# A Novel Hybrid Algorithm for Tracking and Super Resolution Enhancement of a Moving Object

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**Abstract: This paper develops the hybrid algorithm for tracking and super resolution enhancement of an object in a video. The background weighted histogram (BWH) algorithm attempts to reduce the interference of background in target localisation in mean shift tracking.BWH does not introduce any new information because the mean shift iteration is invariant to the scale transformation of weights. The proposed corrected background weighted histogram (CBWH) formula is developed by transforming only the target model. The CBWH scheme can effectively reduce background's interference in target localisation. The experimental results show that CBWH can lead to faster convergence and more accurate localisation than the usual target representation in mean shift tracking. The proposed algorithm can still robustly track the object, which is hard to achieve by the conventional target representation, the other strategy is to improve the quality of the image which is tracked by using CBWH algorithmic problem of generating super resolution (SR) image from a single low-resolution input image. The approach of this problem is from the perspective of compressed sensing. The lo-resolution image is viewed as down sampled version of a high resolution image, whose patches are assumed to have a sparse representation with respect to an over-complete dictionary of prototype signal atoms. The effectiveness of sparsity as a prior for regularizing the ill-posed super resolution is demonstrated. We further showed that a small set a randomly chosen raw patches from training images of similar statistical nature to the input image generally serve as a good dictionary, in the sense that the computed representation is sparse and the recovered high-resolution image is competitive or even superior in quality to images produced by other SR methods.**

**Keywords: Super Resolution, Sparsity, background weighted histogram, object tracking, background weighted histogram.**

## I. INTRODUCTION

Object tracking is an important task within the field of computer vision. The proliferation of high powered computers, the availability of high quality and inexpensive video cameras, and the increasing need for automated video analysis has generated a great deal of interest in object tracki ng algorithms[1].These algorithms have been proposed to solve the various problems like noises, clutters, and occlusions in the appearance model of object to be tracked. There are three important steps in video analysis: detection of interesting videos, tracking of such objects from frame to frame and analysis of object tracks to recognize their behaviour[1]. Therefore the use of object tracking is based on the tasks of 1.motion based recognition [i.e. human identification based on Gait steps, automatic object detection etc.].Automated surveillance [i.e. monitoring a scene to detect suspicious activities or unlikely events.], Video indexing [i.e. automatic amotation and retrieval of the videos in multimedia content.], Human computer interaction [i.e. gesture recognition, eye gaze tracking for data input to computers etc.], Traffic monitoring [i.e. real time gathering of traffic statistic to direct traffic flow].

Vehicle navigation [i.e. video based path planning and obstacle avoidance]Tracking can be defined as the problem of estimating the trajectory of a n object/target in the image plane as it moves around a scene[1]. In other words, a tracker assigns consistent labels to the tracked objects in different frames of a video. Tracking objects can be complex due to noise in images, complex object motion, loss of information caused by projection of 3D or 2D image etc[ 2].There are many object tracking algorithms like mean shift algorithms, kernel based algorithms, fast multiple object tracking using particle filters. Among those algorithms, the efficient algorithms are mean shift algorithm [3]. Mean shift is a non-parametric feature, space analysis technique for locating the maxima of a density function, so called mode seeking algorithms [4]. Application domains include the cluster analysis in computer vision and image processing. This algorithm has been adopted to solve problems mainly in image filtering, image segmentation and object tracking [4].

