Tabu Search Based Implementation of Object Tracking using Joint Color Texture Histogram.

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Abstract—**Object tracking has many applications like security and surveillance, traffic control and many others. In this Paper new methodology has been proposed which uses tabu search algorithm along with joint color texture histogram to track object. Texture featurelike edges and corners are extracted using uniform linear binary pattern, which will help in increasing the robustness of the object to be tracked. After features are extracted battacharyya coefficient is calculated to measure similarity between target's raw feature in the previous frame and raw feature in present frame. This coefficient is used as objective function in tabu search algorithm framework. In tabu search, parameters like length of tabu list and radius of search region are chosen appropriately. The experimental results shows that the proposed algorithm can track object more robustly under complex scenario's like object is similar to background in a static video.**

Key words: tabu search; object tracking; local binary pattern; joint color histogram; texture; static video.

I. INTRODUCTION

Object tracking in a video sequence is a growing field in the field of computer vision. There are many tracking algorithms which are used in computer vision[1-3].currently researcher's are concentrating on increasing the robustness of the object to be tracked [4]. The challenging part comes in tracking the target even under complex scenario's like object is similar to background,for this an optimization algorithm is required..Tabu Search[TS][5,6] is one such algorithm which can be used.

Some algorithm's like meanshift[2],camshaft[1] have been used for kernel based object tracking.Recentlyattemts were made to use meta-heuristic algorithms in combination with statistical tools like bhattacharya coefficient[7,8] .Zhenbo Jiang *et al,*2011[9] has used Tabu search and found that robustness has increased considerably but in Target representation only color histogram was used.

Target representation plays vital role in tracking the object robustly, currently widely used target representation is color histogram[10,11]. If this color histogram information is combined with texture features and TS algorithm object can be tracked robustelyunder complex scenarios like object is similar to background[12].

TS is a meta-heuristic[5,6] method which will avoid falling a solution into local optima by creating a special list called tabulist.TS algorithm has wide applications in the field of scheduling, network topology design and so on. In TS algorithm the center of the tracking window which we chose in the first frame is the initial solution to TS algorithm and it is the optimal solution. In this paper we have used Joint color texture histogram method to extract target feature and combined with TS algorithm and meanshift algorithm to track the object selected more robustly.

The focus of this paper is to track the object more robustly which is of real time and is selected by the user. For this purpose we have used TS algorithm combined with joint color texture histogramto find the optimal solution[13].

The rest of the paper is organized as follows section II presents the basic TS algorithm ,target feature extraction using joint color texture histogram, calculation of objective function. Section III explains about tracking algorithm procedure.Section IV presents experimental results and analysis which are conducted on static video. And finally conclusion is discussed in section V.

II. TARGET FEATURE EXTRACTION AND TRACKING ALGORITHM

Before moving to the object tracking using TS algorithm, general introduction is provided which describes basic TS algorithm, target extraction, texture feature extraction.

A. Need of TS Algorithm

The local search strategies are memoryless and does not keep track of the past solutions, because of this there may be possibility that the new solution may stuck up at local optima. But the search should extend to neighborhood and select the solution which decreases the objective function. There are many algorithms proposed to solve this optimization problem[14], one of the concept is Tabu search algorithm. This algorithm is introduced by Fred Glover, and later developed by other researcher's.TS algorithm is meta-heuristic method which extends the search beyond local optimality to find better solution. To do this, algorithm maintains a special list called Tabu list which keep track of

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recent solutions. To do this memory structures are incorporated ,likerecency based memory structure.

B. Basic TS algorithm Template.

The core of Tabu search is to increase the search space by maintaining a tabulist to find optimal solution.The skeleton of the TS algorithm can be visualized as follows.

