Target acquisition and tracking based on a priori knowledge and an image sensor

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ABSTRACT

When intercepting and tracking low-observable point-source or highly maneuvering big targets, the electro-optical (E-O) system will meet a fatal problem that the target lost easily. No effective method intercepts it again according to the dispersed azimuth and elevation tracking data. First, the paper gives an intelligent ATP control system architecture based on the data mart. Then an automatic real-time control algorithm is proposed, which is found on linguistic cloud model and fuzzy logic techniques. The linguistic cloud model is used to translate a linguistic term of qualitative concept into its numerical representation, such that the ATP control system can take full advantage of a priori knowledge which is always presented in natural language to refine the results of sequence images processing. The fuzzy logic technique is adopted to associate these results to target’s trajectories. The paper offers an automatic reacquisition and tracking method to solve the targets lost problem.

Keywords: target acquisition and tracking, sequence images, a priori knowledge, fuzzy logic, data mart, data mining

1. INTRODUCTION

Acquisition, tracking and pointing (ATP) functions are basic for an electro-optical (E-O) systems used in the surveillance and measurement control system. The previous video auto-tracking system utilized an initial acquisition of the target trajectory which is accomplished by radar or designated tracking trajectory, otherwise by the operator according to a priori knowledge always expressed as natural language which has received in advance. However, with the higher dynamic requirements of today’s environment, a crucial problem when intercepting and tracking a low-observable point-source or highly maneuvering big target is the target lost easily. It is very difficult to intercept the target again merely depend on the previous dispersed azimuth and elevation. We need a new method to utilize a priori knowledge which expressed in natural language depending on the high-speed computer system rather than the operator.

The natural language processing is difficult to be integrated in the conventional ATP architectures of E-O system. This paper provides a theoretical solution for this problem. Both a priori knowledge and the information mining from sequence images are fuzzed, and a fuzzy logic acquisition and tracking method based on these fuzzed data is introduced.

An intelligent ATP structure based on the data mart techniques for E-O system is presented in next section. It is a flexible evolution architectures for target acquisition and tracking. A linguistic cloud model based data mining method for a priori knowledge was introduced in section 3. Fuzzy logic data mining method based on sequence images is the topic of section 4, the most likely target trajectory prediction which used as the source of acquisition designation will also be formed at this section. In section 5, the acquisition and tracking procedure of E-O system is described based on the intelligent ATP structure. Section 6 contains the performance analysis and further work suggestion of the method. Conclusions are given in section 7.

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2. INTELLIGENT ATP ARCHITECTURES FOR E-O SYSTEM

The major ATP subsystems in the conventional E-O system usually include: (1) the sensor, (2) the gimbal system, (3) the video tracker, and (4) the gimbal control system \[1-5\]. In an intelligent ATP control system as depicted in Fig. 1, the function of the video tracker is integrated into the local data mart based automatically tracking system, in which includes four functional units. Each functional unit is an event driven thread, i.e., the priori knowledge data mining thread is driven by every received new priori knowledge (PK), the sequence images data mining thread and the video tracking thread are driven by the sequence images (SI) and video frame/field (VF) coming from image sensor package, respectively, and the acquisition thread is driven by the innovative information (II) generated by the priori knowledge data mining thread or the sequence images data mining thread.

The local data mart is a decisive support system incorporating a subset of the surveillance control system’s data focused on ATP functions and the mission of the E-O system. It has specific ATP related purposes such as automatically selecting the proper object model classes according to the E-O system’s condition and mission, providing proper targets acquisition and tracking algorithms which included in the object model classes, and providing data mining capability both from the inner (image sensor) and the external (a priori knowledge) sources. It also has the ability of evolution through the previous knowledge to improve the object model classes and the predict acquisition candidate trajectory. On the other hand, the local data mart is a natural component of the data warehouse of the surveillance control system. With the development of data warehouse, the distributed information, such as acquisition object models and targets’ information in the different local data mart should be shared in every subsystem. Obviously, this local data mart based system is intelligent architectures. It will feasibly improve the capability of both the E-O system and the all surveillance and measurement control system. The next four sections will focus on the real-time algorithm which is of great advantage to the acquisition and tracking objectives for the E-O system.