In this algorithm in order to represent the target/object the colour histogram is used. In order to overcome the robustness to scaling, rotation and partial occlusion, we use mean shift algorithm. Back weighted histogram (BWH) algorithm is proposed further in order to reduce the background interference in the target representation. The main aim of the BWH is to explain about simple representation of background features and it is used to choose the components from target model and target candidate model[5].BWH mainly used to reduce the probability of prominent background features both in target model and target candidate model and thus reduce the background interference in target localization. The object is partitioned into number of fragments and then the target model of each fragment is enhanced by BWH model. The difference between the fragment and background models leads to weights of background features. The combination of BWH and adaptive kernel density estimation results in mean shift algorithm. The strategy of BWH is to reduce the distraction of background in target localization to enhance mean shift tracking[6]. Mean shift tracking with BWH is similar to the mean shift tracking with target representation. The main strategy of mean shift tracking is to reduce the weight of prominent background features. We formulate the pixel weights in the target candidate model. Corrected background weighted histogram (CBWH) which is the extension of BWH can truly solve the problem which reduces the interference of background in target localization. CBWH is robust in nature such that it can work even there is more background information in the target model. This minimizes the sensitivity of mean shift tracking. It tracks the target very easily and accurately. After tracking the target using CBWH algorithm, we going to capture that object which is tracked in the video and enhance that object using super resolution concept. Image Super Resolution plays an important role in multimedia application. It is used to achieve high resolution from low resolution image[7]. When image captured by low resolution video, three main artifacts occurs namely aliasing, blurring and additive noise. Aliasing occurs due to low sampling rate which causes the loss of high frequency contents from the content which losses information at the edges and textures[8].

Blurring occurs due to relative motion of image. Atmospheric noises like rainy atmosphere and dusty atmosphere causes adaptive noise in image[9]. In the case of a video sequence, global motion of objects in the scene may be adequate in the temporarily shifted frames. Super resolution is a task to analyze the inverse problem of recovering the original high resolution images by fusing the low resolution image based on types of problem in the target. The strategy of reconstruction constraint is that applying image formation model to the recovered image should produce the same low resolution images [10]. In high to low generation process the information is lost mainly. in the case of super resolution of an image there is a performance of reconstruction algorithms degrades rapidly if magnification factor is large (or) if there are not enough low resolution images to constraint solution, as in the extreme case of only a single low resolution input image. To find out the correspon dence (or) similarities between low resolution and high resolution image patches and concurrence these prior approaches is another case of super resolution methods [11].

Markov Random Field (MRF) this is used to predict whether the image has low resolution/high resoluti on image. [Primal sketch priors] is used to enhance blurred edges, ridges and corners. The above methods need more databases. More patch patterns can represent small training database. K neighbours for reconstruction often results in bl urring effects, due to over under fitting [12]. Sparse signal re presentation is the method which ensures that linear relationships among high resolution signal recovered from their low projection signals. The main goal of this paper is to have the video is tracked by using corrected background hist ogram and the tracked image is applied with super resolutio n with sparse representations[13]. Image resolution determined by two main factors. Blurring, due to optical limits and various other processes (like the effect of the atmosphere and motion blur, for example),results in soft images, while low-sensor density of the imaging device causes aliasing. Signal processing based super-resolution (SR) methods are typically concerned with overcoming the resolution limitation resulting in aliasing (although such techniques do take blur into consideration)[14]. In this context, 'resolution' refers to the sampling interval, or pixel size. Super-resolution (also spelled as super resolution and super resolution) is a term for a set of methods of up scaling video or images[14]. Terms such as "upscale", "upsize", "up-convert" and "uppers" also describe increase of resolution in either image processing or video editing. Most super-resolution techniques are based on the same idea: using information from several different images to create one upsized image [15].

