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Multiple-feature Tracking Based on the Improved Dempster-Shafer Theory

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Abstract

Dempster-Shafer evidence theory is widely used in the fields of decision level information fusion. In order to overcome the problem of the counter-intuitive results encountered when using Dempster's combination rule to combine the evidences which exist high conflict, a modified sequential weighted evidence combination is proposed. Firstly, the credibility of each evidence can be obtained based on K-L distance, besides, the uncertainty of each evidence can obtained based on information entropy. Simultaneously, using the uncertainty of each evidence to improve the credibility of each evidence, then the weights of the bodies of evidence are obtained based on the improved credibility of each evidence, the weights generated are used to modify the bodies of evidence including the previous combination result, the previous evidence and the new arriving body of evidence at current step. Finally, according to the Dempster's combination rule, the weighted average combination results can be obtained. In the experimental part, the improved method is used to fuse video multiple features in target tracking system and compared the results with the standard D-S theory. The simulation results show that the proposed method has better performance.

Key words*: object tracking, particle filter, D-S evidence theory, multi-feature fusion*

1. Introduction

Object tracking has many applications in the field of computer vision, such as visual surveillance, Intelligent meeting system, automatic navigation of robots, human-computer interaction, multi-media system and so on [1]. In the real tracking process, different features are used to represented object, such as color histograms [2], edge [3] and motion. Due to the unpredictable complex change of background and object's feature can change over time. Hence, using a single feature can't track object robustly. The fusion of multi-feature is an effective means to solve the problems.

Recently, many tracking algorithms based on multi-feature fusion are proposed by researchers. The main differences of algorithms is that the feature extraction and the different fusion strategies. The D-S evidence theory fusion has attracted many researchers' attention. Evidence theory, also known as Demspter-Shafer (D-S), first proposed in 1967 by the Dempster [4], later be improved and promoted in 1976 by Shafte [5]. Evidence theory is a useful uncertainty reasoning theory and provides a powerful method for the expression and synthesis of uncertain information. Given these advantages, it has been successfully applied to data fusion, target recognition and intelligent decision-making system [6]. In the framework of particle filter, the idea of Evidence theory is used to fuse the block color histogram and Distance measure of the maximum gradient by Zou [7]. The idea of evidence theory is also used to fuse pluralities features of target by Cao [8, 9]. Although these methods adopts evidence theory to fuse target's multiple features, D-S evidence theory is sensitive to noise and has low tracking robustness in strong noise environment. Simultaneously, D-S evidence has "one ticket veto", "poor robustness"and other defects.

In order to solve the problems of D-S evidence, many algorithms have been improved by scholars, which can be divided into three categories. The first method is a amendment of combination rules of D-S evidence theory, and its essence is to remove normalization step which deals with the redistribution of conflict information in combination rules. The typical improved algorithm by [10] assigned the conflicts information of evidence to the focal element

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which is assigned a greater basic probability assignment among the focal elements, which called absorption method. This algorithm is simple in application, but lost the combination of multi-source data interchange ability. The second method is only to modify the source of evidence, and doesn't modify the combination rule. The typical improved methods are: Murphy [11] using a method of simple averaging, the disadvantage of this method doesn't consider the relationship between the evidences. On the basis of Murply, Deng [12] introduced the evidence distance function to obtain the credibility of evidence. It converges faster than Murphy's averaging method. The third method is to modify the rules of evidence combination on the basis of handing the evidence source. The typical improved algorithm is Li [13]. This algorithm firstly discounted the processing of the evidence source, and then used Dempster combination rules which remove the normalization factor to combine and allocated conflict information according to the support of focal element. The method can dealt with the evidences under high conflict situation. These improved methods were lack of practical application, only used numerical examples to verify their validity. However, for the multi-sensor data fusion, the change of data source is sustained and the environment is more complex.

For the complexity and instability of target tracking system; this paper proposed a new tracking algorithm of multi-features fusion based the improved evidence theory. But currently the fusion of evidence theories is based on batch fusion. In the actual time, the time of obtaining information with sensor successively divided. The sensors can't receive all the evidence sources at the same time. Thus this paper adopts sequential fusion method. When the system collects a new evidence, using K-L distance and the evidence uncertainty to modify the previous combination result, the previous evidence and the new arriving body of evidence at current step; according to Demspter combination rules to complete the current step evidence combinations. On the one hand, we use numerical examples to demonstrate the effectiveness of the proposed algorithm. On the other hand, the algorithm is introduced to video multi-features fusion, which has a significant practical meaning.