3. A PRIORI KNOWLEDGE BASED DATA MINING

Data mining, or Knowledge discovery in databases, is the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data \[6\]. Obviously, the objective of data mining for the ATP system is to find the potentially useful targets’ information from the data mart and everywhere we could as to carry out the ATP function automatically or to help the operator to intercept and track the targets. A priori knowledge may come from the superior, the companions, the operator, and the local data mart etc.; and usually expressed in natural
language. Data mining from it includes two aspects: (1) to discover all of the useful quality and quantity information, this is the basic function of the local data mart, and (2) to quantify the targets’ quality information based on the nature language processing, we presents a linguistic cloud models (LCM) based technique to complete this task. However, since important details of the LCM theory can be found in [7] this section emphasizes the quantifying method which enable its incorporation in targets test for the application of acquisition and tracking based on the sequence images data mining, which will be discussed in the next section.

Cloud model is a model of the uncertain transition between a linguistic term of a qualitative concept and its numerical representation. In short, it is a model of the uncertain transition between qualitatives and quantitatives.

At first, define a linguistic variable that is semantically associated with a list of all the linguistic terms within a universe of discourse as:

$$\{X, T(x), U, S, Cx(u)\}$$  \hspace{1cm} (1)

Where $X$ is the name of the variable. $T(x)$ is the term-set of $X$; that is, the collection of its linguistic values. $U$ is a universe of discourse. $S$ is a syntactic generator that generates the terms in $T(x)$. $Cx(u)$ is a compatibility function. It denotes the relationship between a term $x$ in $T(x)$ and $U$. More precisely, the compatibility function maps the universe of discourse into the interval $[0,1]$ for each $u \in U$.

Generally speaking, a linguistic variable is structured in the sense that it is associated with two rules. The first is the atom generator rule. It specifies the manner in which a linguistic atom can be generated. The second, the semantic rule, specifies a procedure for computing composite linguistic terms, based on linguistic atoms.

Now, let $U$ be the set $U=\{u\}$. The membership degree of $u$ in $U$ to the linguistic term $T$, $C_r(u)$, is a random member with a stable tendency. $C_r(u)$ takes the values in $[0,1]$. A compatibility cloud is a mapping from the universe of discourse $U$ to the unit interval $[0,1]$. That is:

$$C_r(u) : U \rightarrow [0,1], \forall u \in U \rightarrow C_r(u)$$  \hspace{1cm} (2)

The normal compatibility clouds are most useful in representing linguistic atoms because normal distributions have been supported by results in every branch of both social and natural sciences. A normal compatibility cloud characteristics:

$$A(Ex, En, D)$$  \hspace{1cm} (3)

where $Ex$, $En$, and $D$ are the expected value, entropy and deviation of the cloud respectively. A given set $\{Ex, En, D\}$ uniquely defines a particular compatibility cloud $A$. Suppose the universe of discourse $U$ has $n$ dimensions that are independent from each other. The $n$-dimensional normal compatibility cloud for a linguistic term in the universe is characterized with $3n$ digital parameters:

$$A(E_1, En_1, E_2, En_2, E_3, En_3, ... , E_n, En_n, D_n)$$  \hspace{1cm} (4)

where $E_1, E_2, ..., E_n$ are the expected values, $En_1, En_2, ..., En_n$ are the entropies which represent the fuzziness of the concept, and $D_1, D_2, ..., D_n$ are the deviations which are the randomness measures of the concept, i.e., the compatibility value has a relationship with both fuzzy logic and probability [7].

