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REAL TIME TRAJECTORY TRACKING OF MOVING OBJECTS USING ADAPTIVE FUZZY TIME SERIES AND EXPONENTIAL SMOOTHING FORECASTING TECHNIQUES

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Abstract: In his study; in cases where the targeted object which is taken from a real time camera shot is in a circular motion, quasi projectile motion and maneuvering dynamic motion, its later location where it will be is examined using the Adaptive Fuzzy Time Series (AFTS) and Exponential Smoothing (ES) estimation methods. Error evaluation of these motions was performed according to the Mean Absolute Percentage Error (MAPE) method. In the conducted evaluation, with AFTS, the circular motion was found to be 3.65%, quasi projectile motion 9.12%, and maneuvering dynamic motion 19.23%, and with ES, circular motion 4.48%, quasi projectile motion 1.13% and maneuvering dynamic motion was found to be 0.61%. AFTS gives better results than ES for the circular motion but ES gives better results than AFTS for quasi projectile and maneuvering dynamic motions.

Keywords: Target tracking, Estimation algorithms, Adaptive fuzzy time series, Exponential smoothing

Hareketli Nesnelerin Uyarlanabilir Bulanık Zaman Serileri ve Üssel Düzeltme Tahmin Tekniklerini Kullanarak Gerçek Zamanlı Yörüngelerinin İzlenmesi

Öz: Bu çalışmada; gerçek zamanda kamera görüntüsünden alınan hedef cismin; dairesel, eğik atışa benzer ve manevralı dinamik hareket yapması durumunda, bir sonraki konumu veya nerede olacağı Adaptive Fuzzy Time Series (AFTS) ve Exponential Smoothing (ES) tahmin yöntemleriyle incelenmiştir. Bu hareketlerin hata değerlendirmesi, ortalama mutlak yüzde hata (MAPE) yöntemine göre yapılmıştır. Yapılan değerlendirmede, AFTS ile dairesel harekette %3.65, eğik atışa benzer harekette %9.12, manevralı dinamik harekette %19.23, ES ile dairesel harekette %4.48, eğik atışa benzer harekette %1.13 ve manevralı dinamik harekette ise %0.61 elde edilmiştir. Dairesel harekette AFTS ES'den, eğik atışa benzer ve manevralı dinamik harekette ise ES AFTS'den daha iyi sonuç vermiştir.

Anahtar Kelimeler: Hedef takibi, tahmin algoritmaları, uyarlanabilir bulanık zaman serileri, üssel düzeltme

1. INTRODUCTION

The location estimation and the trajectory estimation of a moving object are important in civilian and military applications. In military applications location estimation is used to hit to moving enemy target with a rocket Yang and et al. (2007); Kosut and al. (2007); Tang and Huang (2006); Marques and Dias (2007) in traffic used in vehicle control applications Hu et. al. (2004); Shen et. al. (2011), in robotics used to control robot manipulator Yagimli and Varol (2008); Ohno et. al. (2006); Vallery et. al. (2009); Kumar and Garg (2004) and in industry in quality control (Bourne et. al., 2011; Facco et. al., 2009; Zhou et. al., 2004; Hu et. al., 2008).

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In the literature, there are trajectory estimation studies in which different techniques are used. These studies are relevant to the trajectory-based Yang and Ji (2010); Chakraborty and Meher (2011); Chakraborty and Meher (2012); Hsieh et. al. (2012); Unrath et. al. (2007), Kalman filter Eustice et. al. (2004); Chen et. al. (2007); Ryan et. al. (2004); Prėvost et. al. (2007) and Jacobian methods (Piepmeier et. al. 1998; Piepmeier et. al. 2004).

In this study the point where a moving object which was tracked be next was calculated. The real time camera shot was relayed to the software. The targeted image taken from the camera and the images located in the database were compared with each other in terms of color and shape. When a 90% similarity was found between both images, identification of the targeted image was done. The image area acquired from the camera that was relayed to the software was scaled on the horizontal axis between 0-4800 and on the vertical axis between 0-3600. Mid-point coordinates of the targeted object and the distance it bears from the reference point were determined via the prepared database (Yagimli and Varol, 2009a, 2009b, 2009c).

