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DWT Based Compressive Underwater Object Tracking Using Modified Background Weighted Histogram

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Abstract

The background weighted histogram (BWH) calculation proposed endeavours to diminish the interferences of background in target confinement in mean shift tracking. Be that as it may, in this paper we demonstrate that the weights allotted to pixels in the target candidate area by BWH are corresponding to those without background data, i.e. BWH does not present any new data because of the fact that the mean shift iteration formula is invariant to the scale change of weights. We then propose a modified BWH (MBWH) equation by changing just the target model however not the target candidate model. The MBWH algorithm can viably diminish interferences of background in target localization. The DWT based compressive mean shift tracking algorithm reduces the processing time by selecting only approximation coefficients. The test results demonstrate that the proposed MBWH can provide faster and effectively track the objects in lesser time even if background contains much information. The proposed MBWH strategy is that it can work powerfully regardless of the possibility that the target model contains much background data. In this way it diminishes significantly the affectability of mean shift tracking to target initialization

Keywords: background weighted histogram, DWT, mean shift tracking and object tracking

I. Introduction

Object tracking is an essential undertaking in computer vision applications. Numerous algorithms [6] have been proposed to take care of the different issues emerged from clamours, jumbles and impediments in the appearance model of the object to be tracked. Among different tracking techniques, the mean shift tracking algorithm [1, 2 and 4] is a well known one because of its straightforwardness and effectiveness. In the mean shift tracking algorithm, the target is represented by color histogram because of its strength to scaling, revolution and incomplete impediment [1, 2 and 5]. If the target features present in the background, the mean shift tracking is inclined to local minima. Subsequently, in [2], Comaniciu et al. further proposed the background weighted histogram (BWH) to diminishing background interferences in target representation. BWH will at the same time diminish the likelihood of noticeable background data in the target and target candidate model. Accordingly BWH is equal to a scale change of the weights obtained by the standard target representation technique in the target candidate region. Intern the mean shift iteration is invariant to the scale change of weights. Hence, the mean shift tracking algorithm with BWH in [2, 7- 9] is precisely the same as the mean shift tracking algorithm with normal target representation.

At that point we propose to change just the target model yet not the target candidate model. Another recipe for registering the pixel weights in the target candidate region is then inferred. The proposed modified background weighted histogram (MBWH) can genuinely accomplish what the first BWH strategy needs: decrease the impedance of background in target localization. A vital point of preference of the proposed MBWH strategy is that it can work powerfully regardless of the possibility that the target model contains much background data. In this way it diminishes significantly the affectability of mean shift tracking to target initialization. The proposed MBWH algorithm can accurately track the object, which is difficult to accomplish by the typical target representation. The DWT based compressive object tracking technique requires less processing time and hence reduces the converging time of mean shift iteration.

II. DWT based Mean Shift Algorithm

1. Discrete Wavelet Transform

A signal can be deteriorated into numerous shifted and scaled representations of the first mother wavelet. A wavelet transformation can be utilized to break down a signal into part wavelets. When this is done the coefficients of the wavelets can be decimated to expel a portion of the subtle elements. Wavelets have the considerable point of preference of having the capacity to separate the fine subtle elements in a signal. Small wavelets can be utilized to segregate fine points of interest in a signal, while large wavelets can distinguish coarse points of interest. Also, there are a wide range of wavelets to look over. Different sorts of wavelets are: Morlet, Daubechies, and so on.

In the proposed algorithm we used Daubechies-1 (db1) wavelet transform which is similar to haar transforms. It selects only approximation coefficients and withdraws horizontal, vertical and diagonal coefficients. Hence reduces the converging time of tracking algorithm as shown in figure1.