In the rest of this paper, we explain the shortcomings and our algorithm in Section 2. Experimental results and analysis are reported in Section 3. We conclude this paper in Section 4.

2. The Proposed Algorithm

The basic concepts of D-S evidence theory can be seen in the references [1,2]. This section firstly introduces the shortcomings of D-S evidence theory, and then our algorithm is given.

2.1 D-S Evidence Theory's Shortcomings

The rationality of combinatorial theory is proved in theory by Dempster and Shafer. Other algorithms in dealing with uncertainty can not be compared with D-S evidence theory. Actually the utilization of D-S evidence theory may cause some problems. We often use examples to analyze the insufficient of D-S evidence theory.

Table 1. The BPA for EX1

Evidence	A	B	C
m_1	0.99	0.00	0.01
m_2	0.00	0.99	0.01

Table 2. The BPA for EX2

Evidence	A	B	C	D	E
m_1	0.2	0.2	0.2	0.2	0.2
m_2	0.2	0.2	0.2	0.2	0.2

Table 3. The BPA for EX3

Evidence	A	B	C
m_1	0.99	0.00	0.01
m_2	0.00	0.99	0.01
m_3	0.99	0.00	0.01

EX1: Two groups of Basic Probability Assignment (BPA) evidence reports are show in table 1. After evidence combination formula, we can obtain the fusion results as:

$m(A)=m(B)=0.\ m(C)=1,\ K=0.9999.$

Results show that fusion target is C, This is obviously against with our normal cognition. In D-S evidence, K reflects the conflict between evidences. In this example it is concluded that K is 0.9999, it means that the conflict between two groups of evidence is considerable. The fusion result is not advisable in this situation.

EX2: Two groups of Basic Probability Assignment(BPA) evidence reports are show in table 2. After evidence combination formula, we can obtain the fusion results as:

m(A)=m(B)= m(C)= m(D)=m(E)=0.2, K=0.8.

Although the two evidences are exactly same in table 2, it is concluded that K is 0.8, it means that the coefficient K can not really represent the relationship between the two evidences.

EX3: We give some evidences groups and make the fusion according the D-S evidence theory. The groups of Basic Probability Assignment (BPA) evidence reports are show in table 3. After evidence combination formula,we can obtain the fusion results as:

m(A)=m(B)=0. m(C)=1, K=0.999999.

The fusion results clearly not fit to people's normal logic, the reason of this kind problem is that the basic trust distribution of $\{A\}$ is 0 which from the second evidence. The result of $\{A\}$ always equal to zero, no matter how much the basic trust distribution from other evidences support $\{A\}$. Owning the characteristics of one ticket veto, this shortcoming for D-S evidence theory is very deadly.

2.2. Weighted Evidence Amendment Based on K-L Distance and Evidence Uncertainty Measure

Weighted evidence amendment based on K-L distance which proposed by [14] and evidence uncertainty measure consists of two steps. The first step obtains the credibility of evidences based on K-L distance. The second step further amendments the credibility of evidence based on evidence uncertainty measure to strength the effects of excellent evidences and to suppress the effects of interference evidences.

K-L distance is also called the relative entropy, it is a measure of the distance between probability distribution P and probability distribution Q. Assuming P and Q are probability distribution functions, the relative entropy of P with respect to Q can be defined in equation (1):

$$D(P \| Q) = \sum_{i=1}^{n} p_i \lg p_i / q_i \tag{1}$$

K-L distance can measure information distance and has the nature of asymmetric. However, it will happen the situation of $\lg^0 = -\infty$ when using K-L distance directly measure the distance of evidences. Then the modified K-Ldistance can be defined in equation (2):

$$d(m_1, m_2) = \sum_{i=1}^{k} [m_1(A_i) + \alpha] \lg \frac{m_1(A_i) + \alpha}{m_2(A_i) + \alpha} \tag{2}$$

In equation (2), $\alpha = 0.0001$, m_1 and m_2 are basic probability assignment.

Establishing the recognition framework of fusion system is U. $m_1, m_2 \ldots m_n$ as the basic probability assignment on the recognition framework.

Define 1: The distance between evidence m_1 and m_2 can be defined in equation (3):

$$D(m_1, m_2) = d(m_1, m_2) + d(m_2, m_1) \tag{3}$$

Define 2: After obtained the distance of all evidences, the support of m_i can be defined in equation (4):

$$\lambda_i = \frac{1}{\sum_{j=1, j \neq i}^{n} D(m_i, m_j) + 0.0001} \tag{4}$$

Define 3: The credibility of evidence m_i can be defined by equation (5):

$$Crd(m_i) = \lambda_i \Big/ \sum_{i=1}^{n} \lambda_n \tag{5}$$

$Crd(m_i)$ reflects the credibility proportion of evidences. It can also reduce the influence of fusion result by low credibility evidence.

