A Fuzzy Prediction Based Trajectory Estimation

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Abstract: - Image processing, object tracking and trajectory estimation are the integral topics of computer vision which are rapidly gaining importance due to their non-ignorable relation with defense, security and also health sectors. In this paper; by use of image processing techniques, real time images containing tracked object from the camera are transferred to a Visual Basic based software; tracked object in images is discerned from the background and using segmentation process transferred into matrix form via which object centre point coordinates are determined. After determination of centre point coordinates, the trajectory the moving object is estimated with an adaptive fuzzy time series forecasting model using the determined coordinate values.

Key-Words: - Object tracking, Trajectory estimation, Adaptive estimation, Fuzzy time series.

1 Introduction

Image processing is one of the remarkable research area that much draw attention especially in recent years as it involves techniques and processes of amending and analyzing images. The input image(s) from an image source are transformed into useful input forms according to the needs of technique, software or processes that will be used in analyzing or modifying the image(s) to obtain the desired output(s). Image segmentation is one of the most common techniques used in image processing via which a feature within an image can be isolated or identified including size and shape of the feature [1]. On the other hand, object tracking (OT); which is also one of the relatively new, complicated and vital subjects of computer vision that attract a deep attention, can simply be defined as "the problem of estimating the trajectory of an object in an image plane as it moves around the scene" [2]. As researches in OT are almost completely nested to the researches in security systems and defense technologies domain, OT processes are carried out using various methods and algorithms in literature such as studies that have enabled the development of neural network-based systems [3]. To ensure system continuity and also to increase flexibility of adaptation to possible system changes; especially, adaptive control methods are preferred in target tracking [4, 5].

Since pioneer work of Zadeh [6]; in which fuzzy logic (FL) was introduced, many studies have been done related to this brilliant subject. FL is also used successfully in processes requiring real-time comparisons as well as in image-based tracking [7, 8]. As the nature of prediction contains uncertainty or vagueness which are the facts to be deal with for accurate forecasting, it best fits for the applications of FL and fuzzy set theory [9, 10, 11, 12].

Time series forecasting models have been successfully applied and used in science, engineering and business activities and studies. The name time series analysis is given as the structural dependencies related parameters and observation data from random phenomena are indexed by only time parameter [13]. The model that will be used for forecasting mainly depends on the class of time series. Depending on the data, time series can be classified under four groups as;

- stationary (when the underlying stochastic process is in a particular state of equilibrium) or non-stationary;
- seasonal or non-seasonal
- linear (the shape of time series depends on it's state, like ARMA models) or non-linear
- univariate or multivariate.

Thought traditional forecasting models which are selected and used due to the characteristic of time series can handle forecasting process for the decision making, when historical demand data that will use to calculate the desirable forecast value are linguistic values and (or) are in small amounts, fuzzy time series model best fit the aspect [14, 15, 16, 17, 18, 19, 20]. In this study an image processing technique is used to determine the location of a moving object and then fuzzy time series (FTS) forecasting model is used for the trajectory estimation.

The following sections of the paper are organized as follow. In section 2, FTS forecasting is introduced. In section 3, proposed system structure is explained. Finally; in sections 4 and 5, the application and research findings together with conclusions are presented.

2 FTS Forecasting Model

As stated before, the uncertainty or vagueness nature of forecasting makes it best fits for the applications of FL and fuzzy set theory. Generally, fuzzy rules are the main stay of fuzzy forecasting. But building proper fuzzy rules and determining appropriate membership functions for the parameters of forecasting activity according to the system that will be analyzed is; unfortunately, not a simple activity. Due to this fact, the studies on fuzzy forecasting and their application to different system structures are considerably much. Kahraman [9] have made comprehensive literature reviews about the fuzzy set theory applications in forecasting area.

A definition of fuzzy time series is given Lee and Chou [21] as follow:

Definition: Let $X(t)\,(=...,1,2,....)$, a subset of real line R, be the universe of discourse on fuzzy sets $\widetilde{A}_i(t)\ (i=1,2,\ldots)$ are defined and $FTs(t)$ is the collection of $\widetilde{A}_i(t)\ (i=1,2,\ldots)$. Then $FTs(t)$ is called a fuzzy time series on $X(t)\,(=...,1,2,....)$.

Song *et al.*[16, 17, 18, 19] fuzzifying the enrollments of the University of Alabama, used fuzzy time series in forecasting problems and proposed a first-order time-variant fuzzy time series with first-order time-invariant fuzzy time series for the solution of the forecasting problems. Later authors introduced a new FTS model and betrayed that best results are held by applying neural network for defuzzifying data as stated before.