In our study, trajectory estimation of a moving object whose location values are present was carried out with the AFTS and ES estimation techniques, whose application we are yet to know if or not is existent in the literature, and then both methods were compared.

2. ADAPTIVE FUZZY TIME SERIES (AFTS) FORECASTING TECHNIQUE

Fuzzy sets and fuzzy logic are based on people by taking the ability of humans to think as a model, being able to summarize the information and to extract information from the data in our brains. Thinking processes of humans in the fuzzy-style are represented using fuzzy sets. These masses are named as the membership function. In classic masses, an expression is either right or wrong. In fuzzy masses, an expression has a membership value between 0 and 1 (Zadeh, 1965).

Random information is only indexed as a time series and its name is given as time series analysis. The adaptive modeling of the fuzzy time series is as follows (Pantazopoulos and Pappis, 1996; Huang et. al., 2012):

$D_{\min}$ and $D_{\max}$ values are obtained from the data and Uint distance between the two units is determined.

The number of equal intervals is decided and itv is found. This value is used in the fuzzy mass Ud.

Ur is used with this increasing values in the equality below:

$$\text{Ud}=[\text{Dmin}-(\text{itv}-\text{Ur}), \text{Dmax}+\text{itv}] \tag{1}$$

In the equality no (2), some simple values represented with the fuzzy masses were given.

$$\begin{aligned}
\tilde{S}_1 &= \left\{ 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + 0/u_5 \right\} && \text{Descending}\\
\tilde{S}_2 &= \left\{ 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + 0/u_5 \right\} && \text{Slowly descending}\\
\tilde{S}_3 &= \left\{ 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + 0/u_5 \right\} && \text{Similarly}\\
\tilde{S}_4 &= \left\{ 0/u_1 + 0/u_2 + 0.5/u_3 + 1/u_4 + 0.5/u_5 \right\} && \text{Slowly increasing}\\
\tilde{S}_5 &= \left\{ 0/u_1 + 0/u_2 + 0/u_3 + 0.5/u_4 + 1/u_5 \right\} && \text{Increasing}
\end{aligned} \tag{2}$$

For example, when the Ud value is divided into five equal intervals, we get itv=5. When the information from three periods is used to make assumptions, we get O3(t) 3x5 matrix, R(t) and Z(t) 1x5 matrix. When we take the values from the slowly increasing fuzzy sets into account;

$$Z(t)=[0 \quad 0 \quad 0.5 \quad 1 \quad 0.5] \tag{3}$$

$$R(t)=\begin{bmatrix} O_{11} \text{ x } Z_1 & O_{12} \text{ x } Z_1 & \ldots & O_{1m} \text{ x } Z_m \\ O_{21} \ x \ Z_2 & O_{22} \text{ x } Z_2 & \ldots & O_{2m} \text{x} Z_m \\ O_{31} \text{ x } Z_1 & O_{32} \text{ x } Z_2 & \ldots & O_{3m} \text{ x } Z_m \end{bmatrix} \tag{4}$$

$$O^3(t)=\begin{bmatrix} FTs(t-2) \\ FTs(t-3) \\ . \\ . \\ FTs(t-n-1) \end{bmatrix} \tag{5}$$