Fundamentally speaking, the essence of evidence combination is the integration of inconsistent information, deriving a more definitive conclusion from the process of combination. Each received evidence has uncertainty, but some evidences which have very small uncertainty have high conflict with other evidence. Therefore, the evidence which have small uncertainty should assign small weight.

In order to measure evidence uncertainty, we apply the proposed equation by Klir [15].

Define 4: The evidence's nonspecific can be defined by equation (6):

$$N(m) = \sum_{A \in \Theta} m(A) \log_2^{|A|} \tag{6}$$

Define 5: The evidence's inconsistency can be defined by equation (7):

$$ST(m) = -\sum_{A \in \Theta} m(A) \log \sum_{B \in \Theta} m(B) \frac{|A \cap B|}{|A \cup B|} \tag{7}$$

Define 6: The evidence's uncertainty factor based on the evidence's nonspecific and the evidence's inconsistency can be defined by equation (8):

$$\beta(m) = N(m) + ST(m) \tag{8}$$

When the focal element A is a single point set, the evidence's nonspecific is zero, the overall uncertainty is inconsistency. Then the evidence's uncertainty can be defined by equation (9):

$$\beta(m) = -\sum_{A \in \Theta} m(A) \log_2^{m(A)} \tag{9}$$

The credibility of evidences based on K-L distance only consider the relative distance between evidence, it don't consider the inherent uncertainty of evidence. For this defect, we apply the evidence's uncertainty to amend the credibility of evidences.

Define 7: Regarding the evidence's uncertainty as questioned factor for the credibility of evidence. Then the amended credibility of evidence can be defined by equation (10):

$$Credm(m_i) = Cred(m_i) \times \beta(m_i) \tag{10}$$

Define 8: The weights of evidences can be defined by equation (11):

$$\omega(m_i) = Credm(m_i) \Big/ \sum_{i=1}^{n} Credm(m_i) \qquad (11)$$

Amended results make the evidences which have high uncertainty get greater weights, and make the evidences which have lower uncertainty have smaller weights.

Evidence of traditional correction method is batch-type, it means that the evidences which wait for combination are modified when the system collect all evidence. However, in the actual application, obtaining evidences are sequential. So this paper proposes a new sequential weighted evidence combination approach. The specific steps of evidences combination as follows:

Step 1: for obtained first evidence and second evidence: m_1^{new} and m_2^{new}, and regard $m_1^{comb} = m_1^{new}$ as the result combination of step 1.

The results of modified evidences as:

$$m_2^w = \omega(m_1)m_1 + \omega(m_2)m_2 .$$

The evidences combination results of step 2 as:

$$m_2^{comb} = m_2^w \oplus m_2^w .$$

Step 2: for i=3:k: Assuming combination results of at current step is related to previous combination result, previous collected evidence and the new arriving body of evidence at current step as:

$$m_i^w = \omega(m_{i-1}^{comb})m_{i-1}^{comb} + \omega(m_{i-1}^{new})m_{i-1}^{new} + \omega(m_i^{new})m_i^{new}$$

Then the result of combination at current step can be defined by: $m_i^{comb} = m_i^w \oplus m_i^w$.

Algorithm flowchart is shown on the right.

Figure 1 shows that the combination results of each step are not only related to the new arriving body of evidence at current step, but also related to previous collected evidence and previous combination result. Besides, In each combination step, not only the distance of evidence and but also the uncertainty measure is utilized to determine the weights of the bodies of evidence. Then the weights generated are used to modify the bodies of evidence including the previous combination result, the previous collected evidence and the new arriving body of evidence at current step.