Notations used:

- S Temporary best solution
- T Tabu list
- S* Next best solution
- N(S) Neighborhood of S
- I Iteration number

1) Initialization: Choose an initial solution S, assign I=1 and T=ϕ
2) Generate N(S) from initial solution S.
3) Search:
   a) If T=ϕgo to 2) regenerate Neighborhood set N(S).else, find S* from N(S).
   b) If S* belongs to T and S* doesn't satisfy aspiration criteria make N(S)=N(S)–{S*}.go to a); else make S=S*, S* is better than S
4) Refresh T ,if termination criteria is satisfied then output S*,otherwise add S to T. go to 2)

The algorithm suggests that by aspiration and termination criteria optimization can be achieved. TS algorithm requires some solutions from which the best solution is obtained.To generate solutions the features of the target are to be extracted.

C. Target Feature Extraction.

1) Target Representation:

In a frame object is defined in the rectangular region and color histogram is used to represent the target[11,12]. Cosider that target has n pixels in the region defined.The normalized pixels in the target region is denoted by $\{x_i^*\}_{i=1,2\ldots n}$. The histogram $q_u$for the bin u is calculated as follows. Consider histogram has m bins.

$$q=\{q_u\}_{u=1,2..m};q_u=C\sum_{i=1}^{n}K(\|x_i^*\|^2)\delta[b(x_i^*)-u](1)$$

Where q_u is the probability of u^{th}element of q,q is the target model,δ is the delta function, $b(x_i^*)$ relates to bin number to which x_i is associated to in histogram, k(.) is kernel function which is non decreasing function and constant C is defined as[11,12]

$$C=1/\sum_{i=1}^{n}(\|x_i^*\|^2)\ (2)$$

similarly target feature in the K^{th} frame (K>1) is calculated as follows let the center position of target candidate model be y [11,12].

$$p=\{p_u\}_{u=1,2\ldots m;}$$

$$p_u(y)=C_h\sum_{i=0}^{n}K(\|(y-x_i)/h\|^2)\delta[b(xi)-u]\ \ (3)$$

p(y) is target model in K^{th}frame, p_u is the probability of u^{th} element of p(y).$\{x_i^*\}_i$=1,2..n are pixels in target candidate region centered at y, h is the bandwidth[11,12]

$$C_h=1/\sum_{i=1}^{n}(\|y-x_i/h\|^2)(4)$$

In the proposed tracking algorithm apart from color histogram,texture features are also extracted using LBP technique.

D. Texture Feature Extraction

The texture features which holds spatial information of the object use to represent and recognize the target. Since Texture feature add some more information apart from what color histogram conveys, using joint color texture histogram is more reliable for target representation[8].For this linear binary pattern (LBP) is used to extract texture features.

The linear binary pattern thresholds neighborhood pixels to its center value and considers result as a binary number(binary pattern).LBP operator is defined as[11].

$$LBP_{P,R}(X_C,Y_C)=\sum_{p=1}^{P-1}S(g_p\text{-}g_c)2^p\quad(5)$$

Where g_c denotes grey level value of center pixel, and g_p denotes grey level value of the P equally spaced neighborhood pixels which are located at radius R from center.

Figure 1 explains the simple example of LBP operator with P=8,R=1.By varying P and R multiresolution analysis can be achieved. As it can be observed that center pixel value is 3, it is subtracted from the neighborhood values (5,9,3,2,2,6,9,1) , say the result is x then , The function s(x) is 1 for x $\geq$0 and 0 otherwise.

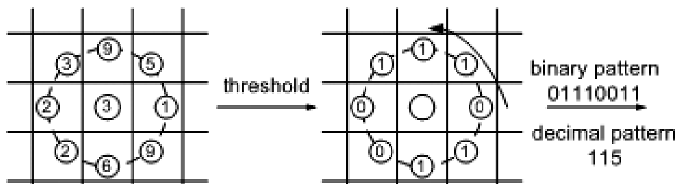

Figure 1 : Example showing LBP texture model [8] with P=8,R=1.

The model combining color and texture can be constructed and it consists of color feature and LBP texture pattern as explained by JifengNing*et al*2009[9].Now the extracted featute can be considered as discrete distributions.For comparing target and candidate features(distributions) similarity function called Bhattacharyya coefficient is used.