Algorithms try to extract details from every image i n a sequence to reconstruct other frames. Super-resolution (SR) works effectively when several low resolution images contain slightly different perspectives of the same object. Then total information about the object exceeds information from any single frame. The best case is when an object moves in the video. Motion detection and tracking are then employed to benefit up scaling [16]. If an object doesn't move at all and is identical in all frames, no extra information can be collected. If it moves or transforms too fast then it looks very different in different frames and it's too hard to use information from one frame in reconstructing the other. Super-resolution is used now in two tasks: extracting single frames from video (or a set of images/photos) with high quality, or upsizing the whole video.[17] SR methods are usually based on two important algorithms: high quality spatial (in-frame) up scaling, and motion compensation for finding corresponding areas in neighbour frames. Many practical implementations of super-resolution software upscale original material two times [18]. If we need to upsize it four times, we usually apply SR twice (this can be done internally in implementation). Super resolution is an approach that attempts to resolve this problem with software rather than hardware. Super-resolution algorithms recover information about the original high resolution image by exploiting sub-pixel shifts in the low-resolution data [19]. These shifts are introduced by motion in the sequence and make it possible to observe samples from the high-resolution image that may not appear in a single low-resolution frame. Unfortunately, loss encoding introduces several distortions that complicate the super-resolution problem. For example, most compression algorithms divide the original image into blocks that are processed independently. At high compression ratios, the boundaries between the blocks become visible and lead to "blocking" artifacts. If the coding errors are not removed, super-resolution techniques may produce a poor estimate of the high-resolution sequence, as coding artifacts may still appear in the high-resolution result. Additionally, the noise appearing in the decoded images may severely affect the quality of any of the motion estimation procedures required for resolution enhancement.[19] The term super-resolution has been applied to a wide variety of problems ranging from blur removal by deconvolution in single images through to the creation of a single high resolution image from multiple low resolution images having sub-pixel relative displacements. In all cases the goal is to increase the resolution (number of pixels) in the image while at the same time adding appropriate high frequency information. Reconstruction-based super-resolution is possible because each low-resolution image we have contains pixels that represent subtly different functions of the original scene, due to sub-pixel registration differences or blur differences [20]. W e can model these differences, and then treat super-resolution as an inverse problem where we need to reverse the blur and decimation [21]. Each low-resolution pixel can be treated as the integral of the high-resolution image over a particular blur function, assuming the pixel locations in the high resolution frame are known, along with the point-spread function that describes how the blur behaves [22].

## II PROPOSED ALGORITHM

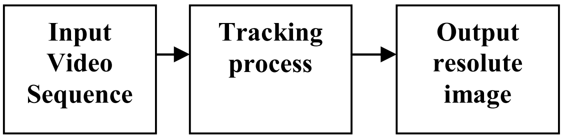


Fig: 1 Block diagram of hybrid model

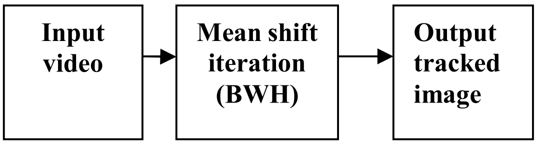


Fig: 2 Block diagram of tracking process

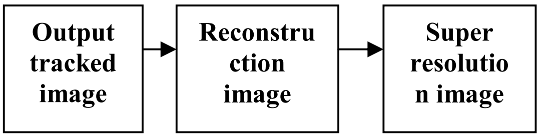


Fig: 3 Block diagram of resolution process

This block diagram mainly consists of three blocks input video sequence, tracking process, output Super resolute image as shown in fig1. The input video sequence consists of different number of frames. In order to track the moving target in the given video sequence, we go for the corrected background weighted histogram using mean shit tracking algorithm as shown in fig 2, in which the output moving object is then captured and reduces the blurring effect in the object using super resolution concept using sparse representation in which the constructed image as shown in fig 3 is detected and then the qualitative image is determined in the last block. The super resolution concept is used to convert low resolution image to high resolution image.

## III.CORRECTEDBACKGROUND WEIGHTED HISTOGRAM

### 3.1 Background weighted histogram

Back ground weighted algorithm was used to reduce the interference of background in target localization in mean shift tracking. The mean-shift algorithm is an efficient approach to tracking objects whose appearance is defined by histograms[1]. The mean-shift algorithm is useful when the object represented by its colour density is being explored. The mean-shift algorithm is applied for seeking colour density similarity maxima, i.e.[2] the mode of the colour density similarity corresponds to a location of the searched object. Mean-shift is an iterative method that uses the gradient ascent steps to find the local maxima of a given function. The colour density function is widely used feature within an image processing and the mode seeking process comes useful for exploring this feature space.[2] To be able to transform the problem of maximizing similarity function into the mean-shift mode seeking, few modifications are to be made. These modifications were introduced by Comaniciu et al.