Note that the entropy of a linguistic atom is defined by the bandwidths of the MEHS (mathematical expected hyper surface) of the normal compatibility cloud showing how many elements in the universe of discourse could be accepted to the linguistic atom. The MEHS of the multi-dimensional normal compatibility cloud to a linguistic atom is:

$$MEHS_{\alpha}(x_1, x_2, ..., x_n) = \exp\left[ -\frac{1}{2} \sum_{i=1}^{n} \frac{(x_i - E_i)^2}{En_i^2} \right]$$  \hspace{1cm} (5)

This expression is very important for mining the targets’ association rules, in the next section we will use it to decide whether the measurements are valid to a priori knowledge. In a common case, we have no chance to know all the $n$ parameters of the measurement $u$, if we have: $(x_i, x_2, ..., x_k)$, $1 \leq k < n$, then we get a partial MEHS as an approximate estimate:

$$MEHS_{\alpha}(x_1, x_2, ..., x_k) = \exp\left[ -\frac{1}{2} \sum_{i=1}^{k} \frac{(x_i - E_i)^2}{En_i^2} \right], \hspace{0.5cm} 1 \leq k < n.$$  \hspace{1cm} (6)

For example, we can get the $A, E$ of a candidate target with the video tracking thread, then $k=2$; furthermore, if we could get the target’s pitch, roll, and yaw through the sequence images processing techniques, $k=5$, etc.

Sometimes we could have a better condition: the more accurate information about the target such as numerical
expression could be used to estimate the tracking results. Thus, we can directly compare the measurements to a priori knowledge. To calculate the MEHS, the maximum permitted errors could be used as the \( E_n \).

4. SEQUENCE IMAGES BASED DATA MINING

Data mining from the sequence images of the image sensor package needs to use the advantages of the motion and object recognition techniques as well as the knowledge saved in the local data mart. These recognition techniques can include the following steps [8].

Intra-scan (Single Image) Level: 1) Spatial noise filtering by image processing principles (like averaging kernels), 2) identifying potential targets by image segmentation, and 3) calculation of centroid of each of the identified targets.

Inter-scan Level: 1) Tracking centroids using single or multiple target tracking techniques, and 2) separation of the true and false targets by association based on the motion and object characteristics.

The intra-scan level recognition techniques are summarized in the next subsection and a new inter-scan level processing method based on the fuzzy clustering means algorithm will be presented in the subsection 4.3. In the last subsection, the knowledge being kept in the local data mart, including a priori knowledge acquired from the preceding section will be used to optimize the acquisition results.

4.1 Image preprocessing and target attitudes estimation

Once an image is acquired, the target is to be separated from the background and the noise is to be eliminated by preprocessing. For example, appropriate application-dependent filters and thresholding algorithms may be used to get an innovations image sequence, i.e., a background of independent noise samples with additive, constant amplitude probable target points. These points are probably from real targets or clutter noises. Generally, the video camera is aligned with the telescope and sampling the light coming into the telescope, the azimuth and elevation of an target can be represented by distance between the center of mass of the target and the center of the focal-plane array of the camera which directly represents the telescope’s line-of-sight. Some other attitudes of a probable target point such as the identity, yaw, pitch, and roll etc. parameters can be calculated through sequence images processing techniques while the image of the probable target has enough scale, SNR, and a priori knowledge [9,10].

These attitudes are used to calculate the linguistic clouds’ MEHS to cut out those improbable target points in the acquired innovations image sequence; this procedure will reduce the complexity of feasible targets association. These MEHS greater than user-specified minimum gate \( \tau_m \) are remained into the local data mart and to be used in the next steps. Let \( k \) be the number of matching parameters, \( p \) is the number of trajectories decided by a priori knowledge, i.e., the expected target trajectories. If a target point satisfying:

\[
\text{Max}\{\text{MEHS}_i (x_1, x_2, \ldots, x_l)\} \geq \tau_m \quad 1 \leq i \leq p
\]

then this target point is categorized to expected target trajectory \( i \), otherwise, it was rejected. The MEHS is calculated by (6). A \( p \) row and \( q \) column likely target matrix was generated:

\[
\begin{bmatrix}
O_{11} & O_{12} & \cdots & O_{1q} \\
O_{21} & O_{22} & \cdots & O_{2q} \\
\vdots & \vdots & \ddots & \vdots \\
O_{p1} & O_{p2} & \cdots & O_{pq}
\end{bmatrix}
\]

where \( q \) is the maximum number of probable target points for expected target trajectory \( i \) \((1 \leq i \leq p)\). Note that one probable target points could be categorized to several expected target trajectories, i.e., the problem of targets intersection is resolved easily. The insufficient elements of any row of above matrix are filled with zero.