E. Bhattacharyya Coefficient

This coefficient is used to measure the resemblance between the target model and the candidate model[7], it measures the similarity between the two probability distribution functions which are either discrete or continuous.In the field of statistics it tells the amount of overlap or amount of closeness between the two samples [8].Figure 2 explains the role of bhattacharya coefficient in creationg objective function where q_u and Pu(y) are the target and candidate models respectively

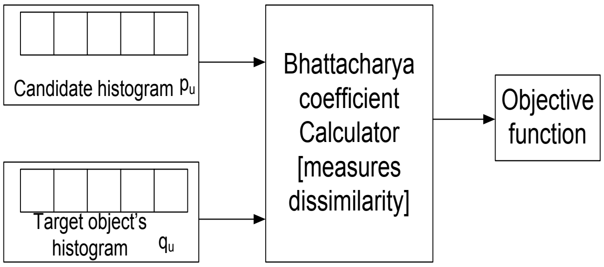

Figure 2: Visualization of the role of Bhattacharya coefficient (function /operator) in Objective Function.

After raw features of the tracking object in the present frame and K^{th} frame are calculated we can use this coefficient to calculate the similarity between the target and the candidate using the formula.

$$\dot{\rho}(y)=\sum_{i=1}^{m}\sqrt{p_u(y) * q_u} \quad (6)$$

In eq(6) and Figure 3, q_u represents target raw feature, $p_u(y)$ represents objects feature in K^{th}frame(k>1).This coefficient is 0 if there is no similarity or overlap ,and if it is equal to 1 target raw feature is same in 1^{st} frame and K^{th} frame.

III. OBJECT TRACKING

All the ingredients like texture,colorhistogram,andbattacharya coefficient required for object tracking are obtained ,these are applied to the Tabu framework which is designed for object tracking .

A. Design of Tabu framework for Object Tracking

The basic TS framework involves a lot of concepts which are identified according to the application . The algorithm , which is used is the first level tabu search approach [5] which involves following concepts :

1) Neighborhood: The neighborhood is the set of m pixels randomly taken from the rectangle ((rmin,cmin),(rmax,cmax)) (pixel values of two diagonally opposite points) in the image feature space. The rectangle refers the tracking window. Where, m is maximum offset of solution from the previous/initial solution .
2) TabuList: If a solution is added to Tabu List it is prohibitedto besearched in a few following steps. The length of the Tabu List is a constant value of T. Tabu List is FIFO data structure , that is whenever the Tabu List is full, in other words, it has T solutions in it, if there are other solutions need to be added into the List, the first solution in Tabu List will be released.
3) Tabu Condition: This condition avoids trapping of search in local optimum. If this condition is satisfied then the solution is added to tabu list. We have incorporated two different tabu conditions. One is if it satisfies aspiration criteria, it will be added to Tabu List , another is discussed below :
   a). Calculate the objective function value f(S) of current solution S.
   b). Then compare the value with all the objective function values of the solutions in the Tabu List denotedS_{list} .
   c). If f(S) – f(S_{list}) > epsilon , solution S can be added into the Tabu List, otherwise, it won't .
4) Aspiration Criteria: Aspiration Criteriais designed in such a way that it prevents some valuable solution from being forbidden. It is defined as follows:
   a)Theobjective function value f(S) of current solution S is calculated.
   b). Then it is compared the value with the best solution's (S*)objective functionvalue f(S*) which is calculated in step 3)
   c). If f(S) > f(S*), it indicates that this solution can be aspired.

   With regard to the solution that satisfies the Aspiration Level Condition, there is no need to check out whether it satisfies the Tabu Condition.Figure 3 shows the best solution calculation from different Candidate solutions $p_u(y)$.