Differently from Song *et al.* [16, 17], Hwang *et al.* [20] (using the same data) described heuristic rules, established fuzzy relationships defining a fuzzy set for each year and using the relation matrix compute the forecast values. The error analysis of model betrayed that the average error rate of the proposed model is significantly lower than Song et al.'s model. Considering this result, Hwang *et al.*'s model with same extensions is used in this study. The steps of Hwang *et al.*'s FTS model can be summarized as follow [11, 20]:

i.)First, the variation between two historical data is to be calculated and minimum/maximum variation values (i.e., $D_{\min}/D_{\max}$) are to be determined,

ii.) Next step is to define the universe discourse (U_d) with following equation using $D_{\min}$ and $D_{\max}$.

$$U_d = [D_{\min} - D_1\,,\, \mathrm{D}_{\max} + D_2] \tag{5}$$

where D_1 and D_2 are positive appropriate values that fits for separating U_d into equally length intervals.

iii.) Then, fuzzy sets on U_d are to be defined and variation data is to be fuzzified. Defining fuzzy time series $FTs(t)$ as

$$FTs(t) = {p_{Z1}}/{u_1} + {p_{Z2}}/{u_2} + ... + {p_{Zm}}/{u_m} \tag{6}$$

where the memberships p_{zi} are $0 \le p_{zi} \le 1$. The fuzzy sets $\widetilde{S}_i$ of U_d then can be represented as;

$$\widetilde{S}_i = \left\{ {p_{Z1}}/{u_1} + {p_{Z2}}/{u_2} + ... + {p_{Zm}}/{u_m} \right\} \tag{7}$$

Fuzzifications of variations are determined according to interval u_i of U_d that they fit.

iv.) Next step includes composing the relation matrix; $R(t)$, which is governed by operation ($O^w(t)$) and criterion matrixes ($Z(t)$), and defuzzifying the calculated variation which will be used for estimating the forthcoming value using the relation of the chance value gathered from relation matrix . In this step the windows basis; w ($w = 2, 3, ..., \mathrm{n}$), have to be determined which shows the number of periods of variations that will be used for forecasting. For period t, $O^w(t), Z(t)$ and $R(t)$ is defined respectively as follow:

$$Z(t) = FTs(t-1) = \left[Z_1,\ \ Z_2,\ Z_3, ...Z_n \right] \tag{8}$$

$$O^{w}(t)=\begin{bmatrix} FTs(t-2) \\ FTs(t-3) \\ . \\ . \\ FTs(t-w-1) \end{bmatrix}=\begin{bmatrix} O_{11} & O_{12} & \dots & O_{1m} \\ O_{21} & O_{22} & \dots & O_{2m} \\ . & . & . & . \\ . & . & . & . \\ O_{w1} & O_{w2} & \dots & O_{wm} \end{bmatrix} \tag{9}$$

$$R(t)=\begin{bmatrix} O_{11}\text{ x }Z_1 & O_{12}\text{ x }Z_1 & \dots & O_{1m}\text{ x }Z_m \\ O_{21}\text{ x }Z_2 & O_{22}\text{ x }Z_2 & \dots & O_{2m}\text{x}Z_m \\ . & . & . & . \\ . & . & . & . \\ O_{w1}\text{ x }Z_1 & O_{w2}\text{ x }Z_2 & \dots & O_{wm}\text{ x }Z_m \end{bmatrix} \tag{10}$$

Let O_{ik} x $Z_k = R_{ik}$ (for $1 \le \mathrm{i} \le w$ and $1 \le k \le m$) then, equation 6 can be rewritten as;

$$R(t)=\begin{bmatrix} R_{11} & R_{12} & \dots & R_{1m} \\ R_{21} & R_{22} & \dots & R_{2m} \\ . & . & . & . \\ . & . & . & . \\ R_{w1} & R_{w2} & \dots & R_{wm} \end{bmatrix} \tag{11}$$

Then the estimated variation will be determined with the following equality;

$$Fv(t)=\left[r_1, r_2, \dots\dots r_m\right] \tag{12}$$

where $r_j = Max(R_{ik})$

v.) Last step of the model implies defuzzification of the predicted variations and computing the forecast value for the desired time period. There are three rules for defuzzification [13]; a) if membership of an output is zero then no change exist, b) if the membership of an output has single maximum u_i, then forecast value of variation is the midpoint of the interval, c) if the membership of an output has more then one maximum u_i, then take the average u_i as the forecast value of variation.

And finally, the forecast value for the period t; F_t is computed as;

$$F_t = Fv(t) + A_{t-1} \tag{13}$$

where A_{t-1} is the one-step back actual observation value of the time series.