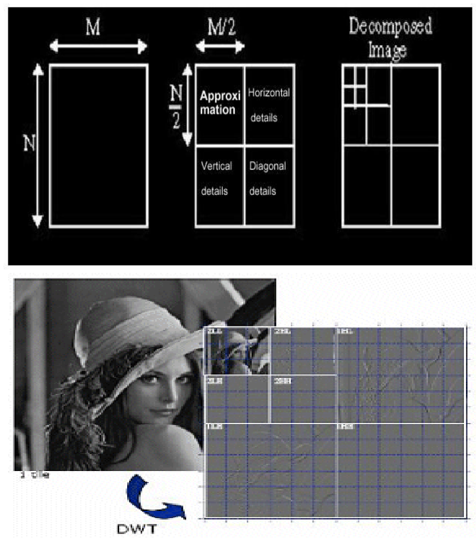

Figure 1 : Wavelet decomposition

2. Target Representation

In target representation we can choose a feature space (Feature space: 16x16x16 quantized RGB, Target: physically chose on first frame) by describing the object. The reference target model is depicted by its probability density function (pdf) in the feature space [1]. The objective applicant is characterized at region y and is portrayed by the probability density function (pdf) p(y).

Let be the standardized pixel areas in the target model, which is focused at origin (0). So the likelihood of the component u=1....m in the target model is acquired as

$\hat{q}$ = $\{\widehat{Qu}\}_u$ = 1..m

$\{\widehat{Qu}\}$ = C $\sum_{i=1}^{n} k$ ($\|Xi\|2$) $\delta[b(Xi) - u]$ (1)

Where $\hat{q}$ target model, δ is the kronecker delta function and C = 1/[$\sum_{i=1}^{n} k$ ($\|Xi\|2$]

Let be the standardized pixel areas in the target candidate model, which is focused at origin (0). So the likelihood of the component u=1....m in the target candidate model p(y) is acquired as

$\widehat{p(y)}$ = $\{\widehat{Pu}\}_u$ = 1..m

$\widehat{Pu}(y)$ = Ch $\sum_{i=1}^{nh} k$ ($\left\|\frac{y-Xi}{H}\right\|$ 2) $\delta[b(Xi) - u]$ (2)

Where $\hat{p}$ (y) is target candidate model, and

Ch = 1 / [$\sum_{i=1}^{nh} k$ ($\left\|\frac{y-Xi}{H}\right\|$ 2]

Bhattacharyya coefficient 'ρ' that is utilized to ascertain the similarity between the target model and target candidate model [1], [2], [3] and [4]. In the mean shift tracking calculation the target focus move from current area y to another area y1 as per the mean movement iteration statement.

$$y1= \frac{\sum_{i=1}^{nh} XiWi \text{ g}[(\|(y-Xi)/h\|2]}{\sum_{i=1}^{nh} Wi \text{ g}[(\|(y-Xi)/h\|2]} \quad (3)$$

Where,

$$Wi = \sum_{u=1}^{m} \sqrt{[\frac{\widehat{Qu}}{\widehat{Pu\,(y)}}]}\, \delta[b(Xi) - u] \quad (4)$$

And denote g(i) by

$gi=g[\left\|\frac{y-Xi}{h}\right\|$ 2]

Hence equation (3) becomes,

$$Y1 = [\sum_{i=1}^{nh} XiWi \text{ gi} / \sum_{i=1}^{nh} Wigi\ ] \quad (5)$$

3. Background Weighted Histogram

In target tracking, regularly the background data is incorporated into the recognized target area. When the correlation between target and background is high, the confinement exactness of the target will be diminished. To decrease the impedance of striking background features in target limitation, a representation model of background features was proposed by Comaniciu et al. [2] to choose discriminative elements from the target region and the candidate region.

The background is gotten by utilizing target encompassing region. The background is indicated by $\{\widehat{\boldsymbol{Ou}}\}\boldsymbol{u = 1..m}$. The background area is spoken to with the assistance of $\widehat{\boldsymbol{O}}*$ the insignificant non-zero worth in $\{\widehat{\boldsymbol{Ou}}\}\boldsymbol{u = 1..m}$ .The coefficients are used to indicate transformation between target and candidate model. It is given by

$$\left\{Vu = \min(\frac{\widehat{O*}}{\widehat{Ou},1})\right\} \quad (6)$$

At that point the new target model and candidate models are characterized by as

$\{\widehat{Q'u}\}$ = C Vu $\sum_{i=1}^{n} k$ ($\|Xi\|2$) $\delta[b(Xi) - u]$ (7)

$\widehat{P'u(y)}$= Ch Vu $\sum_{i=1}^{nh} k$ ($\left\|\frac{y-Xi}{H}\right\|$ 2) $\delta[b(Xi) - u]$ (8)

For the scale transformation of weights , the mean shift iteration formula is constant. Hence transforming the representations of target and candidate model doesn't improve the mean shift tracking.