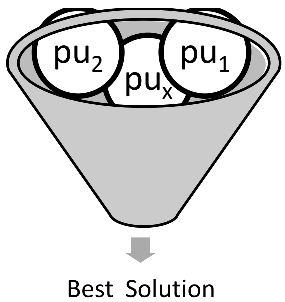

Figure 3: Visualization of Tabu Search as Optimization Algorithm.

B. Design of Objective Function :

The objective function has been designed in such a way that the drawbacks of the previous implementation by Zhenbo Jiang *et al*[14] will be removed. Proposed algorithm incorporated the texture feature with RGB and formed the objective function

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For the analysis of the simulation experiment, we select the R, G, B feature in the RGB feature space. The objective function forms the base of proposed algorithm.

C. Proposed Algorithm

The objective function is designed in the previous section which forms the base of the proposed algorithm. This objective function is useful in checking aspiration criteria and tabu criteria.

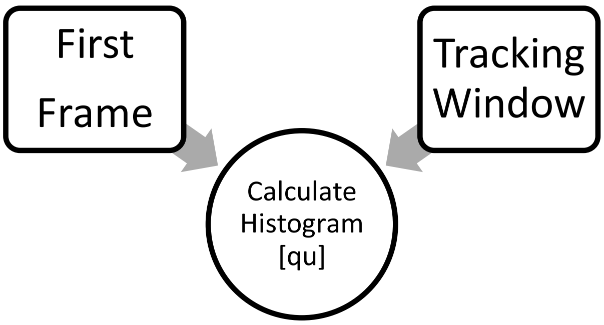

Figure 4: Histogram Calculation for Initial Frame (Image).

In the initial frame, the user defines the target to be tracked in the form of a rectangular region. For this rectangular region , the target features are extracted in the form of histogram q_u. From the implementation point of view, the center and the window size is calculated from the rectangular region. This can be visualized by the Figure 4. This window size remains constant throughout all the frames.

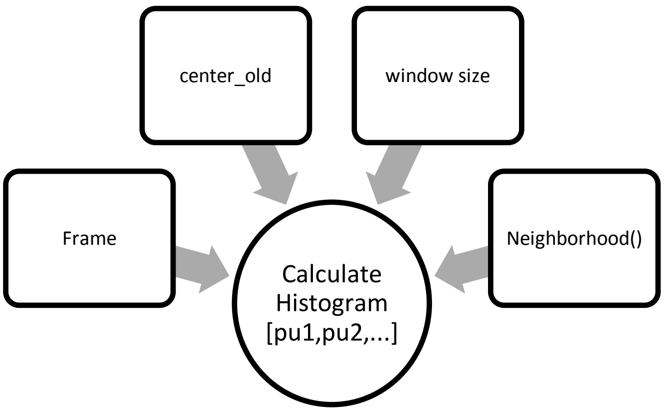

Figure 5 : Histogram Calculation for Frames to be tracked (Image)

From the second frame onwards, the algorithm tries to track the target. Previous center is initially considered as the best solution and the neighborhood solutions are generated for thesame.Figure5 explains the histogram calculations for the neighborhood solutions for the given frame. Then the best solution is compared with the neighborhood solution according to aspiration and tabu criteria. If the aspiration criterion is satisfied then the neighborhood solution is made as the best solution and it is added to the tabu list. Only if the aspiration criterion fails, tabu criteria are checked. Finally, the termination criterion is checked. If it satisfies the termination criterion, then the best solution is set as the result of the tabu search for the current frame. This solution is then depicted in the form of tracking window in the frame. Figure 6 shows the flowchart for this procedure.