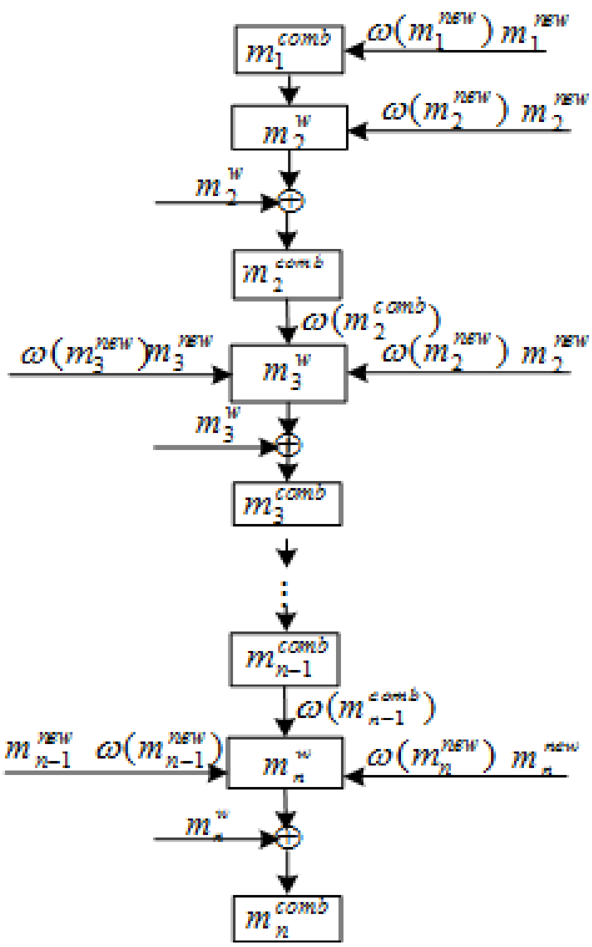

Figure 1. Algorithm flowchart

3. Results and Analysis

In order to fully verify the validity of proposed algorithm, on the one hand, we applied numerical example to analysis proposed algorithm and some classic D-S theory algorithm. On the other hand, our new algorithm is applied to the video target tracking. Furthermore, our tracking results are compared with the tracking results used D-S theory.

3.1. Fusion Modeling Based on D-S Evidence

In this paper, we establish a D-S fusion model for video multiple features under the framework of the particle filter. The particle filter can solve the problem tracking under the nonlinear, non-Gaussian model [16, 17].

The D-S fusion model for video multiple features under the framework of the particle filter is shown in Figure 2. Read the kth frame image from a video sequence. Extract color feature and edge feature of the target. Map color feature as evidence m_1 and edge feature as evidence m_2 .At the same time, read the (k-1)th frame particle set and get the kth frame particle set $\{X_1^k, X_2^k \cdots X_{Ns}^k\}$ by state transition. Map the particle set as the frame of discernment θ. According to the color feature of the target, match feature by calculating Bhattacharyya distance between current characteristic and object characteristic. Define an observation probability density function of the particle to measure the similarity. At this point, we have established the D-S fusion model for video multi-feature fusion. In the model, the basic mappings are summarized as follows:

$$\{X_1^k, X_2^k, \cdots X_{Ns}^k\} \rightarrow \textit{frame of discernment } \theta$$

$$\textit{color histogram feature} \rightarrow \textit{evidence } m_1 \text{ , } \textit{edge feature} \rightarrow \textit{evidence } m_2$$

$$\{w_1^c, w_2^c, \cdots w_{Ns}^c\} \rightarrow m_1(X_i^k)_{i=1,2\cdots Ns} \text{ , } \{w_1^t, w_2^t, \cdots w_{Ns}^t\} \rightarrow m_2(X_i^k)_{i=1,2\cdots Ns}$$