III. Proposed Algorithm (MBWH)

In spite of the fact that the possibility of BWH is great, we find in previous section that the BWH calculation does not enhance the target confinement. To really accomplish what the BWH needs to accomplish, here we propose another change technique, to be specific the modified BWH (MBWH) algorithm. In MBWH, Eq. (6) is utilized to change just the target model however not the target candidate model. That is to say, we lessen the conspicuous background features just in the target model in any case, not in the target candidate model. We characterize new weight recipe

$$\ddot{W}i = \sqrt{(\widehat{Q'u'}/\widehat{P'u'(y)})} \quad (9)$$

By omitting constant scaling factor and simplifying above equation we get

$$\ddot{W}i = \sqrt{(Vu'.Wi)} \quad (10)$$

Where $\ddot{\boldsymbol{W}}\boldsymbol{i}$ is the modified weight histogram and **Vu'** is background information. The above equation speed up the mean shift's convergence towards the salient features of the target. If we do not use background information, **Vu'** will be 1 and $\ddot{\boldsymbol{W}}\boldsymbol{i}$ will degrade to **Wi** with usual target representation.

Background model updating in MBWH

The background will regularly change in target searching because of the varieties of light, perspective, impediment and scene content, and so on. On the off chance that the first background shading model is still utilized without overhauling, the following exactness might be lessened on the grounds that the present background might be altogether different from the past background model. In this way, it is important to powerfully upgrade the background model for speedier tracking performances. We propose simple background model updating method. First the background features $\{\widehat{\boldsymbol{O'u}}\}\boldsymbol{u} = \boldsymbol{1..m}$ and $\{\widehat{\boldsymbol{V'u}}\}\boldsymbol{u} = \boldsymbol{1..m}$ in the current frame are calculated. Then Bhattacharya similarity between $\{\widehat{\boldsymbol{O'u}}\}\boldsymbol{u} = \boldsymbol{1..m}$ and the old background model $\{\widehat{\boldsymbol{Ou}}\}\boldsymbol{u} = \boldsymbol{1..m}$ is computed by

$$\rho = \sum_1^m \sqrt{(\widehat{Ou}.\widehat{O'u})} \quad (11)$$

If **ρ** is smaller than threshold, there are considerable changes in the background and we update $\{\widehat{\boldsymbol{Ou}}\}\boldsymbol{u} = \boldsymbol{1..m}$ by $\{\widehat{\boldsymbol{O'u}}\}\boldsymbol{u} = \boldsymbol{1..m}$ and update $\{\widehat{\boldsymbol{Vu}}\}\boldsymbol{u} = \boldsymbol{1..m}$ by $\{\widehat{\boldsymbol{V'u}}\}\boldsymbol{u} = \boldsymbol{1..m}$.

IV. Mean Shift Algorithm flow with MBWH

1. Read video file to be process.
2. Apply the DWT to each frame and obtain only approximation coefficients
3. Compute the target model $\{\widehat{q}\}$ by (1) & background weighted histogram, and then calculate transformation coefficients {Vu} by (6) and transformed target model $\{\widehat{q'u}\}$ by (7). Initialize the position 'y0' of the target candidate region in the previous frame
4. Assume $k \longrightarrow 0$
5. Obtain target candidate model $\widehat{P(y0)}$ using (2) in the current frame
6. Compute the weights $\{\ddot{W}i\}$i=1..m by (9)
7. Obtain new position 'Y1' of the candidate region using equation (5)
8. Assume that $d \longrightarrow \|Y1 - Y0\|$. And Set the error threshold $\epsilon 1$(default value: 0.1) and the background model update threshold $\varepsilon 2$ (default value: 0.5).
9. If d < $\varepsilon 1$ then compute $\{\widehat{O'u}\}$u=1..m and $\{\widehat{V'u}\}$u=1..m
10. If Bhattacharya similarity $(\rho) < \varepsilon 2$ the update $\{\widehat{Ou}\}u = 1..m$ by $\{\widehat{O'u}\}u = 1..m$