As selection of the appropriate D_1 and D_2, which are used to separate U_d into equal length intervals, depends on the data set and the judgment of forecaster in this model, Lee *et al.* [21] proposed a modification of this model which defines U_d with a more improved way with the following procedure.

$$U_d=\begin{cases} \left[\left(D_{\min}-\left(\sigma/\sqrt{n}\right)t_\alpha(n)\right), \left(D_{\max}+\left(\sigma/\sqrt{n}\right)t_\alpha(n)\right)\right] & \text{if } n \le 30; \\ \left[\left(D_{\min}-\left(\sigma/\sqrt{n}\right)z_\alpha(n)\right), \left(D_{\max}+\left(\sigma/\sqrt{n}\right)z_\alpha(n)\right)\right] & \text{if } n > 30; \end{cases} \tag{14}$$

where $t_\alpha(n)$ is the $100(1-\alpha)$ percentile of the t distribution with n degree of freedom, and z_α is the $100(1-\alpha)$ percentile for the standard normal distribution.

3 Proposed System Structure

The system software is an I/O (Input/Output) based program where images are input to the program from the external environment via a camera. Images can be transferred from the camera to the processor in real-time. System design is realized in two main steps: image processing and trajectory estimation with FTS forecasting model.

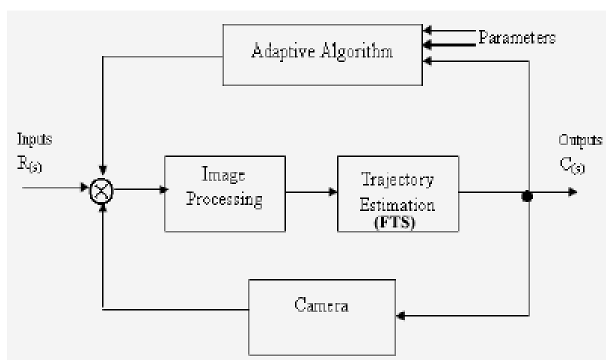


Fig. 1: System model

3.1 Image Processing Process

Object processing is the part, which captures the camera image and determines location and time information of the object with the help of the segmentation algorithm. In the present study, the image was transferred to computer media via a PCMCIA card interface, 1/3 inch, CMOS sensor-equipped wireless camera. A CapturePRO active X control was used to digitize the camera image and transfer it to the software.

The digital image is created by aligning small colored squares called pixels In the image received from the camera, all the pixels in the form of rows and columns are checked, and pixels at a certain color level are identified and transferred to a series. Thus, the location information of the target is obtained in matrix form [22].

Fig. 2: Scanning of the target image [22]

The filtering process in system is performed with RGB function. Values between a scale of 0-255 is defined to the RGB function in which, with RGB(0, 0, 0) is white, RGB (255, 255, 255) black, RGB (255, 0, 0) red, RGB (0, 255, 0) green and RGB (0, 0, 255) blue colors are selected. As to sum up, in the grey shades, 0 represents complete black, and 255 represents complete white, while the values between 0 and 255 are the shades of grey. In color images, red, green and blue are represented by values between 0 and 255. The value 0 indicates that none of these three basic colors is present, and the value 255 indicates that the amounts of these colors are at a maximum.

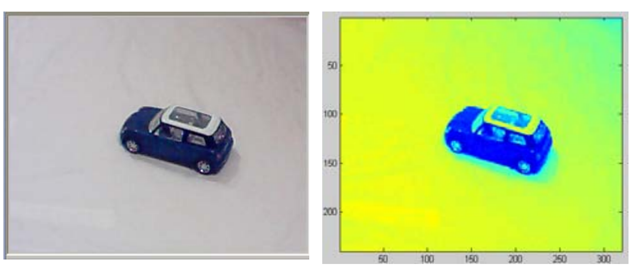


Fig. 3: Filtered image.

Figure 3 illustrates an image after the filtering process in which blue color is selected. As can be seen from the figure, if the filtering process is performed with respect to background, object can be discerned from the background with clear borders. Object is reproduced after each filtering process and the new image generated after each filtering process is different from the previous one and also is unidimensional.

Segmentation can simply be defined as the process of partitioning the image into significant parts [23]. Image received from the camera is scanned via software and binary image is obtained by assigning "1" for the pixels that contains the object and "0" for the background. Pixels with the same color are contradistinguished and others (i.e., those are not discerned) are accepted as empty spaces. In this way the target location information is obtained in the matrix and the object is distinguished from the background.

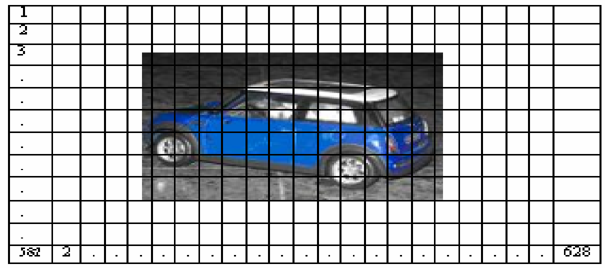


Fig. 4: Row and column values of the object image.

As can be seen in figure 4, pixels are comprised of 628x582 sub units, each with an equal area. The centre point of the object can be found using these pixels. Images received from the camera are transformed into matrices with respect to their resolutions which are used in the image processing algorithm. In Table 1 an 628x528 matrix is illustrated (M628x528).