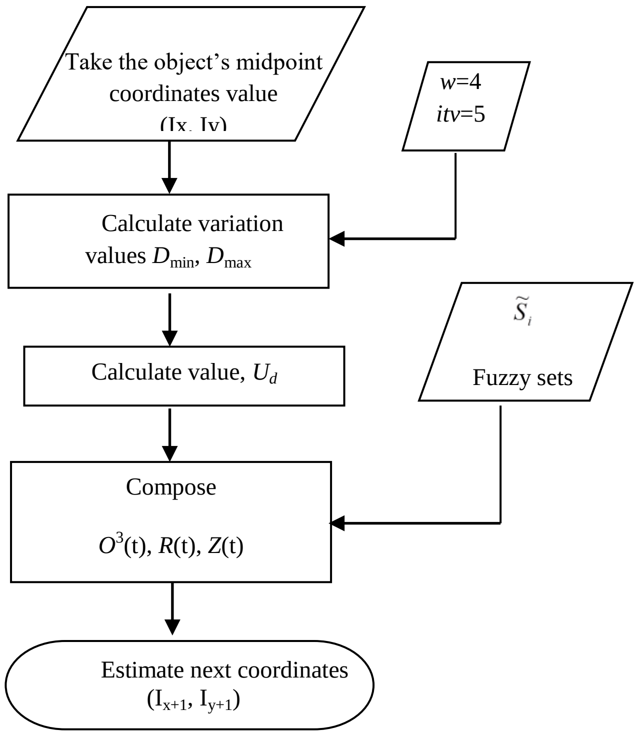

Figure 1:
Flow diagram of the developed AFTS

A flow diagram of the AFTS developed is shown in Figure 1. In the developed estimation method, the first four values of the x and y coordinates of the mid-points according to the motion the object follows are accepted as (w=4). D_{min} and D_{max} and are then divided into five equal pieces (itv=5). It is determined in which range each data falls in the fuzzy set. And it is estimated in which range the next data will fall.

2.1. Circular Motion

Let's think that the object carries out a motion similar to a circular motion, as seen in Figure 2. Table 1 illustrates the real values.

Table 1. Real coordinates values of the circular motion

I_x	I_y	I_x	I_y
1150	1800	3600	2000
1200	2100	3600	1800
1300	2400	3580	1600
1400	2600	3550	1400
1540	2800	3470	1200
1700	2970	3350	1000
1900	3100	3150	750
2100	3170	2780	190
2300	3200	2260	470
2500	3200	1900	600
2800	3140	1600	800
3050	3000	1430	1000
3250	2800	1320	1200
3400	2600	1250	1400
3500	2400	1200	1600
3560	2200	1160	1800

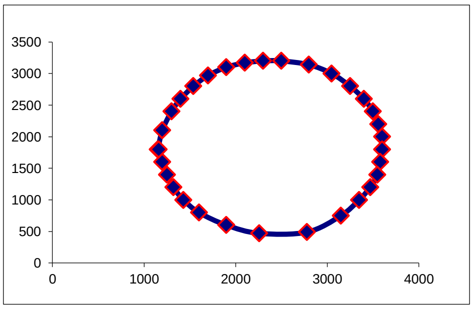

Figure 2:
Circular motion

Table 2. Estimated values for the circular motion

$I_{(x+1)}$	$I_{(y+1)}$	$I_{(x+1)}$	$I_{(y+1)}$
1150	1800	3600	2033
1200	2100	3600	1828
1300	2400	3580	1625
1400	2600	3550	1422
1540	2800	3470	1220
1700	2970	3350	1018
1900	3100	3150	816
2100	3170	2780	562
2300	3200	2260	297
2500	3200	1900	286
2800	3200	1600	730
3050	3080	1430	964
3250	2900	1320	1176
3400	2667	1250	1382
3500	2450	1200	1585
3560	2240	1160	1788

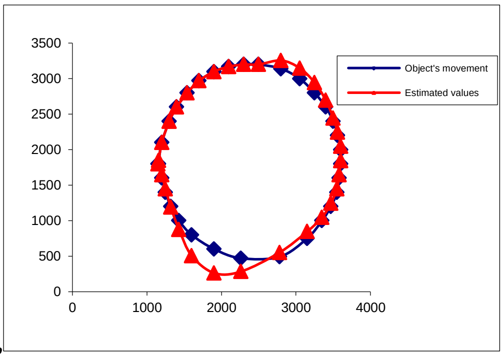

Figure 3:
Real and estimated location values belonging to the circular motion using AFTS

The values estimated with AFTS are shown in Table 2. In the Figure 3, the graphic of the real location values and the location values estimated with AFTS is shown.

2.2 Quasi Projectile Motion

Let's assume that the object carries out a motion similar to a quasi projectile motion, as seen in Figure 4. Table 3 illustrates the real values.