4.2 Candidate targets

Many documents have focused on the critical problem of partitioning target observations into tracks associated with each target in a dense, multtarget environment [11]. Deterministic algorithms [12,13] make hard associations at the end of every frame; probabilistic data association algorithms [14,15] incorporate all observations in the target-track gate into a subsequent state estimate; while multiple hypothesis tracking (MHT) algorithms [11,16-19] make soft (i.e., not irreversible) decisions at the end of every frame by attempting to consider all possible associations over a number of frames. Multiple hypotheses are maintained with the knowledge that most likely hypothesis at a given stage may be the continuation of a less likely hypothesis from a previous stage.
Detail algorithms, which have been integrated into the data mart of the intelligent ATP system, could be found in the corresponding reference. The appropriate algorithms will be performed by the data mart to generate the original trajectories, named new candidate trajectories. To a fixed expected trajectory \(i\) \((1 \leq i \leq p)\), candidate trajectories are calculated with the corresponding row of (8), and at most \(Nm\) new candidate trajectories are gained unless the stage fuzzy clustering means algorithm (see next subsection) used some of them. The stage fuzzy clustering means algorithm will use \(Sl\) available candidate trajectories (named standby candidate trajectories) to provide an observation-to-track association method. By now, the candidate trajectories sets for a fixed expect trajectory in clude:

\[
\{T_{0i}, T_{S1}, T_{S2}, \ldots, T_{S\ell}, T_{N1}, T_{N2}, \ldots, T_{Nm}\}
\]

where \(T_{0i}\) is a priori knowledge based trajectory of fixed expected trajectory \(i\) \((1 \leq i \leq p)\), \(T_{S1}, T_{S2}, \ldots, T_{S\ell}\) are standby candidate trajectories used by the stage fuzzy clustering means algorithm, and \(T_{N1}, T_{N2}, \ldots, T_{Nm}\) are new candidate trajectories ready for the stage fuzzy clustering means algorithm. Candidate trajectories vacancy is filled with zero.

### 4.3 Targets association using fuzzy clustering means algorithm

The most widely used clustering algorithm is the fuzzy clustering means algorithm (FCM) developed by Bezdek. This subsection introduces the FCM algorithm which will be used for measurements-to-tracks association (correlation) [20]. The goal of any fuzzy clustering algorithm is to classify the data into a number of clusters (groups). The clustering algorithms produce a degree (grade) of membership for each data point in each cluster. Unlike conventional clustering, which involves a partitioning of objects into disjoint clusters, fuzzy clustering allows a data point \(x\) to have a partial degree of membership in more than one set. A fuzzy set \(A\) in a collection of objects \(X\) is defined as:

\[
A = \{ (x, u_A(x)) | x \in X \}
\]

where \(u_A(x)\) is the degree of membership function of data point \(x\) in fuzzy set \(A\). Given a number of data points, it is required to group (cluster) the data into clusters according to some similarity measure. Let \(c\) be an integer which represents the clusters with \(2 \leq c \leq n\), where \(n\) is the number of the data points. Define \(U\) as a partition matrix of elements \(u_{ik} \ (i=1, 2, \ldots, c, j=1, 2, \ldots, n)\) which represents the degree of membership of data point \(j\) in fuzzy cluster \(i\), such that

\[
u_{ik} \in [0,1], \quad 1 \leq i \leq c, 1 \leq k \leq n
\]

\[
\sum_{i=1}^{c} u_{ik} = 1 \quad \forall k,
\]

\[
0 < \sum_{k=1}^{n} u_{ik} < n \quad \forall i
\]