### 3.1.1 Target model

Target model is the object one desires to track. Let $\{x_i^*\}_{i=1,....,n}$ be the normalized pixel locations of target model region, centred in 0. Using an isotropic kernel with a convex and monotonic kernel profile k(x), smaller values are assigned to the peripheral pixels which are often being affected by occlusions or background interference. Histogram representing the target model is constructed

$$\hat{q}_u = C_h \sum_{i=1}^{n_h} k\left(\left\|x_i^*\right\|^2\right)\delta\left[b\left(x_i^*\right)-u\right] \quad \text{... (1)}$$

Where function $b : R^2 \to \{1,....,m\}$ associates to the pixel at location $x_i^*$ the bin index $b(x_i^*)$ in the histogram, $\delta$ is Kronecker delta function, which returns $b(x_i^*) = u$ the value 1 if and only if and C is normalization constant such that $\sum_{u=1}^{m} \hat{q}_u = 1$

### 3.1.2 Target candidate model

Let $\{x_i\}_{i=1,...n_h}$ be the normalized pixel locations of the target candidate centred a y in the current frame. Using the same kernel profile k(x) as for the target model with bandwidth h, the histogram representing the target candidate is construed as

$$\hat{p}_u = C_h \sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta\left[b\left(x_i^*\right)-u\right] \quad \text{... (2)}$$

normalized by $C_h$ such that $\sum_{u=1}^{m} \hat{p}_u = 1$. Since the normalization constant $C_h$ is only dependent on kernel proportions [3], it can be pre calculated when the kernel profile doesn't change in time. This can be achieved only when the size of target candidate remains the same, otherwise when changing h the normalization constant Ch must be recomputed as well.

Mean-shift with background histogram is the tracking method implemented in this work. It is based on a kernel-based object tracking using mean-shift algorithm.[5,6] The method adopts the background-weighted histogram as proposed in .

Let $\{\hat{o}_u\}_{u=1,....,m}$ (with $\sum_{u=1}^{m} \hat{o}_u = 1$) be the histogram of the background in the feature space and $\hat{o}^*$ be the smallest nonzero entry, where the representation is computed in a region around the target. Let us now denote the weights

$$\left\{ v_u = \min\left(\frac{\hat{o}^*}{\hat{o}_u}, 1\right)\right\}_{u=1,...,m} \quad \text{... (3)}$$

These weights will transform the target model histogram such that the importance's of those features which have low vu, i.e., are prominent in the background, will be diminished [7,8,9,10]. The background manipulation was already proposed in [7], where the background information was decreased both in the target model and in the target candidate. The manipulation of just target model histogram that is adopted in this work was proposed in [7]. Employing the background-weighted target model histogram significantly improved the performance of the tracker. It solves the problem of the slow convergence of the algorithm, which often leads to an early termination of the mean-shift algorithm because the shift happens within one pixel after one iteration.

## IV. SUPER RESOLUTION

The goal of super resolution methods is to recover a high resolution image from one (or) more low resolution input images [13]. Methods of super resolution can be broadly classified into two types Multi image super resolution.

Example based super resolution.

Each low resolution image impose a set of linear constraints on the unknown high resolution images are available (at sub-pixel shifts), then the set of equations becomes determined and can be solved to recover the high resolution image [14,15]. These limitations leads to the development of example based super resolution also termed as image hallucination. There are many representation of image signal by using super resolution technique

Super Resolution using sparse representation.

Super resolution using Adaptive Filtering.

Super resolution using Patch Redundancy.

