ENERGY MINIMIZATION APPROACH FOR ONLINE DATA ASSOCIATION WITH MISSING DATA

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Keywords: Online data association, energy minimization, prior informationless and non-rigid motion.

Abstract: Data association problem is of crucial importance to improve online target tracking performance in many difficult visual environments. Usually, association effectiveness is based on prior information and observation category. However, problems can happened when targets are quite similar. Therefore, neither the color, nor the shape could be helpful informations to achieve the task of data association. Likewise, problems can also arise for target tracking, under the constraint of missing data, with complex motions and randomly deformations over time. Such restrictions, i.e. the lack in prior information, limit the association performance. To remedy, we propose a novel method for data association, inspired from the evolution of the target dynamic models, and based on a global minimization of an energy vector. The main idea is to measure the absolute geometric accuracy between features. The parameterless constitutes the main advantage of our energy minimization approach: only one information, the position, is used as input to our algorithm. We have tested our approach on several sequences to show its effectiveness.

1 INTRODUCTION

Traditionally, multiple target tracking deals with the state estimation of moving targets. A track is a state trajectory estimated from the available measurements that have been associated with the same target (Vermaak et al., 2005). The main difficulty, however, comes from the assignment of a given measurement to a target model. These assignments are generally unknown, as are the true target models. The idea of data association remains to find a partition of observations such that each element is generated by a target, or clutter, whose statistical properties are different from one target to another. The literature contains some classical approaches to solve the problem of data association: we can distinguish the deterministic approaches from the probabilistic ones.

Deterministic approaches selection the best of several candidate associations, without taking into account its context correctness, by using a score function (Vermaak et al., 2005). The simplest deterministic method for data association is the Nearest-Neighbor Standard Filter (NNSF) (Rong and Bar-Shalom, 1996) that selects the closest validate measurement to a predicted target and uses it for its state estimation. The usually distance measure used is the Mahalanobis one. Since the filter does not take into account the possibility of incorrect associations, the performance of this filter might be poor in some cases, resulting in an incorrect association between measurements and targets. In some tracking applications, the color is exploited for the problem of data association. One can measure the color histogram difference between a measurement and the objects of the previous frame using the histogram intersection technique. Unfortunately, the color metric is not a sufficient for a correct data association in many cases: for deformable objects, which color distribution may differ from one frame to another, or in the case of several quite identical objects, because the probability of a correct matching is not only depending on the color distribution.

Probabilistic approaches are based on posterior probability and make an association decision using the probability error (Rasmussen and Hager, 2001). Among probabilistic approaches, we can cite the most general one, called Multiple Hypothesis Tracking
In this paper, we propose a novel method for data association based on minimization of an energy vector. The outline of this paper is as follows. In section 2, we expose the energy minimization approach, derive its geometrical representation and its mathematical model. The proposed method is then evaluated and tested on several sequences in section 3. Finally, concluding remarks and perspective works are given in section 4.

2 ENERGY MINIMIZATION FOR DATA ASSOCIATION

We first need to define some terms that will be often used in this paper. We dispose a video sequence describing a dynamical scene. This scene is observed by a set of sensors, each one can deliver exactly one observation of the scene at a precise time step \( t \). Each observation is a set of measurements such as position, shape, color distribution, etc.. Notice that the number of available measurements can be different from one observation to another. Each measurement can be associated with a specific object in the scene (i.e. target), or can be a false alarm.

At a specific time \( t \), observations (containing at least one measurement) are assumed to be available from \( N_{\text{obs}} \) sensors, whose locations vary with time. The set of measurements coming from all sensors is given by \( y = (y^1, ..., y^{N_{\text{obs}}}) \), where \( y^i = (y^i_1, ..., y^i_{M^i}) \) is the vector containing the \( M^i \) measurements coming from the \( i^{th} \) sensor, also called observation. We suppose that each sensor can generate at most one observation at a particular time step and that the number of measurements delivered by the sensors varies with time. When a set of observations is available at a specific time \( t \), coming from different sensors, our goal is to associate a maximum one measurement per target, and then to make the dynamic system evolve to predict its position at time \( t + 1 \). The number \( K \) of targets can also vary with time.