Table 1. Matrix algorithm for the object image

Row Scan	Column Scan	
$Y_g[0]=0$	$X_g[0]=0$	Empty Spaces
Yg[1]=0	Xg[1]=0	
Yg[2]=0	Xg[2]=0	
Yg[3]=0	Xg[3]=0	
. .	. .	
Yg[X1]=1	Xg[Y1]=1	Target Matrix
Yg[X2]=1	Xg[Y2]=1	
Yg[X3]=1	Xg[Y3]=1	
Yg[X4]=1	Xg[Y4]=1	
. .	. .	
Yg[628]=0	Xg[582]=0	Empty Spaces

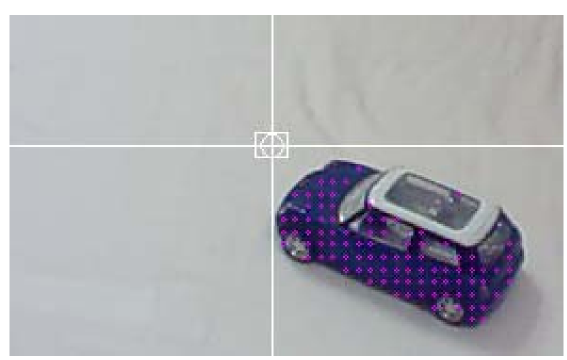


Fig. 5: Size and color tone determination [22]

Figure 5 illustrates the determination process of size and color tone of the moving object via aforementioned matrix algorithm.

In figure 6, the distances to the point taken as reference for the determination of the centre point of the object are shown. As the image is comprised of 628 rows and 582 columns, the formula can be expressed as;

$$x_g = \frac{\int_0^{628} x\,dl}{\int_0^{628} dl}, \quad y_g = \frac{\int_0^{582} y\,dl}{\int_0^{582} dl} \tag{15}$$

Fig. 6: Centre point calculation [22]

The coordinates of the centre point are found as an ordered series obtained by calculating the Euclidean distance (E) between the centre point (x_1, y_1) and each border pixel (x_i, y_i). When creating an ordered series, the area of each pixel was considered a unit square. Euclidean distance (E) describes the shortest path between two points. Here, as i=1, 2, 3, ...N;

$$E=\sqrt{(x_i - x_1)^2 + (y_i - y_1)^2} \tag{16}$$

where N indicates the number of corner pixels. The Euclidean distance between pixels P and Q is calculated as follows for $P=(x_1, y_1)$ and $Q=(x_2, y_2)$ points [24]:

$$\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{17}$$

Starting from the centre point of the object, the pixels which have the specified color values are determined in the images received from the camera. The intersections of the Euclidean distances of each of these identified pixels are found relative to a reference point. The intersection found gives the centre point of the recognized object. For instance, let's assume that an object comprised of 5x6 pixels as in figure 7:

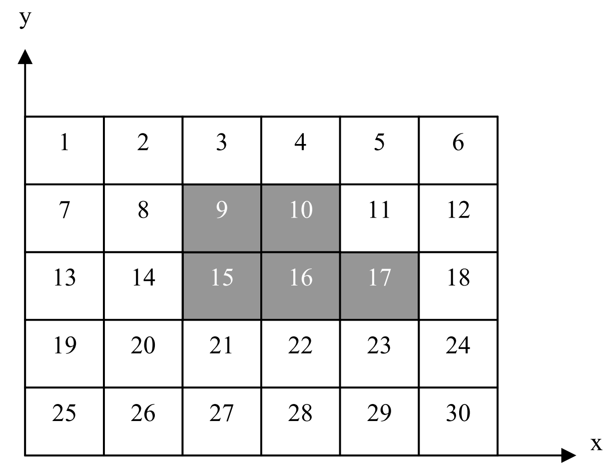


Fig. 7: An image comprised of 5x6 pixels

Considering that the pixels numbered 9, 10, 15, 16 and 17, represent the image and colors of the selected object; the software identifies the centre point relative to a certain reference point by scanning these pixels as follows:

$$Ctr = \frac{1}{n}\left[\sum x, \sum y\right] \tag{18}$$

The origin point of the coordinate axis (0, 0) is accepted as the reference point. It is assumed that the image is in the pixels numbered 9, 10, 15, 16 and 17, and that there is no image in the other pixels. When these pixels are selected, an object as in figure 8 is obtained.

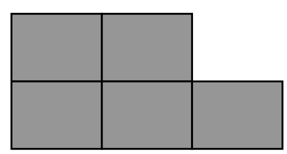
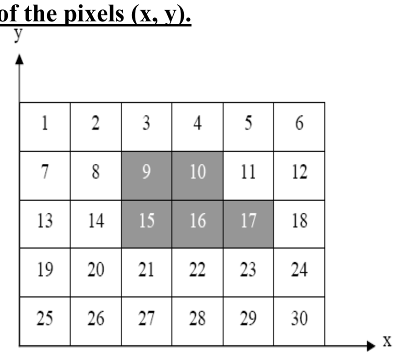


Fig. 8: Image comprised of pixels numbered 9-10-15-16 and 17.

