ألفا بيتا، وتناقش بعض الخواص النظرية لهذا المعقب مع التركيز على طريقة اختيار المعلمتين ألفا و بيتا. تستعرض أولاً طريقتين تقليديتين في اختيار هاتين المعلمتين ومن ثم تقترح ثلاثة خوارزميات جديدة لهذا الغرض. تجرى تجارب بالمحاكاة على مشاهدات مولدة في حالتي التشويش الأبيض و الملون، وتظهر الخوارزميات المقترحة كفاءة جيدة مقارنة بالطريقتين التقليديتين.