# FAST AND EFFICIENT INTRA-FRAME DEINTERLACING USING OBSERVATION MODEL BASED BILATERAL FILTER

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## ABSTRACT

Recently, a few bilateral filter based interpolation and intra-frame deinterlacing algorithms have been proposed, but these algorithms only use prior information (bilateral filter). In this paper, we propose an efficient and fast intra-frame deinterlacing algorithm using an observation model based bilateral filter (using both likelihood and prior information). Our proposed algorithm is also able to use approximated horizontal pixels for the deinterlacing, which results into the better prediction of the edges. From extensive experiments, it is observed that the proposed algorithm has the capability of provide satisfactory results in terms of both objective and subjective quality.

***Index Terms***— Deinterlacing, Bilateral filter, Kernel ridge regression, Correlation, Intra-frame.

## 1. INTRODUCTION

As the transmission of interlaced scanning reduces the requirement of bandwidth and memory. Hence, interlaced scanning is a very important phenomenon and is widely used in video broadcasting standards (e.g., NTSC, PAL, SECAM and some of the HDTV formates). The interlaced scan contains only half of the pixels of the original frame, and either odd or even rows are retained. While deinterlacing is the process of predicting the missing rows of the interlaced frame at the decoder side. However, interlaced scanning is affected by the some visual artifacts such as, interline flickering, line crawling and field aliasing [6].

In order to, overcome the problems described above, many intra and inter frame deinterlacing algorithms have been reported in the literature. Most inter-frame deinterlacing algorithms are based upon motion compensation and try to find the correlation in both the spatial and temporal domain. However, the computational complexity associated with these methods is quite high.

On the other hand intra-frame deinterlacing algorithms are preferred in real-time applications, as these algorithms are computationally simple and require to find the correlation within a single frame. In this view, line average [14] and modified edge based line averaging (MELA) [1] algorithms have been proposed. These algorithms are computationally simple but not able to efficiently adapt in the presence of sharp edges. In [2], the fine directional deinterlacing (FDD) algorithm was proposed using the sobel operator, and Chen et al proposed the low-complexity interpolation method (LCID) for deinterlacing [3]. However, these methods are not able to produce satisfactory results because of the exploitation of the limited edge directions. Recently, a few adaptive weighted scheme based deinterlacing algorithms have been proposed such as AWSD [4] and FDIF [5]. Behnad et al. proposed a deinterlacing algorithm using the hidden markow model [13]. In [6] Jeong et al. proposed the filter switching interpolation method for deinterlacing (FSID), in which a bilateral filter is used for the exploitation of information from the neighboring pixels. While Wang et al. proposed weighted least squares based deinterlacing [11], but the computational complexity requirement of this method is very huge.

In order to overcome the problems described above, we propose a fast and efficient intra-frame deinterlacing algorithm using an observation based bilateral filter. The main contributions of the proposed algorithm are as follows:

1. Our proposed algorithm is able to merge both observation (likelihood) and a bilateral filter (prior).

2. Our algorithm is also able to use approximated horizontal pixels for prediction. Hence, the proposed observation based bilateral filter is able to produce sharp edges.

The rest of paper is organized as follows. Section 2 describes the proposed observation model based bilateral filter and kernel ridge regression based least squares optimization for the generation of the approximated pixels. The comparison and implementation results are provided in Section 3 and the concluding remarks are given in Section 4.

## 2. PROPOSED OBSERVATION MODEL BASED BILATERAL FILTER FOR DEINTERLACING

In the last once decade, bilateral filter has been used in many applications such as denoising [7], [8] and prediction based

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algorithms [9], [10]. A bilateral filter predicts the pixel of interest (missing/noisy) with the weighted average of the neighboring pixels. These weights are inversely proportional to the spatial and radiometric distance between the pixel of interest and it's neighborhood [7], [8]. In this paper, we propose a fast and efficient intra-frame deinterlacing algorithm using observation model based bilateral filter. We propose to formulate the intra-frame deinterlacing problem as follows

$$\underset{I}{arg\,min} \quad \{(I - I_{Obs})^2 + \lambda \sum_{k=1}^{8} w_k (I - I_k)^2\} \tag{1}$$