Table 2. Coordinates of the pixels (x, y).

Piksel No	x	y
9	2.5	3.5
10	3.5	3.5
15	2.5	2.5
16	3.5	2.5
17	4.5	2.5
Toplam	16.5	17.5



The centre point coordinates can be found as follow;

$$Ctr = \left[\frac{1}{5}16.5, \frac{1}{5}14.5\right] = (3.3; 2.9)$$

The coordinates in Table 2, at the same time give the Euclidean distance of the centre points of these pixels relative to the origin. Euclidean distance gives the intersection of the centre points of the pixels selected, the centre point of the object. The centre point when the empty spaces are subtracted from the total area; *Ix=3.3, Iy=2.9*. *Ix* and *Iy* give the centre point of the selected pixels.

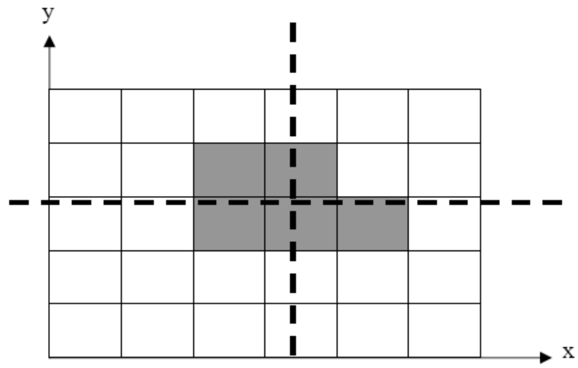


Fig. 9: Object centre point.

The centre point of this object can also be found without subtracting the empty pixels, by adding the centre points of each part one by one relative to the reference point. The following figure illustrates the flowchart of centre point determination process for the moving object.