2.1 Data association approach

Generally, an effective data association method is based on measurements category. Sensor can provide a various number of measurements such as shape, color, position, direction, etc. Furthermore, when the measurement is limited to the position, and falls inside the validation region of several targets and is
equidistant from them (see Figure 1.(a)), it will be associated with all these targets if we use the NNF or Monte Carlo JPDAF approaches. As well as, in multiple target tracking, feature targets can be quite similar. Accordingly, even if information about their color distribution or shape is available, the association task is difficult under such assumptions or impossible in case of complex dynamics. In this paper, we expose an algorithm for data association restricted to one category of measurement: the position. Furthermore, we affirm the total lack of prior information concerning targets. Exclusively the two anterior predicted positions are used as input to our algorithm. We will first give the concept on our approach before starting its mathematical modeling. Our intention is to formalize a method able to associate an observation (only containing a position information) according to the restrictions displayed in the previous section. We define a novel energy vector in the directed affine euclidean space \((O, i, j, k)\). This energy is inspired from the evolution of the target dynamic model. The dynamic is described in terms of displacement in the target space \((x, y)\). If we only consider the linear translation in one direction, the problem of data association is limited to the computation of an energy \(E^1\) (see after for details). Thus, in case of complex dynamic such as non linear displacement, oscillatory motions and non-constant velocity, we are vis-a-vis a problem because \(E^1\) will be an inadequate informative source. To remedy, we incorporate a second energy \(E^2\) which measures the absolute accuracy between the dynamic features and indicates how much their parameters are closely. Moreover, we distinguish some dynamic cases, that will be clarified by geometric descriptions afterward, where \(E^2\) should be added to the proximity energy evolution \(E^3\) for an advance guiding of the data association problem.

We notice that the energy vector \(E\) is only computed when the measurement falls within several validation regions. The measurement is considering as a clutter if it is not included in any validation region of targets. In our case, the validation region is an ellipsoid that contains a given probability mass under the Gaussian assumption. The minor and major axes of this ellipsoid are respectively given by the largest and smallest eigenvalues of the covariance matrix, their directions are given by the corresponding eigenvectors, and the center is the mean of the target.

We define the energy vector between the \(k^{th}\) \((k = 1, \ldots, K)\) and the measurement \(y_{j}^{t}\), i.e. \(j^{th}\) measurement of the \(t^{th}\) sensor by:

\[
(E_k)_{j} = \frac{1}{\sqrt{3}} \sum_{i=1}^{3} \alpha_i (E_k^i)_{j}
\]

where \(\alpha_i = \frac{1}{\sum_{i=1}^{3} ||(E_k^i)_{j}||} \) is a weighted factor introduced to sensibly emphasize the relative importance attached to the energy quantities \(E^1\).

Before interpreting each energy, we consider a target \(A\) and an observation \(y_{j}^{t}\). Besides, we call (see Figure 1 for illustration):

- \(\hat{A}(t-2)\) and \(\hat{A}(t-1)\), respectively the prediction of \(A\) at \((t-2)\) and \((t-1)\);
- \(\hat{A}(t)\) the prediction of \(A\) at \(t\) without updating the parameters of the dynamic model with the occurred observation \(y_{j}^{t}\) at instant \(t\);
- \(\hat{A}_1(t+1)\) the prediction at \((t+1)\) without updating the dynamic model set;
- \(\hat{A}_2(t+1)\) the prediction at \((t+1)\) by updating the dynamic model set according to measurement \(y_{j}^{t}\).

Prediction is based on using a dynamic model which parameters are generally fixed by learning from a training sequence to represent plausible motions such as constant velocity or critically damped oscillations (North et al., 2000; Blake and Isard, 1998). For complex dynamics, such as non-constant velocities or non-periodic oscillations, the choice of the parameters for an estimation algorithm is difficult.
Furthermore, the learning step becomes particularly more difficult in the case of missing data, where the dynamic between two successive observations is unknown. For these reasons, the parameters of our dynamic model are set in an adaptive and automated way once a measurement is available (Abed et al., 2006).

The energy vector \( (\bar{E}_k)_{y_j} \) contains three components, \( \{\bar{E}_1^1, \bar{E}_2^2, \bar{E}_3^3\} \), as defined below:

1. The Mahalanobis distance energy, \( (\bar{E}_k^1)_{y_j} \), measures the distance between a measurement \( y_j^t \) occurred at instant \( t \) and the prediction of the target \( \hat{A} \) at \( (t - 1) \). This energy is sufficient to the data association problem if the motion is limited to translation in one direction (case of linear displacement). It is given by:

\[
(\bar{E}_k^1)_{y_j} = \|((\bar{E}_k^1)_{y_j})\|^2
\]

where \( \Sigma_k \) is the covariance matrix of the \( k^{th} \) target (we have designed the \( k^{th} \) target by \( A \) in the equations).