Table 3. Real coordinates values of the quasi projectile motion

I_x	I_y	I_x	I_y
200	2100	1500	500
300	1950	1800	400
400	1800	2040	300
500	1650	2200	250
600	1500	2360	200
750	1300	2600	250
850	1150	2800	300
1000	1000	3000	400
1100	900	3200	500
1200	800	3320	600
1300	700	3450	700
1400	600	3570	800

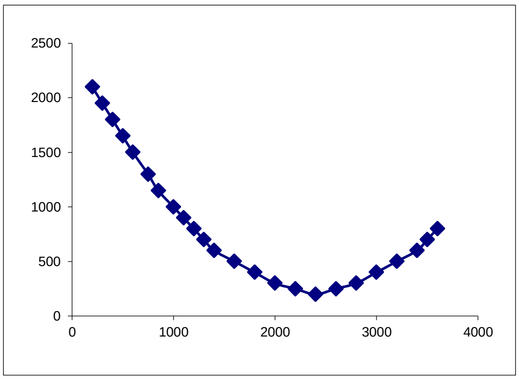

Figure 4:
Quasi projectile like motion

Table 4. Estimated values of the projectile motion

$I_{(x+1)}$	$I_{(y+1)}$	$I_{(x+1)}$	$I_{(y+1)}$
1080	1158	1943	400
1087	1016	2100	384
1194	1016	2300	242
1301	874	2500	226
1408	858	2800	280
1515	716	3100	380
1622	700	3300	510
1729	558	3400	580
1836	542	3550	690

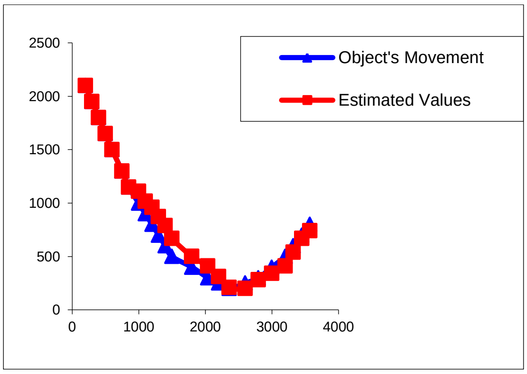

Figure 5:
Real and estimated values for the quasi projectile motion with AFTS

The values estimated with AFTS are shown in Table 4. In Figure 5, the graphic of the real location values and the location values estimated with AFTS belonging to quasi projectile motion is shown.

2.3 Maneuvering Dynamic Motion

Let’s accept that an object changes its present trajectory with a maneuver in a very short time, as seen in Figure 6. Table 5 illustrates real coordinates values of the maneuvered dynamic motion.

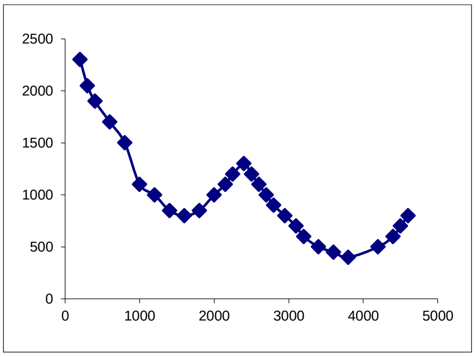

Figure 6:
Object's maneuvering dynamic motion

Table 5. Real coordinates values of the maneuvered dynamic motion

I_x	I_y	I_x	I_y
200	2300	2500	1200
300	2050	2600	1100
400	1900	2700	1000
600	1700	2800	900
800	1500	1950	800
1000	1100	3100	700
1200	1000	3200	600
1400	850	3400	500
1600	800	3600	450
1800	850	3800	400
2000	1000	4200	500
2150	1100	4400	600
2250	1200	4500	700
2400	1300	4600	800

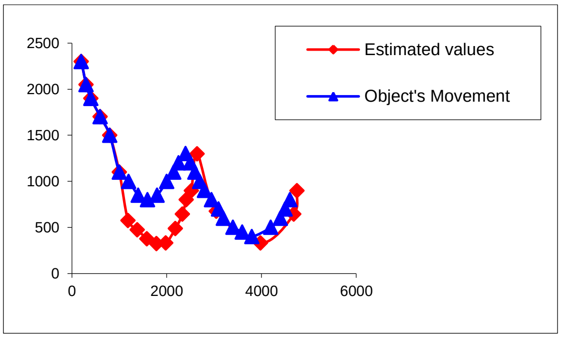

Figure 7:
Real and estimated values for maneuvering dynamic motion for AFTS application

Tablo 6. Estimated values for the maneuvered dynamic motion

$I_{(x+1)}$	$I_{(y+1)}$	$I_{(x+1)}$	$I_{(y+1)}$
200	2300	1984	331
300	2050	2184	487
400	1900	2334	643
600	1700	2413	799
800	1500	2521	899
1000	1100	2642	1299
1284	575	3050	675
1384	475	3984	331
1584	375	4682	643
1784	325	4749	899

In Figure 7, the graphic of the real location values and the location values estimated with AFTS belonging to maneuvering motion is shown. Table 6 illustrates estimated values for the maneuvered dynamic motion.