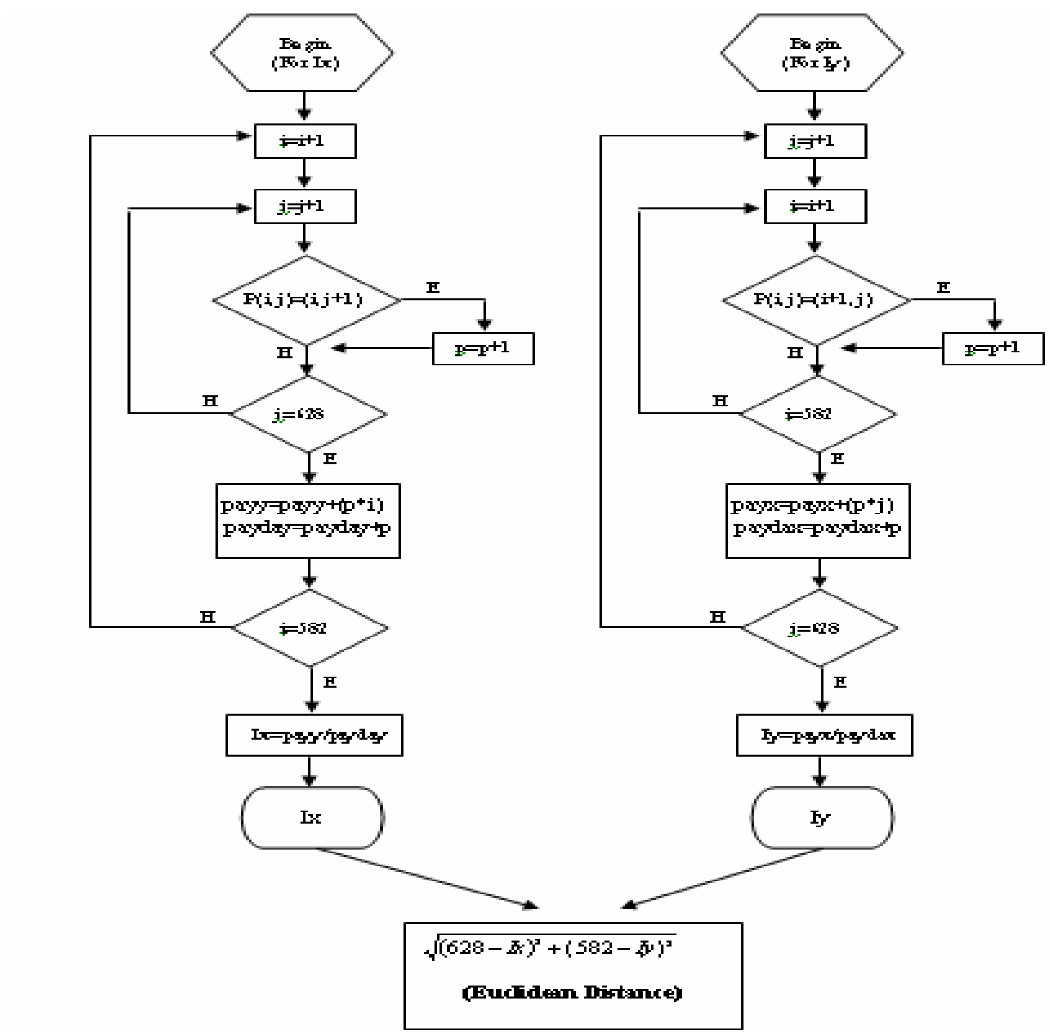


Fig.10: Centre point determination process flowchart

3.2 Trajectory Estimation

In this study the centre point and x-y coordinates of the moving object is determined with the image processing techniques above and trajectory estimation is made using adaptive FTS forecasting model. The results gathered via application of FTS forecasting model for different motions and trajectories of the moving objects are illustrated with the following tables and figures.

Here; as can easily be seen from the figure 11, the image zone received from the camera is scaled as 4800 horizontally and 3600 vertically.

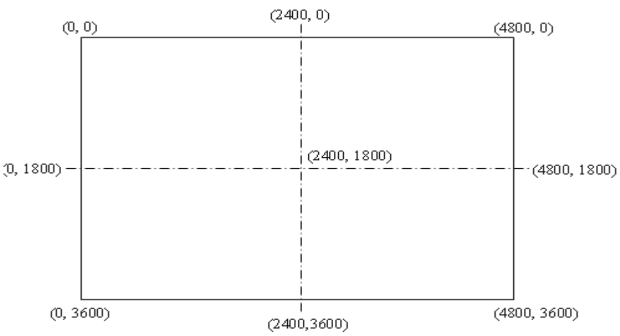


Fig. 11: Camera image zone

Figure 12 illustrates the situation in which the object only moves along the horizontal axis with the centre point coordinates given in table 3.

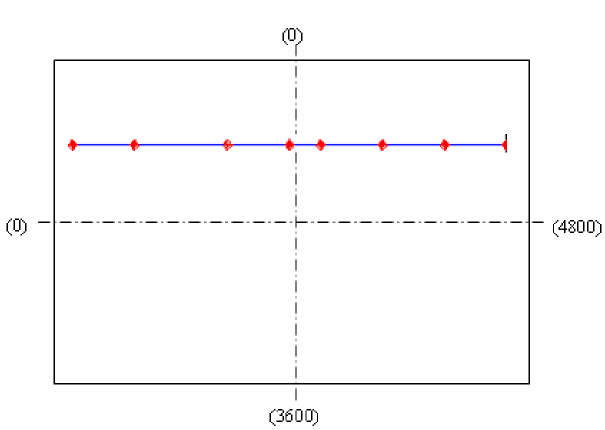


Fig. 12: Horizontal axis motion.

Table 3. Object centre point coordinates (Horizontal)

Ix	200	600	1200	1600	1800	2200	2600	3000
Iy	1000	1000	1000	1000	1000	1000	1000	1000

With the input values given in table 3 and additional Ix values 3422, 3844 and 4266 the estimated one step ahead location values (via centre point) gathered from the model are illustrated in figure 13.

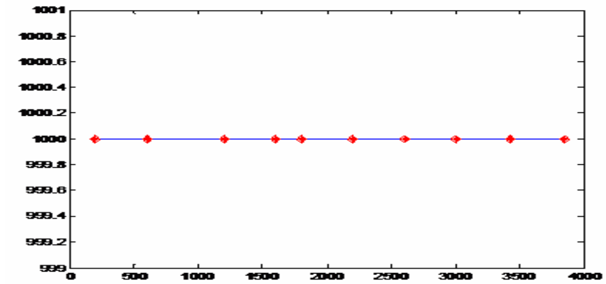


Fig. 13: Estimated values for the horizontal motion.

The results for the horizontal motion gathered from the model illustrates that, motion along only an axis captured with the FTS model and centre points are estimated correctly.

For the free fall motion, only "y" coordinates (I_y) changes due to time and location as given in table 4. Figure 14 the free fall motion. With the input values given in table below the estimated one step ahead location values (via centre point) for I_y coordinates gathered from the model are : $I_{y_{t+1}} = 1912{,}2186$.

Table 4. Object centre point coordinates (Free fall)

Ix	3400	3400	3400	3400	3400	3400	3400	3400
Iy	200	300	400	700	1000	1200	1400	1700

Figure 14 illustrates the real and estimated values for the free fall motion. The results shows that the FTS forecasting model captures the free fall motion nature rapidly and estimates one step ahead values correctly.