2. To consider the case of complex dynamics, such as oscillatory motions or non-constant velocities, we have added the absolute accuracy evolution energy \( (\bar{E}_k^2)_{y_j} \). It introduces the notion of the geometric accuracy between two sets of features whose dynamic evolution is different. The description of both models are followed:

- The updated dynamic model set considers that the occurred measure \( y_j^t \) at \( t \) is generated by the \( k^{th} \) target and updates the parameters of its dynamic model to predict the new state of the target \( k \) at \( (t + 1) \);
- The not updated dynamic model set predicts the new state at \( (t + 1) \) without considering the presence of the observation, i.e. without updating the parameters of the dynamic model.

\( (\bar{E}_k^2)_{y_j} \) extends a numerical estimation of the closeness between two dynamic model. Our idea aim to evaluate the parameters of the dynamic model in two cases if the measurement \( y_j^t \) arises from this target or no. We first predict the states \( \hat{A}_1(t + 1) \) and \( \hat{A}_2(t + 1) \) of the target at \( (t + 1) \). We then determine \( S_1 \), the intersection surface between the two circumscribed circles of the triangles \( (\hat{A}(t - 2), \hat{A}(t - 1), \hat{A}(t)) \) and \( (\hat{A}(t - 1), \hat{A}(t), \hat{A}_1(t + 1)) \), and \( S_2 \), the intersection surface between the two circumscribed circles of the triangles \( (\hat{A}(t - 2), \hat{A}(t - 1), y_j^t) \) and \( (\hat{A}(t - 1), y_j^t, \hat{A}_2(t + 1)) \), (see Figures 1.(b)) and 1.(c)).

\( (\bar{E}_k^2)_{y_j} \) is minimized when the similarity between both dynamic models is maximized and is given by:

\[
(\bar{E}_k^2)_{y_j} = \|((\bar{E}_k^2)_{y_j})\| = |S_1 - S_2|\bar{k}
\]

The aim of comparing these two sets is to measure the ratio of similarity, defined by \( R_k = 1 - \|((\bar{E}_k^2)_{y_j})\| \), between the predictions at \( (t + 1) \) given by two different dynamic models for target \( k \).

Increasing this ratio maximizes the probability that measurement \( y_j^t \) is generated by target \( k \) and the resemblance between two dynamic models.

A question might be asked: is the component \( \bar{E}_2 \) able to handle all type of motions ? Indeed, \( \bar{E}_2 \) evaluates a numerical measure of similarity between dynamic models. This measurement depends on the difference between two surfaces. It is considered as reliable if both positions, \( \hat{A}(t) \) and \( y_j^t \), are on the same side comparing to axis \( (\hat{A}_{t-2} \hat{A}_{t-1}) \), see Figure 1.(d). In Figure 1.(e), we show the case where both surfaces, \( S_1 \) and \( S_2 \), are quite similar, which imply \( \bar{E}_2 \) to be null. This case can occur when the position of \( \hat{A}(t) \) and \( y_j^t \) are diametrically opposite or when their positions are in different side comparing to axis \( (\hat{A}_{t-2} \hat{A}_{t-1}) \).

In such cases, the energy is not a sufficient informative source to achieve the task of association. To compensate this energy, we incorporate the third energy \( \bar{E}_3 \).

3. The proximity energy evolution, \( (\bar{E}_k^3)_{y_j} \), is the inverse of the surface \( S \) defined by the common area between the two triangles \( (\hat{A}(t - 2), \hat{A}(t - 1), \hat{A}(t - 1)) \) and \( (\hat{A}(t - 2), \hat{A}(t - 1), \hat{A}(t)) \) (see the dotted area of Figure 1.(d)). This energy evaluates the absolute accuracy between the prediction \( \hat{A}(t) \) and the measurement \( y_j^t \) at instant \( t \). Increasing \( S \) means that the prediction and measurement at instant \( t \) are close. This energy term is given by:

\[
(\bar{E}_k^3)_{y_j} = \|((\bar{E}_k^3)_{y_j})\| = \frac{1}{S}\bar{k}
\]

Another question could be asked: why do we have to use the intersection surface instead of only calculating the distance between observation \( y_j^t \) and target position prediction at instant \( t \)?