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and update $\widehat{\{Vu\}}u = 1..m$ by $\widehat{\{V'u\}}u = 1..m$ and update transformed target model by (7)

11. Stop iteration and go to step 4 for next frame. Otherwise go to step 5.

V. Results

In this paper we perform an investigation on video sequences and this test has a programming that is keep running on matlab programming. In this test we can utilized a component space i.e. the color model and it has 16x16x16 RGB bins. The kernel function is utilized as a part of tracking field and it is signified by k(x). The investigation performed on underwater movable objects/species and the property details of this grouping are JPG image frames with standard resolution. In the following calculation we can choose initial and final frames to be process. We can choose rectangular box around the object to be tracked manually as shown in figure2. Figure3 demonstrates the manual selection of moving objects.

Figure 4 shows the moving fish is tracked effectively at various frames [62nd]. The proposed MBWH based Mean Shift tracking algorithm proficiently tracks the objects in presence of noise also.

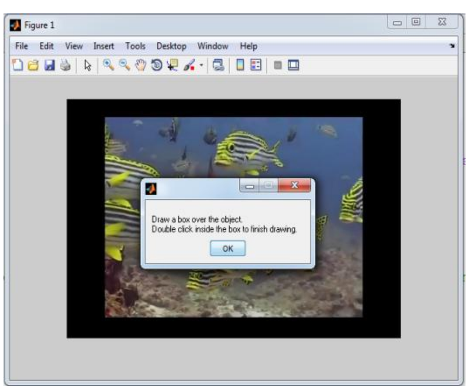

Figure 2 : Rectangular window for target tracking

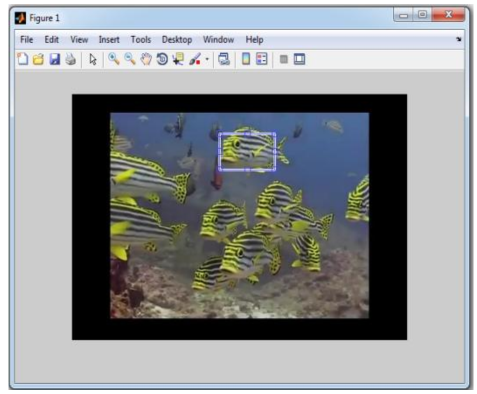

Figure 3 : Manual selection of object to be tracked

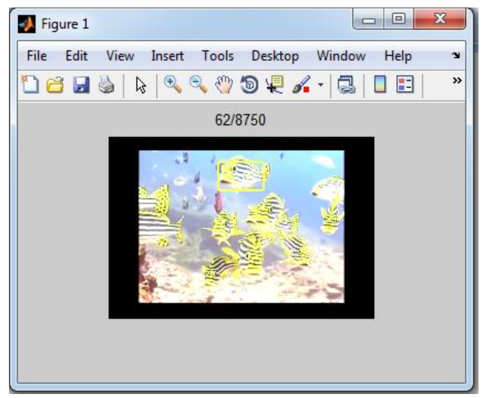

Figure 4 : Tracking of moving fish in the 62nd frame

V. Conclusion and recommendations

In this paper, we demonstrated that the background weighted histogram (BWH) representation in [2] is identical to the standard target representation so that no new data can be acquainted with enhance the mean shift tracking execution. We then proposed a modified BWH (MBWH) technique to decrease the importance of background data and enhance the target localization. The proposed MBWH algorithm just changes the histogram of target model and decreases the probability of target model components that are noticeable out of sight. The MBWH genuinely accomplishes what the BWH needs. The trials results approved that MBWH cannot just lessen the mean shift iteration number additionally enhance the tracking exactness. One of its critical points of interest is that it diminishes the affectability of mean shift tracking to the target initialization so that MBWH can powerfully track the objective even it is not very much initiated. The proposed algorithm can be extended to track multiple objects. We can use high resolution cameras for real time object tracking to track longer distance objects precisely. Also we can use open source software's like opencv, python for much faster process and those software's are freely available.

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