3. EXPONENTIAL SMOOTHING (ES) FORECASTING TECHNIQUES

Simple ES is a very popular, practical and generally accepted method among the smoothing techniques which are used for reducing the variations in time series data (i.e., preparing smoothed time series). A time series can simply be defined as sequence of observations based on time order of a physical or financial variable made at equally spaced time intervals (Palit and Popovic, 2005).

A numerical time series can be defined with the temporal variable t_i and time dependent variable x_i as (x_i, t_i) where $t_i + 1 > t_i$ and $i = 1,2,3,...n \forall_i$ (Nind and Torra, 2009).

Exponential smoothing can be classified as “model-free” forecasting method from the system-theoretical approach (Palit and Popovic, 2005). Similar moving averages, basic idea is to assign weights to the data denoting their importance in the computation systematic. Generally this forecasting model assigns exponentially decreasing weights to the data observed as the data grow obsolete depending on time; more recent the observation more impact on the forecast value. The ES method is based upon the fact of using the future estimation with the present real value and the estimation of a certain weight ratio. This characteristic of exponential smoothing makes it more appropriate for short-time forecasting. Let Ft be the forecast value for period t, then the exponential smoothing model and the error correction are generally defined as;

$$F_t = \alpha A_{t-1} + (1-\alpha)F_{t-1} \tag{6}$$

$$F_t = -(\alpha e_{t-1}) + F_{t-1} \tag{7}$$

where At-1 is the one period ahead actual value of the time series, Ft-1 is the one period ahead smoothed value, α (0<α<1) is the smoothing constant determining the weights assigned and et is the error term. As the value of α directly related to the characteristics of time series that will be smoothed; depending on the nature data and observation methods used for collecting data, there are several way of determining the value of α such as trial and error or adaptive filtering method. Smaller values of α (0.1< α <0.3) are most commonly used as the forecast value within this interval depends on a large number of past observations (Palit and Popovic, 2005). As the determination of value α is snarl and the appropriate value varies from system to system, in addition to the crisp value determination models, successful fuzzy approaches are also used to cope with this problem like Tsaur (Tsaur and Kuo, 2011).

Here, α is the correction coefficient and its value is 0<α<1. The present observation is determined by the weight in the formula. Also, (1- α) expresses the weight of the estimation values belonging to the past observation. While At-1 expresses the real value, Ft-1 expresses the value of the previous period. This method gives more importance to the last observation value.

3.1 Circular Motion

Tablo 7. Estimated values for the circular motion

$\mathbf{I_{(x+1)}}$	$\mathbf{I_{(y+1)}}$	$\mathbf{I_{(x+1)}}$	$\mathbf{I_{(y+1)}}$
1150	1800	3600	2046
1200	2100	3600	1846
1300	2400	3580	1646
1400	2600	3550	1446
1540	2800	3470	1246
1700	2970	3350	1046
1900	3100	3150	846

2100	3170	2780	551
2300	3200	2260	282
2500	3200	1900	262
2800	3257	1600	506
3050	3149	1430	877
3250	2945	1320	1191
3400	2697	1250	1448
3500	2446	1200	1648
3560	2246	1160	1848

Table 7 illustrates estimated values for the circular motion with ES.

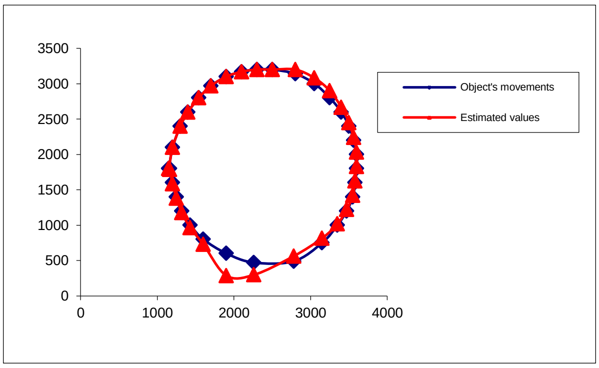

Figure 8:
Real and estimated values for circular like motion for ES application

In Figure 8, real location values and the location values estimated with ES belonging to circular motion is shown.