In Figure 1.(g), we have two predictions at instant \( t, \hat{A}_1 \) and \( \hat{A}_2 \). They are both equidistant from the observation \( y_j^t \). If we only compute the distance to measure the proximity energy, we will get that both models have the same degree of similarity with the initiation model defined by the dynamic model of points \( (\hat{A}(t - 2), \hat{A}(t - 1), y_j^t) \). This result leads to a contradiction with the reality. This contrariety can be explained by the fact that if they
Finally, the measurement $y_j'$ is associated with the target $k$ if its energy magnitude is minimized:

$$y_j' \rightarrow k = \begin{cases} \min_{k=1,...,K} \langle \|\vec{E}_k\|_{y_j'} \rangle \\ \min_{k=1,...,K} \left( \frac{1}{\sqrt{3}} \sum_{l=1}^{3} \alpha_l^2 \|\langle E_{y_j'}^{l}\rangle_k \|^2 \right) \end{cases}$$  \hspace{1cm} (5)

with $0 \leq \alpha_l \leq 1$ and $0 \leq \|\langle E_{y_j'}^{l}\rangle_k \| \leq 1$.

We have described a novel approach for data association based on the minimization of an energy magnitude whose components are extracted from geometrical representations (area and distance) constructed with observations, previous states and predictions. The purpose of choosing a geometrical definition for these energies refers to:

- Show the geometrical continuity of the system between predictions and previous states using two different dynamic models.

- Measure the similarity between predictions, at a particular time for the same object, using two different dynamic models, that logically must be quite similar because they represent the same system.

### 3 Experimental Results

#### 3.1 Synthetic test

To expose the performance of our energy minimization approach, we suggest the synthetic example of figure 2, which explores the case of oscillatory motion with a constant phase. It shows two targets $T_1$ and $T_2$ whose dynamic models are defined by two different sinusoids, $\sin(x)$ and $\sin(2x) + 0.5$. The measurement $y$ (full square in Figure 2) is equidistant from both targets and falls in their validation regions. In such case, both targets are candidates to be associated with this measurement. We compute the energy magnitude for each target (see Table 2) and obtain that $\|\langle E_{y}^{1}\rangle_k \| < \|\langle E_{y}^{2}\rangle_k \|$ and the observation is associated with $T_1$.

We give another example where the complex motion of both targets is given by a sinusoid with a non periodic phase, see Figure 3. At instant $t-1$, both targets have the same position as shown in Figure 3. If we use the NNF method, the measurement will be associated with both targets since it is equidistant from them. To associate the measurement available at instant $t$, we compute the energy magnitude for each target, and the results are in table 2. We obtain $\|\langle E_{y}^{1}\rangle_k \| < \|\langle E_{y}^{2}\rangle_k \|$ and the measurement is associated with $T_1$.

#### 3.2 Van-Plane test

In the following experiment, the observation occurred at instant $t$ contains two measurements $\{M_1, M_2\}$, each one represents a position in the target space.
(x, y).

Figure 3: Sinusoids with a non-constant phase: the dotted lines represent the trajectories of targets T1 and T2. The shapes (square, circle, triangles) are the prediction of the targets at different instant.

Let us now apply our algorithm of energy minimization to associate these measurements to targets by only considering one information: the position. The numerical steps are followed. The predictions of the position of target T1, using the default dynamic model without taking into account the available observation, at instants \{t \in \{t-2, t-1, t, t+1\}\} in the (x, y) space are given by:
\[
\{(50, 275), (75, 292), (139.5, 322), (279.5, 350)\}.
\]

Using the same scheme, the predictions of the position of target T2 at instants \{(t-2), (t-1), t, (t+1)\} are respectively:
\[
\{(412, 307), (331, 292), (148, 300)\}.
\]

The predictions at instant \(t+1\) if we associate the measurements \(M_1, M_2\) with target T1 and if we evaluate the parameters of the dynamic model are:
\[
\left(\frac{382}{355}\right) \text{ and } \left(\frac{290}{323}\right).
\]

In the same way, the predictions of the position of target T2, after the evaluation of the dynamic model and after the assignment of the measurements, are:
\[
\left(\frac{74}{335}\right) \text{ and } \left(\frac{82}{303}\right).
\]

The velocity of both targets at instant \(t-2\) is given by:
\[
\left(\frac{25}{17}\right) \text{ and } \left(\frac{-105}{0}\right).\]