Define \(J_m\) as the sum of the squared errors weighted by the \(m\)th power of the corresponding degree of membership, i.e.,

\[
J_m(U, V) = \sum_{k=1}^{n} \sum_{j=1}^{c} (u_{ik})^m (d_{ik})^2
\]

where

\[
(d_{ik})^2 = \|x_k - v_i\|^2,
\]

and \(\|\|\) is any inner product induced norm, \(m\) is a real number \(\in [1, \infty]\) called the fuzzification constant (or weighting exponent), \(x_k\) is a data point and \(v_i\) is a cluster center. The degrees of membership will be established by minimizing the sum of the squared errors weighted by the corresponding \(m\)th power of the degree of membership. The goal of the fuzzy clustering algorithm is to determine the optimum degrees of membership \(u_{ik}\) \((\forall \ i,k)\) and the optimum fuzzy cluster centers \(v_i\) \((\forall \ i)\) such that the sum of the square errors \(J_m\) is minimum. The results are given by [21]:

\[
u_{ik} = \frac{1}{\left(\sum_{j=1}^{c} (d_{ik} / d_{jk})^{2/(m-1)}\right)} \quad \forall i, k
\]
where (16) is valid for a fixed \( V(V=v_1, v_2, \ldots, v_n) \), and solution (17) is valid for a fixed \( U \). In multi-targets tracking systems, \( c \) is the number of targets, \( n \) is the total number of received measurements, \( x_k \) is the \( s \)-dimensional measurement vector \((k=1, 2, \ldots, n)\), and \( v_i \) is the \( s \)-dimensional predicted vector for target \( i(i=1, 2, \ldots, c) \). The fuzzy \( c \)-means clustering algorithm or the Picard algorithm is guaranteed to converge to a local minimum \[ \text{[22,23]} \].

The fuzzification constant \( m \) plays an important role. It reduces the influence of noise when computing the degree of membership (16) and the cluster centers (17). The weighting exponent \( m \) reduces the influence of a small \( u_{ik} \) (for data that are faraway from the cluster centers) compared to a large \( u_{ik} \) (for data that are close to the cluster centers). As \( m \) increases, its influence becomes stronger.

In our ATP system, the number of a priori knowledge based expected targets is \( p \), for a fixed expected target \( i \), we have carried out \( q \) probable target points, a priori knowledge based trajectory \( T_{0i} \), \( s \)I standby candidate trajectories \((T_{S1}, T_{S2}, \ldots, T_{Sg})\), and up to \( Nm \) new candidate trajectories \((T_{N1}, T_{N2}, \ldots, T_{Nm})\). Our goal is to determine the most probable target point \( O_{ij} \) \((1 \leq i \leq p, 1 \leq j \leq q)\) for each expected trajectory \( i(1 \leq i \leq p) \) by using the fuzzy clustering means algorithm. The targets’ predicted values can be estimated using optimal filtering techniques such as least squares, \( \alpha \cdot \beta \) tracker and Kalman filtering techniques. The choice of particular optimal filtering technique depends on the application and the assumed target state model for the fixed target \( i(1 \leq i \leq p) \). It is not a difficult task for the local data mart to calculate the predicted vector \( V(V=v_{ik}, v_{ik}, v_{ik}, \ldots, v_{ik}) \) of \( T_{S1}, T_{S2}, \ldots, T_{Sg} \). Then we arrange the following steps for each expected trajectory \( i(1 \leq i \leq p) \) (also see [20]):

1. Apply the FCM algorithm for the fixed vector \( V_i \) and find the partition matrix \( U_i \), which represents the degrees of membership of probable target points (i.e., the \( i \)th row of matrix (8)) to candidate trajectories of \( T_{S1}, T_{S2}, \ldots, T_{Sg} \). The association matrix \( U_i \) represents the assignment matrix between all probable target points and candidate trajectories. Each elements in the partition matrix \( u_{ik}(1 \leq i \leq p, 1 \leq k \leq q) \) represents an association measure between the predicted value of track \( i \) and measurement \( k \).
2. Search for the maximum degree of membership \( u_{ik-max} \) (the closest measurement-to-track pair) and make the indicated assignment, i.e., associate measurement \( k (O_{ik}) \) to track \( i (T_{0i}) \).
3. Remove the measurement-to-track pair identified above from the assignment matrix \( U_i \) and obtain the reduced matrix (this step is a virtual operation that aims to simplify the analysis and does not affect the values of the parameters \( u_{ik} \forall i, j \)).
4. Repeat steps 2 and 3 for each remaining track until every track \( T_{0i} \) have assigned a measurement or all exist measurement \( O_{ik} \) have been used.
5. The probable points, which have not been used above, will be used to generate the new candidate trajectories \((T_{N1}, T_{N2}, \ldots, T_{Nm})\).
6. Updating all associated measurement \( O_{ik} \) to track \( T_{0i} \).