3.2 Quasi Projectile Motion

The estimated values obtained when the position values of the quasi projectile motion of Table 8 are applied to the ES estimation algorithm.

Table 8. Estimated values for the quasi projectile motion

$I_{(x+1)}$	$I_{(y+1)}$	$I_{(x+1)}$	$I_{(y+1)}$
190	199	159	505
295	195	178	405
395	180	199	305
495	165	219	253
595	150	239	202

742	131	259	248
845	115	279	297
992	100	299	395
109	905	319	495
119	805	339	595
129	705	349	695
139	605	359	795

In Figure 9, real location values and the location values estimated with ES belonging to quasi projectile motion is shown.

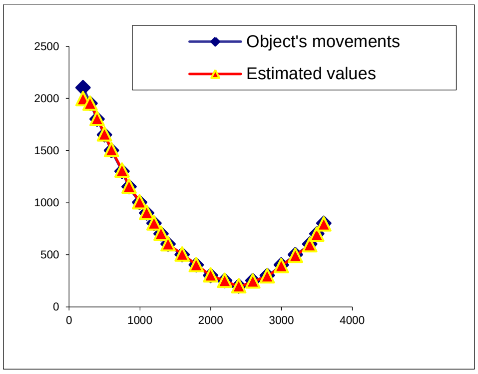

Figure 9:
Real and estimated values for quasi projectile like motion for ES application

3.3 Maneuvering Dynamic Motion

Table 9. Estimated values for the maneuvering dynamic motion

I_x	$I_{(x+1)}$	I_y	$I_{(y+1)}$
190	2185	2495	1205
295	2057	2595	1105
395	1908	2695	1005
590	1710	2795	905
790	1511	2942	805
990	1120	3092	705
1190	1006	3195	605
1390	858	3390	505
1590	803	3590	453

1790	847	3790	402
1990	992	4180	495
2142	1095	4389	595
2245	1195	4494	695
2392	1295	4595	795

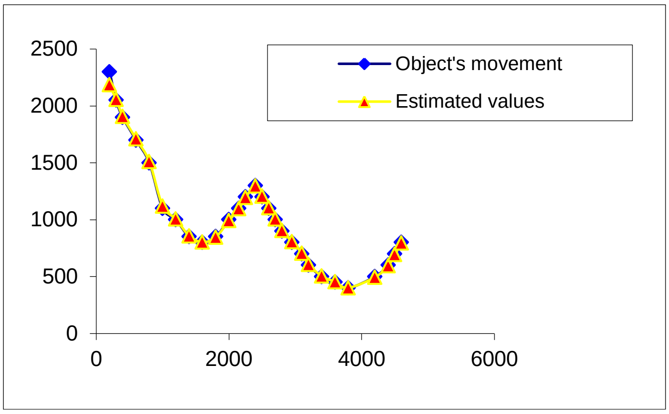

Figure 10:
Real and estimated values for maneuvering dynamic motion for ES application

Table 9 illustrates estimated values for the maneuvering dynamic motion.

4. COMPARISON OF AFTS WITH ES

Total error percentage of the real motion and the estimated motion of the circular, quasi projectile and maneuvering dynamic motions done in both of the estimation methods is carried out according to the "mean absolute percentage error (MAPE)" method. Mean absolute percentage error equality (Nahmias, 1997);

$$MAPE = \left[\left(\frac{1}{n}\right)\sum_{i=1}^{n}\left|\frac{e_i}{D_i}\right|\right]\times 100 \tag{8}$$