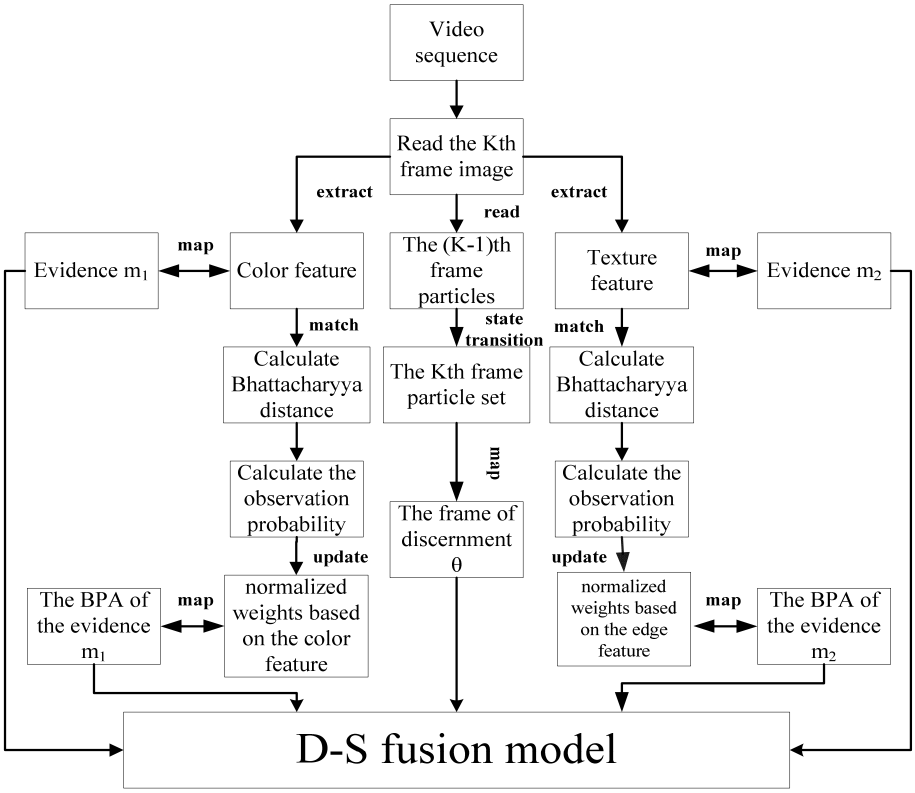

Figure 2. The process of establishing D-S model for video multi-feature fusion

3.2. Numerical Example

Firstly, we applied the new algorithm, Sun [18], Yager [19], Li [20] to simulation for Ex1, We get the fusion results which are shown in Table 4

Table 4. Fusion result of different situation

Combination rule	m(A)	m(C)	m(B)	m(X)
Yager	0.0000	0.0000	0.0001	0.9999
Sun	0.1821	0.1821	0.0038	0.6320
Li	0.4950	0.4950	0.0100	0.0000
This study	0.4999	0.4999	0.0002	0.0000

After simulation the evidence which provided by Ex 1, we can clear observe the result in Table 4. The algorithm by Yager is prone to the phenomenon of one ticket veto. The algorithm of Sun overcomes the phenomenon of one ticket veto, however, this method exists many unknown parts, so combination results are not conductive to making. The fusion results which calculated from the algorithm of Li and our proposed are content people’s normal cognition.

Secondly, this study will compare with some classic D-S evidence theory algorithms. We will demonstrate the superiority the new algorithm. Assume that the target has three most likely states at each moment. The frame of discernment is: $\theta = \{X_1 = State1,\ X_2 = State2,\ X_3 = State3\}$.Data is collected by five cameras. The dates are shown in Table 5.

Table 5. The BPA of evidences

Evidence	BPA	State output
m_1	$m_1(X_1)=0.5$, $m_1(X_2)=0.2$, $m_1(X_3)=0.3$	State1
m_2	$m_2(X_1)=0$, $m_2(X_2)=0.9$, $m_2(X_3)=0.1$	State2
m_3	$m_3(X_1)=0.6$, $m_3(X_2)=0.1$, $m_3(X_3)=0.3$	State1
m_4	$m_4(X_1)=0.8$, $m_4(X_2)=0.1$, $m_4(X_3)=0.1$	State1

From Table 5. We can observe that three evidences support state X1. But the evidence m_2 gives the state X2. So the fusion results should give state X1.

Table 6. Fusion result of different algorithms

Algorithm	m_1,m_2	m_1,m_2,m_3	m_1,m_2,m_3,m_4
Dempster	$m(X_1)=0.0000$, $m(X_2)=0.8571$, $m(X_3)=0.1429$,	$m(X_1)=0.0000$, $m(X_2)=0.6667$, $m(X_3)=0.3333$,	$m(X_1)=0.0000$, $m(X_2)=0.6667$, $m(X_3)=0.3333$,
State output	State 2(Error)	State 2 (Error)	State 2(Error)
Yager	$m(X_1)=0.0000$, $m(X_2)=0.1800$, $m(X_3)=0.0300$,	$m(X_1)=0.0000$, $m(X_2)=0.0180$, $m(X_3)=0.0090$,	$m(X_1)=0.0000$, $m(X_2)=0.0018$, $m(X_3)=0.0009$,
State output	State 2(Error)	State 2 (Error)	State 2(Error)
Sun	$m(X_1)=0.1331$, $m(X_2)=0.4727$, $m(X_3)$ =0.1364,	$m(X_1)=0.2448$, $m(X_2)=0.2851$, $m(X_3)=0.1648$,	$m(X_1)=0.3341$, $m(X_2)=0.2304$, $m(X_3)=0.1416$,
State output	State 2(Error)	State 2 (Error)	State 1(Correct)
Murphy	$m(X_1)=0.1543$, $m(X_2)=0.7469$, $m(X_3)=0.0988$,	$m(X_1)=0.3915$, $m(X_2)=0.5078$, $m(X_3)=0.1001$,	$m(X_1)=0.7995$, $m(X_2)=0.1754$, $m(X_3)=0.0251$,
State output	State 2(Error)	State 2 (Error)	State 1(Correct)
This study	$m(X_1)=0.4206$, $m(X_2)=0.3944$, $m(X_3)=0.1850$,	$m(X_1)=0.6709$, $m(X_2)=0.1292$, $m(X_3)=0.1998$,	$m(X_1)=0.8553$, $m(X_2)=0.0814$, $m(X_3)=0.0632$,
State output	State 1(Correct)	State 1 (Correct)	State 1 (Correct)