4.4 Evolution of candidate trajectories

Three categories of candidate trajectories of a fixed expected target \( i \) are used in the acquisition and tracking procedure, all of them are evolving over the progress of the acquisition and tracking procedure. The first is the \( T_{0i} \) which based on a priori knowledge, and is the only new priori knowledge coming. The second is standby candidate set of \((T_{S1}, T_{S2}, \ldots, T_{Si})\) which originated from the last categories and used by the stage fuzzy clustering means algorithm. The last categories is new candidate set of \((T_{N1}, T_{N2}, \ldots, T_{Nm})\) which formed from probable target points belong to the expected trajectory \( i \) (i.e., the \( i \)th row of matrix (8)) but haven’t been associated with the second categories. The remaining part of this section discusses trajectories evolution rules.

4.4.1 Promoting and rejecting of standby trajectories

Only one of the standby candidate trajectories could be used as the acquisition source to control the gimbal, it is the most likely candidate trajectory \( T_{Si} \). We know the MEHS represents the similarity of a probable target point to the corresponding point of a priori knowledge trajectory \( T_{0i} \). With a fixed standby candidate trajectory \( Sj \), we define:

\[
\gamma_{SI} = \sum_{i=1}^{N} MEHS \; S_j (x_1, x_2, \ldots, x_k)
\] (18)
as a measurement variable. Where the \( km \) is the available probable target points or a maximum user-specified number, \( k \) is the available number of attitudes of measurements.

According to \( \gamma_{ij} \), we sort the standby candidate trajectories descending. The maximum \( \gamma_{ij} \) maps the \( T_{Sj} \), and the minimum maps \( T_i \). Not all of these standby candidate trajectories must be remained for the next step, if some of them are almost unlikely, i.e., corresponding \( \gamma_{ij} \) less than a user-specified gate \( \tau \):

\[
\gamma_{ij} < \tau, \quad (19)
\]

These standby candidate trajectories will be rejected, and its association probable target points should be used to generate new trajectories.

### 4.4.2 Generating and promoting of the new trajectories

The method of generating new candidate trajectories has been narrated in subsection 4.2, we assume that all probable target points for a fixed expected trajectory are used in there. In fact, every vacancy of the standby candidate trajectories of a fixed expected trajectory should be filled with the existing new trajectory, i.e., these new trajectories were promoting to standby candidate trajectories set and deleted from the new trajectories set. Probable target points, which have been associated to standby candidate trajectories, should not be used to generate new trajectories.

## 5. TARGET ACQUISITION AND TRACKING PROCEDURE

### 5.1 Tracking modes

The Gimbals’ control system positions the image sensor package in response to commands from control loops. The command source is determined by the mode of operation. In the intelligent ATP control system for E-O system, the gimbal control system has a tachometer or an inertial rate loop which accepts rate commands from: (1) the acquisition thread, (2) the video tracking thread, and (3) the operator.

In the manual method, the operator positions the gimbal through a positional control (joystick) following the target’s motion on a display or viewing through an optical sight. The limitation of manual systems is the operator’s inability to respond to target dynamics.

When the acquisition thread is effective, the most likely standby candidate trajectory \( T_{Sj} \) of a designate expected target that is prior to the others will be used as the tracking trajectory to operate the gimbal control system. An ideal case is that the target’s trajectory, i.e., the designate tracking trajectory \( T_0 \), can be obtained from an external source such as radar or a priori knowledge. These designate data is directly used to derive the gimbals’ position encoders to known positions. The accuracy of this mode is determined by the tracking accuracies of the external input or the stored trajectory data.