The evaluation of the dynamic model is given in the following form:
\[
\tilde{T}_i(t) = \tilde{T}_i(t-1) + \hat{\beta}_i \tilde{v}_i(t-2) + \hat{\beta}_2.
\]

The values of \(\hat{\beta}_1; \hat{\beta}_2\) for T1 and T2 at instants \(t-1, t, t+1\) are respectively:
\[
\left\{[1;0], \frac{3}{3}; \frac{18}{3}, \frac{2}{2}; \frac{45}{3}\right\} \text{ and } \left\{[1;0], \frac{3}{3}; \frac{-1}{-26}, \frac{2}{2}; \frac{71}{4}\right\}.
\]

Their corresponding values at instant \(t+1\) after association of measurements \(M_1, M_2\) respectively to targets T1 and T2 are respectively:
\[
\left\{[2; \frac{45}{3}], 2; \frac{45}{3}\right\} \text{ and } \left\{[2; \frac{45}{3}], 2; \frac{45}{3}\right\}.
\]
Table 3 shows the numerical value of each energy when \( M_1 \) and \( M_2 \) are associated with targets \( T_1 \) and \( T_2 \). We can notice, according to the results, that \( M_1 \) and \( M_2 \) are associated with \( T_1 \) and \( T_2 \) respectively.

Table 3: Energy magnitude computing for both targets when the measurements \( \{M_1,M_2\} \) are associated with them.

\[
\begin{array}{cccc}
\alpha_k(||E^{i}_{j}||_{M_1}) & \alpha_k(||E^{i}_{k}||_{M_2}) \\
1 & 0.3141 & 0.5621 & 0.2687 \\
2 & 0.6838 & 0.98 & 0.7879 \\
\end{array}
\]

3.3 Ant sequence test

This sequence shows ants moving on a flat surface. Each ant has a complex movement: translation while walking and deformations while moving its head, abdomen, or antennas. These ants are quite similar even non-distinguishable, characterized by the same gray domen, or antennas. These ants just to show their positions from one frame to another. Figure 3.3.c is the observation available at instant \( t + 1 \) and represents the frame 35 from the sequence. Figure 3.3.d is the real frame at instant \( t + 1 \).

Table 4 contains the Mahalanobis distance between measurements, \( (M_j)_{j=1...6} \), and targets, \( (T_i)_{i=1...6} \): the first row contains the measurement’s number and the first column the target’s number. We have put the measurement by the order that the measurement \( M_i \) is provided from target \( T_i \). If we decide to associate measurements with targets only using the distance minimization, we obtain that the distance between \( M_2 \) and \( T_2 \) is minimized and also between \( M_4 \) and \( T_2 \) which leads to a contradiction with the reality. We can remark from Table 5 that the second energy between \( T_2 \) and \( M_2 \) is lower than the energy between \( T_2 \) and \( M_5 \) which remedy the first energy based on the Mahalanobis distance. Table 7 represents the magnitude of the energy function where we observe that each measurement is well associated with its corresponding target.

4 Conclusion

This work proposes a new method for data association based on an energy minimization. The developed approach can handle complex motions and highly non-linear systems, and deals with the lack of of prior knowledge. Its effectiveness returns to the fact it requires few parameters. The geometric illustration of energy components allows to measure the accuracy between two dynamic models and to define their degree of similarity.

As a perspective for this work, we suggest to integrate the energy minimization approach within the classical particle filter to build a new framework for multiple tracking objects. Moreover, since we consider erratic motions that cannot be learned from training sequences, we suggest to use an adaptive and automated
Table 5: The first column contains the ant’s number, \( k = 1 \ldots 6 \) and the first row contains the measurements number. The values represent the absolute accuracy evolution energy, \( \left\| \left( \vec{E}^2_k \right)_{ij} \right\| \times 100 \).

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Table 6: The first column contains the ant’s number, \( k = 1 \ldots 6 \) and the first row contains the measurements number. The values represent the proximity evolution energy, \( \left\| \left( \vec{E}^3_k \right)_{ij} \right\| \times 100 \).

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Table 7: This table contains the values of the magnitude of the energy function \( \left\| \left( \vec{E}_k \right)_{ij} \right\| \times 100 \).

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way to set the parameters of the dynamic model of the filter. The purpose of developing this framework is to track targets under the restriction of the missing of prior information and especially when similar targets are evolving in the scene. This phase is under development.

REFERENCES