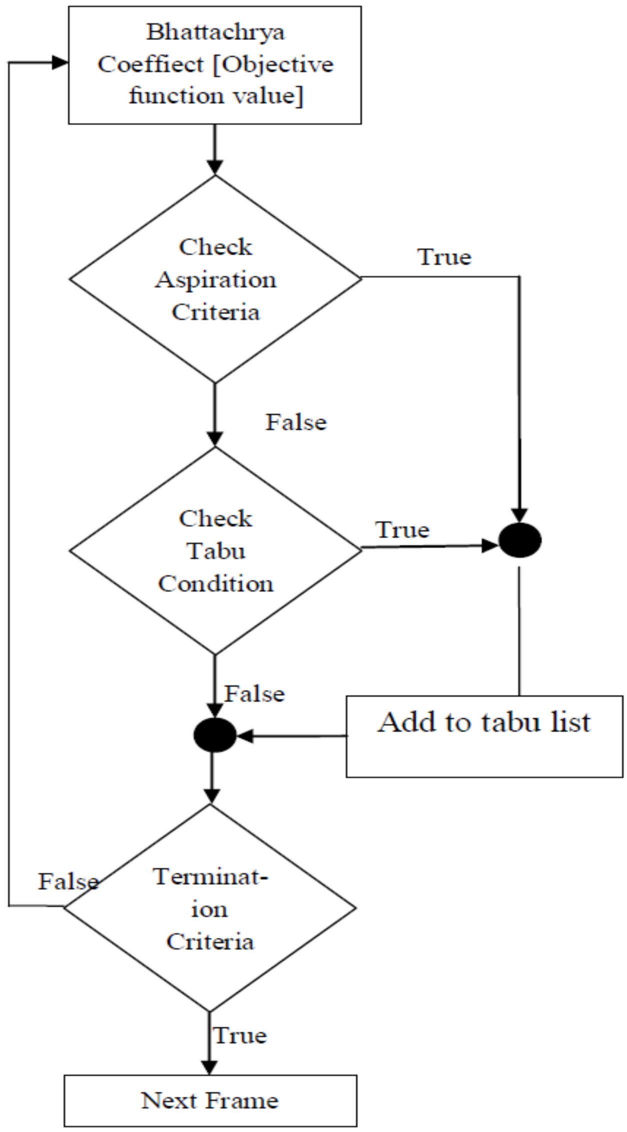

Figure **6** : Tabu Search , in one frame

This procedure is repeated for each frame, until the final tracking window is formed in the last frame.

IV. Experiment and Analysis

A. Experiment

The ideology of proposed algorithm is tested using RGB color space . For same length of tabulist, it was observed that by increasing radius of neighborhood , the total number of iterations decreases (comparatively).

Figure 7 and 8 shows two pictures, first part shows the initial frame where the tracking window has been selected. The second picture shows tracking of the target in car and tabletennis sequences for an intermediate frame using the proposed algorithm

Figure 7 : Tracking in Car1.avi Video Sequence Using Tabu + Joint Color texture histogram.

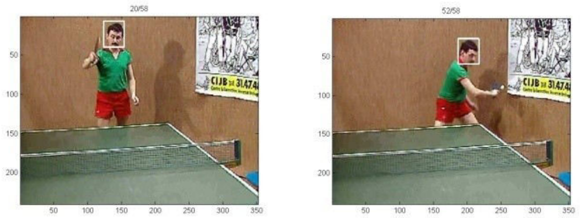

Figure 8: Tracking in Tabletennis.avi Video Sequence Using Tabu + Joint Color texture histogram.in frame number 20 and 52

For the table tennis sequence the number of iterations per frame are plotted and shown in the figure9. It shows that the number of iterations have decreased considerably for large number of frames due to Tabu search. Hence , there is a decrease in average number of iterations per frame.