Before the video tracking thread working, operator or the acquisition thread must have accomplished an initial acquisition, i.e., the target have been identified and selected. Then they handover the gimbal control to the video tracking thread, which positions the image sensor package to the target based on the calculated target position. Three type of video tracking algorithms are most commonly used in tracking systems to minimize the tracker error. They are centroid \([2,4,8,24]\), edge \([25]\), and correlation \([2]\) tracking. It is beyond the scope of this paper to describe these algorithms in detail. All of them are integrated into the local data mart as methods of object model. The purpose of video tracking is to perform a more accurate tracking accuracy comparing to the acquisition and manual methods.

### 5.2 Tracker mode transitions

In the intelligent ATP control system described in section 2, the four main threads are all events driven threads. Once they are initialized, any coming events will start corresponding thread, for example, a priori knowledge will trigger the priori knowledge data mining thread, and its output innovative information \( II \) will trigger the acquisition thread to modify the corresponding trajectory \( T_{Sj} \). Similarly, a valid video frame/field starts both the video and the sequence data mining threads, and its output \( II \) will trigger the acquisition thread to modify the corresponding trajectory \( T_{Sj} \).
When the E-O system is working at auto-tracking method, both the video thread and the acquisition thread can control the gimbal, but at a special time, only one of them is effective. The transition method of the intelligent ATP system is depicted in Fig. 2. The operator decides the ATP system whether working at autotrack mode or at manual mode. While in the autotrack mode, the acquisition thread will decide whether handover the gimbal control to the video tracking thread or withdraw the control.

6. ANALYSIS AND FUTURE WORK

The original purpose of this paper is to design a suitable architecture of a new video tracking system of E-O system in contemporary surveillance control environments. Both hardware and software structure have been discussed at certain. With the import of local date mart techniques, the hardware provides a more flexible platform for the ATP control system and makes it possible to integrate more methods for promoting the functions of video tracking. A realizable real-time ATP control algorithm based on the linguistic cloud [1] and fuzzy logic techniques has been presented, it offers an automatic reacquisition and tracking method to solve the targets lost problem while tracking a low-observable point-source or highly maneuvering big target.

The algorithm uses the cloud model of the uncertain transition to translate a linguistic term of qualitative concept into its numerical representation, such that the ATP control system can use a priori knowledge which is presented in natural language, just as the operator does. For example, it is used to decide whether a target point belong to one or several of the probable target trajectories (subsection 4.1), these simple calculation could feasibly reduce the number of probable target points and solve the multiple targets intersection problem as well. To associate the probable target points of sequence images with the likely target trajectories, fuzzy clustering means algorithm is adopted. This fuzzy logic algorithm is of effective [20] and in harmony with the fuzzy conclusion of the cloud model. As presented in the subsection 4.4, the evolution procedure of candidate trajectory is completed just with several addition operations. But two problems needs to be solved before we could enjoy the advantages of the above ATP system: Because all function units of the ATP system are supported by the local date mart, so the local date mart must have the ability of evolving with the environments, i.e., data mining methods improvement both from new linguistic terms and from sequence images. Secondly, the decisive rules of the user-specified parameters, such as \( \tau_m, p, q, \) and \( \tau_r \) etc., must be determined and integrated into the local date mart. The further work should include data mining from the history data of the local data mart, and analyzing the performance of the intelligent ATP system as well as the efficiency of the algorithm.

7. CONCLUSIONS

The ATP control system of an E-O system need continuously test (associate) if the tracking target is the correct one. The local data mart based ATP architecture is proposed to promote the theoretical processing performance. A linguistic cloud model is implemented to translate a linguistic term of qualitative concept into its numerical representation, such
that the ATP control system can use a priori knowledge, which is always presented in natural language. This method permits the ATP control system to mimic operators’ thinking to decide the probable trajectories when reacquisition the lost targets. The fuzzy logic technique is adopted to associate these trajectories with the results of sequence images processing.

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