After simulation the evidence which provided by Table 5, we can clear observe the result in Table 6. The algorithms by D-S and Yager are prone to exist the phenomenon of one ticket veto, we always cannot get correct state. The algorithms of Sun has disadvantage of slow convergence, so fusion results is not conductive to making. After getting the fourth evidence, we can make correctly decision. The algorithm by Murphy excessive exaggerated the single evidence, this algorithm has disadvantage of slow convergence. Simultaneously, the algorithm by Murphy [21] identifies the correct target's state when getting the fourth evidence. As illustrated in Table 6, the performance of convergence of proposed algorithm is better than above algorithms. The reason is that our proposed algorithm can strengthen the effect of credible evidence further and at the same time weaken the effect of incredible evidence further. So when fusing two evidences we can get correct state. Furthermore, the target's state X1 obtains 0.8553 degree of support when fusing the fourth evidence, so the reliability of our algorithm is best. Overall, our proposed algorithm is rational and effective.

3.3 Video Multi-Feature Fusion Tracking

The below experiment is that we used D-S theory and proposed algorithm to fuse the target's two features including color feature and edge feature. The length of this video sequence is 83 frames, this video sequence has the following characteristics: the background interference is bigger, the target is obscured by other similar goals.

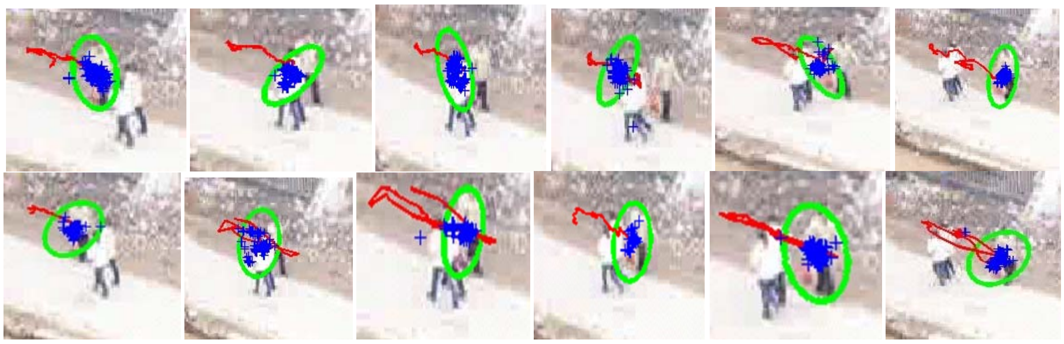

Figure 3. Tracking results by:D-S evidence (the first row), proposed algorithm (the second row) (Frames:48,61,62,66,70,80)

We can clear observe the tracking results in Figure 3. From Figure 3, we can find that D-S evidence don't stably track target in complex environment. Before occlusion as frame 48, because traditional evidence theory don't have preprocessing step, the particles distribution is divergent. Our algorithm has the preprocessing step, so the particles distribution is concentrated. Namely, our algorithm improves the tracking accuracy compared traditional evidence theory. When occlusion occurs as frames (61, 62, 66). The traditional evidence cannot accurately track the target, on the contrary, our algorithm can accurately track the target. After occlusion as frames (70, 80), traditional evidence theory can recover the tracking. This video sequence illustrates that proposed algorithm is better than D-S evidence in terms of overall performance.

4. Conclusion

Dempster's rule of combination can out-come counter-intuitive results when the different evidence to be combined are highly conflicting.The proposed algorithm by jointly using the K-L distance of evidence and the uncertainty measure can efficiently handle conflicting evidence with better performance of convergence.Furthermore ,used our algorithm achieved the tracking of target.This achievement has a certain practical significance.

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