### 4.1 super resolution using sparse representation

This paper mainly used to implement the super resolution from sparsity. Sparse signal representation is the method which ensures that linear relationships among high resolution signal recovered from their low projection signals [16]. Sparse representation applied to many typical problems in image processing (compression), de-noising, restoration, etc. in this the patches of the low resolution and high resolution images are represented as

$$D_l = LD_h \qquad \text{... (4)}$$

Where $D_l$ is the low resolution patch, L is wide variety of matrices, $D_h$ is high resolution patch.

In order to attenuate the reconstruction errors in the recovered high resolution image using sparse representation with respect to low resolution image we are going to apply global optimization. Mainly low resolution dictionary but not high resolution dictionary. This technique is efficient and scalable. Sparse representation selects the most relevant patches in the dictionary to represent each patch of given low resolution image, which leads to superior performance both qualitatively and quantitatively.

#### 4.1.1 Algorithm based on sparse representation of an image

Let us consider the input training dictionaries $D_l$ and $D_h$ are the low and high resolution dictionaries, with low resolution image (Y) and high resolution (X).

**Reconstruction Constraint**:

$$Y = DHX \qquad \text{... (5)}$$

The low resolution image (Y) is blurred and down sampled version of solution (X). D is the down sampling operator; H is the blurring filter. In these methods we further regularize and refine the entire image. The main application is to attenuate possible artificats and make the more consistent and natural

**Sparse representation prior**

Another step of solving super resolution problem using sparse representation is sparse prior [17]. It is used to represent the spatial compatibility between two patches. The main application of sparse priors used to recover lost high-frequency for local details. For: each 3x3 patch y of Y, taken starting from the upper left corner with 1 pixel overlap in each direction. The sparse representation steps recover the coefficients '$\alpha$' by approximately minimizing the sum of the terms. To solve the optimization problem with $\overline{D}$ and $\overline{y}$ defined as

$$\min \lambda \|\alpha\|_1 + \frac{1}{2}\left\|\overline{D}\alpha - \overline{y}\right\|_2^2 \qquad \text{... (6)}$$

Generate high resolution image $x = D_h\alpha^*$ put the patch x in high resolution image $X_0$ by using sparse prior. By ending the process [18]. In order to achieve good super resolution performance. High resolution signal are available these priors can be incorporated.

### 4.2 Dictionary Parameters

#### 4.2.1 Random Raw Patches from training Images:

Over complete dictionary capable of representing broad classes of image patches is a difficult problem,[19] we generate dictionaries by simply randomly sampling raw patches from training images of similar statistical nature. Both high quality reconstruction and sparse prior is used to yield better dictionaries.

Derivative transformations (F) to ensure that the computed coefficient fit the most relevant part of low/high resolution signal. (F) is chosen as same kind of high pass filter. More sensitivity to the high frequency content of the image[20,21]. High frequency components of low resolution image are also arguably the most important for predicting the lost high frequency content in the target high-resolution image. High pass filter to extract the edge information from the low resolution input patches using back projection, find the closet image to $X_o$ which satisfies the reconstruction constraint.

$$X^* = \arg\min \|X - X_0\| \ \text{s.t} \ DHX = Y \qquad \text{...(7)}$$

Output: - Super Resolution image $X^*$ Result $X^*$ from back projection as over find estimate of high resolution image. $X^*$ is close as possible as initial super resolution is summarized[22].

## V. EXPERIMENTAL RESULTS

The proposed method is implemented using background weighted histogram based on mean shift tracking and performed super resolution, sparsity of an image in the video. The algorithms were implemented using MATLAB tools. The RGB colour model was used as feature space and it is divided into 16x16x16 bins. To evaluate BWH we consider a video sequence which has 40frames. The target is to track the person in the video. In frame1 as shown in figure we initialized the target model with a region of size (25x30) which contains many background elements in it. The background model was initialized to be a region of size (50x60) which approximately 3 times that of the target. The salient features of target model are enhanced while the background features being suppressed in CBWH so that the mean shift tracking algorithms can be effectively locate the target. The located target is then captured undergoes super resolution which uses sparse representation which improves the quality of the target as shown in figures 4,5,6,7.