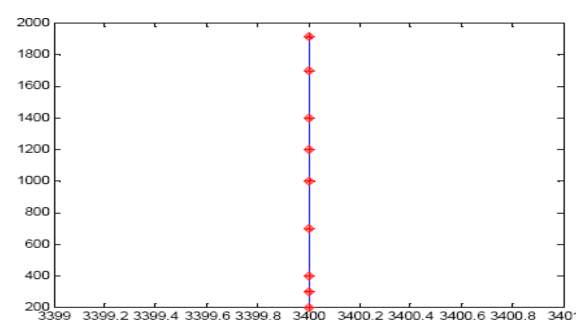


Fig. 14: Real and estimated values for the free fall motion.

When the object make a projectile like motion as illustrated in figure 15 with the coordinate values given in table 5;

Table 5. Object centre point coordinates (Projectile)

Ix	200	300	400	500	600	750	850	1000	1100	1200	1300	1400
Iy	2100	1950	1800	1650	1500	1300	1150	1000	900	800	700	600
Ix	1600	1800	2000	2200	2400	2600	2800	3000	3200	3400	3500	3600
Iy	500	400	300	250	200	250	300	400	500	600	700	800

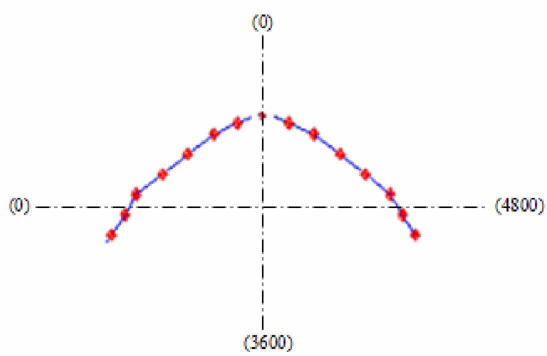


Fig. 15: Projectile motion.

the estimated values derived from the proposed model are as follow.

Table 6. Estimated values for the projectile motion

Ix	3600	3750	3800
I(x+1)	3742	3850	3942
Iy	800	900	1000
I(y+1)	874	974	1074

The model has also tested for the circular motion with the coordinates given in table 7.

Table 7. Object centre point coordinates (Circular)

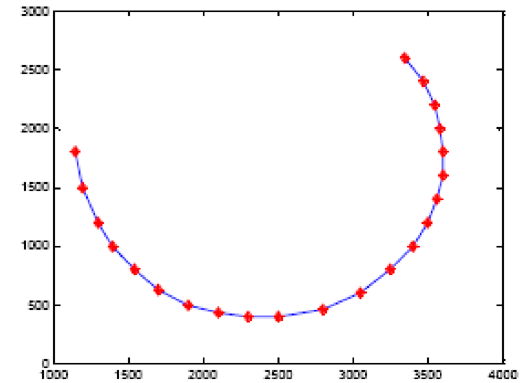
Ix	1150	1200	1300	1400	1540	1700	1900	2100	2300	2500	2800	3050
Iy	1800	1500	1200	1000	800	630	500	430	400	400	460	600
Ix	3580	3550	3350	3150	2780	2260	1900	1600	1430	1320	1250	1160
Iy	2000	2200	2600	2850	3110	3130	3000	2800	2600	2400	2200	1800

In the circular motion, the model captures the nature of the object motion from the images obtained via camera and successfully. The real and estimated values for the circular motion is given table 8.

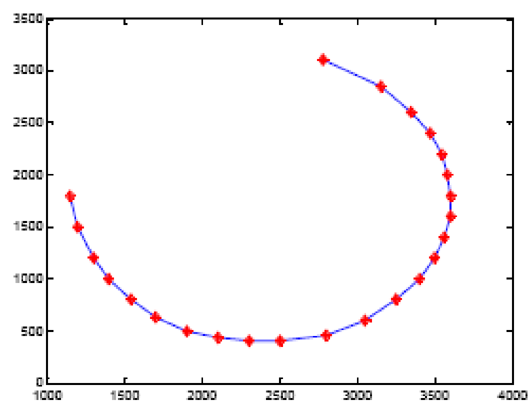
Table 8. Estimated values for the circular motion

Ix	3350	3150	2780	2260	1900	1600	1430	1320	1250	1160
I(x+1)	3311	3047	2609	1901	1458	1158	1154	1127	1140	1052
Iy	2600	2850	3110	3130	3000	2800	1000	2400	2200	1800
I(y+1)	2754	3049	3318	3338	3094	2723	2409	2152	1952	1552

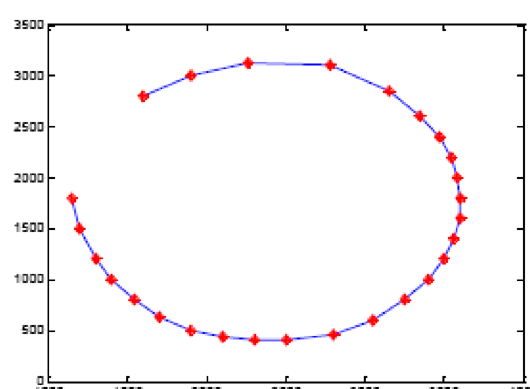
Following figures illustrate the response of model to the circular motion step by step.