n = Observation number
e_i = i'th error value
Di= i'th observation value

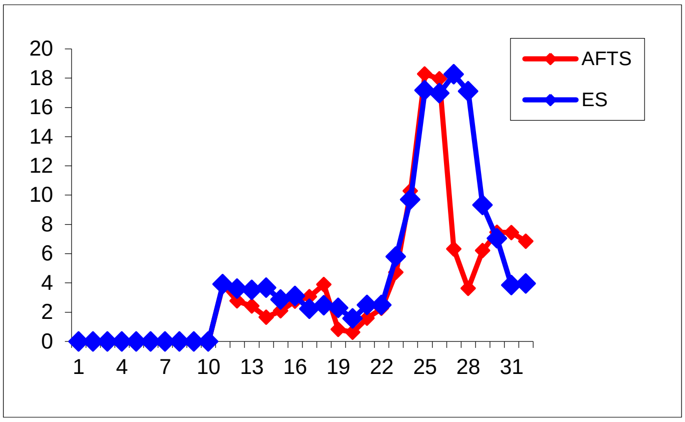

Figure 11:
Comparison of AFTS with ES in the circular motion

As seen in the Figure 11, total error percentage in the circular motion with AFTS is 3.65% and with ES is 4.48%.

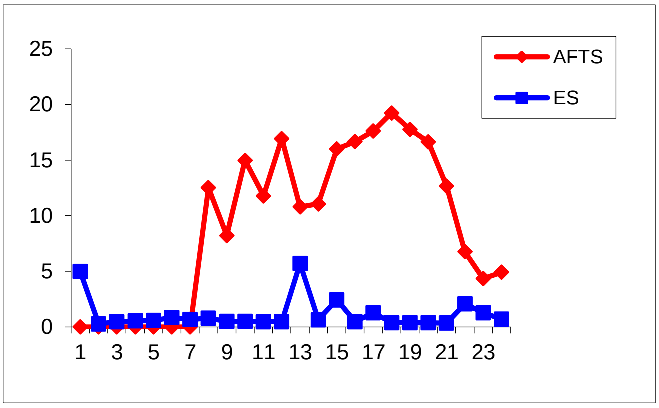

Figure 12:
Comparison of AFTS with ES in the quasi projectile motion

As seen in the Figure 12, total error percentage in the quasi projectile motion with AFTS is 9.12% and with ES is 1.13%.

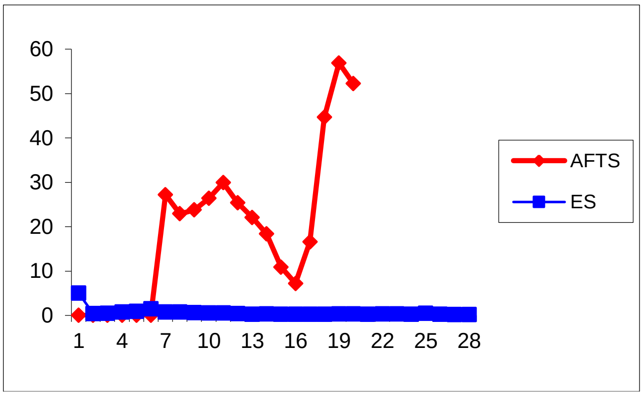

Figure 13:
Comparison of AFTS with ES in the quasi projectile motion

As seen in the Figure 13, total error percentage in the maneuvering dynamic motion with AFTS is 19.23% and with ES is 0.61%.

5. CONCLUSIONS

Table 10. Total Error Percentages of the Motions According to the Estimation Techniques

	AFTS Estimation Technique	ES Estimation Technique
Circular Motion	3.65 %	4.48 %
Quasi Projectile Motion	9.12 %	1.13 %
Maneuvering Dynamic Motion	19.23 %	0.61 %

In the AFTS estimation method while it estimates the next location where the object will be, as it looks at the object's four real location values each time and then it estimates to which interval each datum will fall into, a good estimation was obtained in the circular motion in routine positions. However, as the object descends from the top location point or vice versa, a good prediction was not obtained. While looking at the four real values, the AFTS estimation algorithm again tried to catch a motion similar to that. However, in the ES estimation method the last observation value is more important and thus in the circular motion, better results were obtained with AFTS. A better prediction was made possible with ES in the quasi projectile motion as 1.13% and in the maneuvering dynamic motion as 0.61%. The conducted estimation application was integrated into a robot arm and good results were obtained (Yagimli, 2010).

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