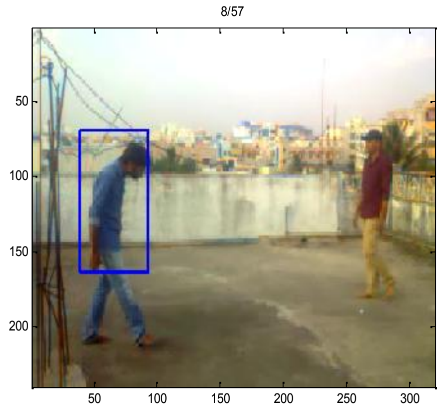


Fig.4 Tracking the target in the video sequence1

Fig.5 Input image which is tracked

Fig.6 Reconstruction target

Fig.7 Super Resolution output target

Let us consider another to evaluate BWH we consider a video sequence2 as shown in fig:8 which has 80 frames. The target is to track the person in the video. The frame8 of a person as shown in figure8 we initialized the target model with a region of size (25x30) which contains many background elements in it. The background model was initialized to be a region of size (50x60) which approximately 3 times that of the target as shown in fig 9. The salient features of target model are enhanced while the background features being suppressed in CBWH so that the mean shift tracking algorithms can be effectively locate the target. The located target is then captured undergoes super resolution which uses sparse representation which improves the quality of the target as shown below figure 10, 11 undergoes both reconstruction and sparse representation.

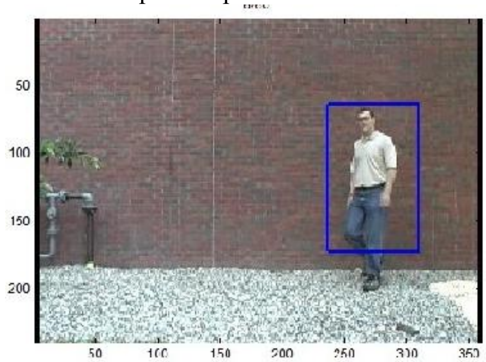


Fig: 8 Tracking the target in the video sequence 2

Fig: 9 Input image which is tracked

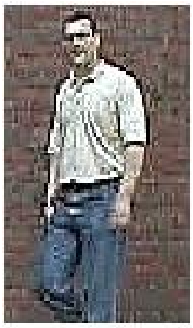

Fig: 10 Reconstruction target

Fig: 11 Super Resolution output target

Let us consider another to evaluate BWH we consider a video sequence3 as shown in fig:12which has 200 frames. The target is to track the person in the video. The frame8 of a person as shown in figure8 we initialized the target model with a region of size (30x35) which contains many background elements in it. The background model was initialized to be a region of size (70x80) which approximately 3 times that of the target as shown in fig 13. The located target is then captured undergoes super resolution which uses sparse representation which improves the quality of the target as shown below figure 14,15 undergoes both reconstruction and sparse representation.


Fig: 12 Tracking the target in the video sequence 2

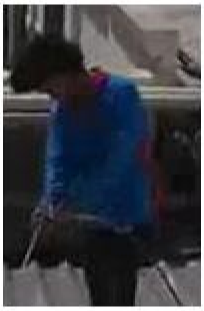

Fig: 13 Input images which is tracked

Fig: 14 Reconstruction target

Fig.15 Super Resolution output target

## VI. CONCLUSION

In this paper, proves that the BWH representation is equal to usual target representation. The mean shift tracking performance can be improved with the extension of BWH model i.e. CBWH model which improves the target localization. CBWH not only reduces the mean shift iteration number but also improves the tracking efficiency and reduces the sensitivity of mean shift tracking. After the tracking of a target in the video, the target is then captured and it is then apply super resolution in order to minimize the blurring effect and noises in the object. The experimental results demonstrate the effectiveness of sparsity as a prior. By applying appropriate dictionary within each segment the super resolution concept is integrated.

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