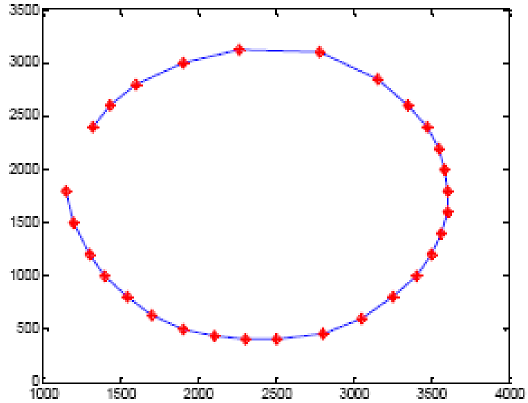
(a) Circular motion



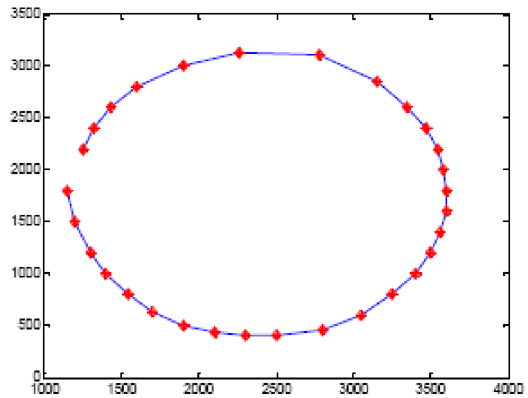
(b) Circular motion



(c) Circular motion



(d) Circular motion



(e) Circular motion

Fig. 16: Real and estimated values for the circular motion.

4 Research Findings and Conclusion

Almost all planning and decision activities in fields of science, engineering and business based on predicting future. As predicted data directly effects the development and performance of all processes of designed systems in every field of science, researchers try to make the prediction process reasonably correct and appropriate. Nahmias [25] defined this process of predicting future as forecasting. Forecasting also plays an important role in OT. For specific systems such as air defense, naval surface warfare and health diagnosing systems which barely have error tolerances, determination and usage of appropriate trajectory estimation techniques play a vital role. This study determines the location of a moving object with an image processing technique and then estimates the trajectory with FTS forecasting model. Results obtained from the applications illustrate that the proposed model easily captures the nature of the motion and successfully estimates the trajectory. Figure 17 and Figure 18 illustrates the real movement and the estimated values obtained from the proposed model for projectile and circular motion respectively.

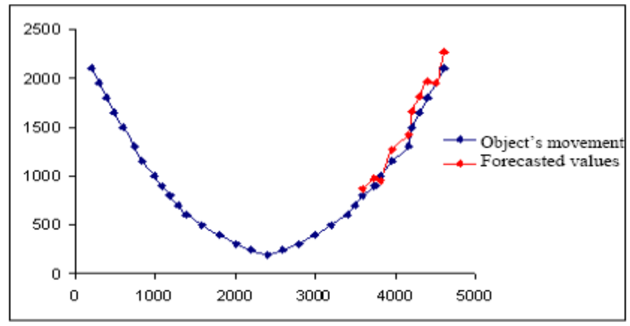


Fig. 17: Real and estimated values for the projectile motion.

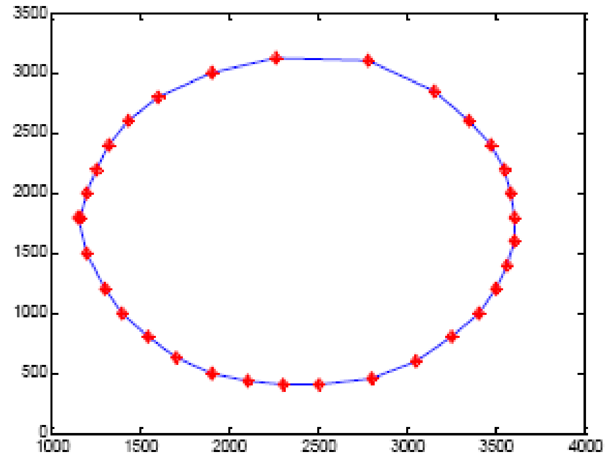


Fig. 18 : Real and estimated values for the circular motion.

Further researches can be made using other fuzzy forecasting techniques and neural networks together with fuzzified system parameters. Also tracking an object not only using image processing techniques but also with acoustic noise identification improving previous studies (such as Guarnaccia, [26]) in the acoustic noise field or incorporating fuzzy neural network based techniques [27] to FTS model for trajectory estimation are other probable dimension for future studies that could be noteworthy.

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