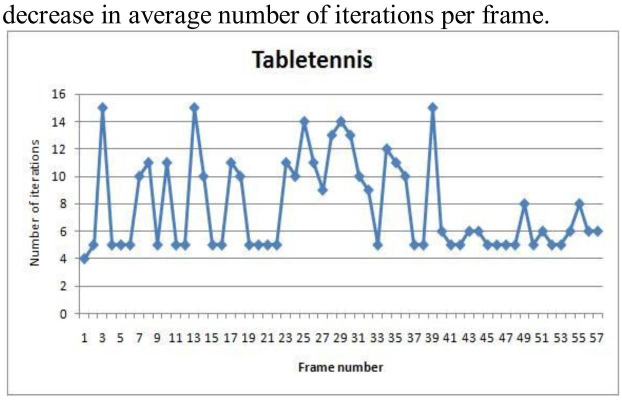

Figure 9 Variation of Iterations per Frame for Tabletennis video

Table 1 shows the comparison between proposed algorithm and mean shift algorithm[11]. It is found that average number of iterations decreased comparatively for particular values of comparison factor and increment value. Then the influence of length of tabu list on the average number of iterations analyzed . Keeping the termination criteria same , it was found that reducing length of tabu list reduces iterations to some extent. Table 2 shows results for various test videos

Table tennis sequence used in the experiment is of 58 frames the average number of iterations are 116 when comparison factor of 0.1 and increment value as 4 are used for Tabu+RGB+LBP algorithm. The same experiment has been used for Tabu+RGB and Mean Shift(RGB), Meanshift(RGB+Texture) and Table 1 show that the results to be better than other algorithms in terms of average number of iterations.

Table 1 : Comparison between Tabu Search and Mean Shift

Algorithm (Table tennis sequence)	Frames	Average number of Iterations	Comparison factor	Increment value =incre
Tabu + RGB +LBP	58	2*58=116	epsilon =0.1	4
Tabu + RGB	58	2*58=116	epsilon =0.1	10
Mean shift +RGB	58	5.02*58= 286	Mindist= 0.1	4
Mean shift +RGB+LBP	58	2.72*58= 158	Mindist= 0.1	4

Table2 shows object tracking results for different videos using the proposed algorithm. It can be seen from the Table 2 for tracking the object robustly in different videos requires different constraint values viz. Increment values (incre) and Epsilon

Table 2 : Tabu+RGB+LBP Search results for various Test Videos

Tabu+RGB+LBP	Frames	Maximum iterations in one frame	Increment value (incre)	Comparison factor (Epsilon)
Tabletennis.avi	58	2	3	0.1
Car2.avi	89	3	5	0.2
Car1.avi	87	2	4	0.3
Nit.avi	68	1	4	0.1
Nit1.avi	26	2	2	0.2

Table 3 : Execution times in seconds for test videos for Tabu+RGB+LBP, Meanshift+RGB+LBP and Meanshift+RGB algorithms.

Videos	Frames	Tabu+RGB+LBP	Meanshift+RGB+LBP	Meanshift+RGB
Tabletennis.avi	58	21.817421	6.195500	2.091384

Car2.avi	89	37.179406	13.887560	8.291290
Car1.avi	87	32.863048	10.962597	6.401826
Nit.avi	68	27.396915	10.072433	5.727494

Table3 shows the time taken by tracking algorithms for the test videos Tabletennis.avi, Car2.avi, Car1.avi and Nit.avi found out using Matlab Profiler.

While performing the experiment on different videos, the length of tabu list and the radius of neighborhood are not same, the optimal parameters were taken. These parameters depends on some specific condition so, we are adapting some changes for further study.

B. Comparison with Tabuand Meanshift

Here ideology is compared with the one implemented by Zhenbo Jiang *et al*[9]considering the feature space RGB. It has been found that number of iterations per frame is reduced comparatively. With the increase in radius of neighborhood accuracy of tracking increases. Results from Table 1 shows that iterations are reduced in proposed algorithm. Considering these factors and by varying the radius of neighborhood, it is found that robustness in tracking of object increases and tracking is well stable with the increase in the radius of neighborhood. This reduces the possibility of losing the target as compared to mean shift algorithm.

V. CONCLUSION AND FUTURE WORK

By the results obtained of various experiments, it can be concluded that the proposed ideology tracks the object with effective robustness. However, lot of details should be considered and optimize them so as to improve the robustness in a great order. Further study needs to be done to deploy this ideology of object tracking in the field where the issues likeauto-calibration, occlusion may occur. And these issues need to be handled for well tracked object.

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