where first and second terms are the likelihood and the prior

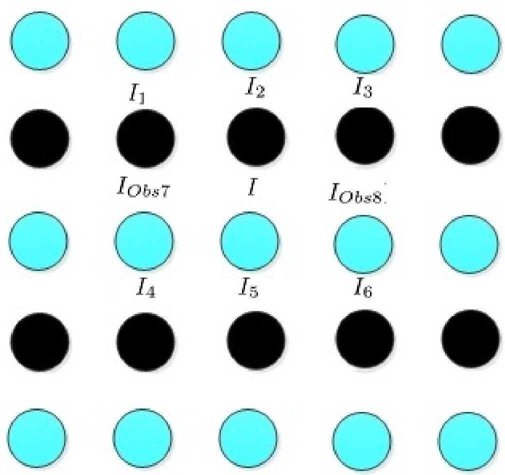


**Fig. 1**. Spatial relationship between the missing pixels (as shown by the black circles) and the it's neighborhood.

respectively. On the other hand, $I$ is the pixel of interest (missing pixel), and $I_k$ (= [$I_1$, $I_2$, $I_3$, $I_4$, $I_5$, $I_6$, $\Delta\times$ $I_{Obs7}$, $\Delta\times I_{Obs8}$]) are the samples used in prediction (neighboring pixels in a $3 \times 3$ window), as shown in Fig. 1. Here, $\Delta$ is the signal dependent parameter. The cost function given in (1) is a convex problem without explicit constraint. Hence, we obtain the optimal predicted value $\hat{I}$ by differentiating (1) and equating to zero. So, the optimal solution of the proposed cost function in closed form is:

$$\hat{I} = \frac{I_{Obs} + \lambda \sum_{k=1}^{8} w_k I_k}{1 + \lambda \sum_{k=1}^{8} w_k} \tag{2}$$

here $\lambda \geq 0$ is the parameter controlling the trade-off between the likelihood and the prior, and $I_{Obs}$ is the observed value of the pixel of interest $I$ (missing pixel). The optimal value of the controlling parameter $\lambda$ highly depends upon the image content. So, for the sake of simplicity, we choose $\lambda$ as 1 in our experiments.

In contrast to the existing bilateral filter based interpolation and deinterlacing algorithms [7], [9], our algorithm is able to merge both the bilateral (prior) filter and observation (likelihood). Hence, we call our proposed filter (2) the observation model based bilateral filter (OBF). In (2), $w_k$ are the weights, which we estimate using the following exponential function:

$$w_k = \exp(-\frac{||I - I_k||_2}{2\sigma_1}) \exp(-\frac{||D - D_k||_2}{2\sigma_2}) \tag{3}$$

Here exp(.) is the exponential operation and $\sigma_1$ and $\sigma_2$ are the variance of the radiometric and spatial distance respectively. On the other hand, $D$ and $D_k$ represent the two dimensional vector of the spatial location of missing pixel $I$ and it's neighboring pixel $I_k$ respectively. As the ground truth value of $I$ is missing in (3), in order to estimate the weights $w_k$ (3) of proposed filter, first we need to estimate the approximated value of $I$ as $I_{Obs}$. Hence, we modify the weights $w_k$ of the proposed filter as

$$w_k = \exp(-\frac{||I_{Obs} - I_k||_2}{2\sigma_1}) \exp(-\frac{||D - D_k||_2}{2\sigma_2}) \tag{4}$$

As the efficiency of the proposed filter is highly depends upon the accuracy of the approximation of $I$ as $I_{Obs}$. In demoisaking using the without observation based bilateral filter, Ramanath and Snyder [12] proposed to use the average of neighboring pixels to approximate the $I$ as $I_{Obs}$. Unfortunately, this approach is not able to adapt near the intensity varying areas (edges, patterns or textures), which results into the poor approximation of $I$. In our algorithm, we proposed to use kernel ridge regression based least squares optimization for the estimation of $I_{Obs}$, which is described in the following subsection.

The existing deinterlacing algorithms [1]-[6] are only able to use correlation in the vertical, diagonal and anti-diagonal directions. Hence, the prediction accuracy of the these algorithms is not efficient in the presence of a horizontal correlation. The proposed algorithm, on the other hand, has the freedom of using approximate horizontal pixels ($I_{Obs7}$ and $I_{Obs8}$) for prediction as shown in (2), so it is able to use correlation in the horizontal direction and produce sharp edges.

### 2.1. Kernel ridge regression based least squares optimization for the estimation of approximated pixels ($I_{Obs}$)

In our algorithm, we propose to approximate the $I$ as $I_{Obs}$ using kernel ridge regression based least squares optimization. In order to perform the block based least squares optimization, we divide the interlaced image of size $M \times 2N$ into blocks of $m \times 2m$. The proposed algorithm estimates the least squares based parameters using kernel ridge regression (KRR) for each block $i$ (where $i \in (1, 2, ...(M \times 2N)/(m \times 2m))$. From extensive experiments, we observed that the

**Table 1**. Simulation results comparison in terms of PSNR in $dB$. Here Proposed1 and Proposed2 represents the proposed algorithm using bilateral filter without and with observation model respectively.

| Method/Image | LA [14] | MELA [1] | FDD [2] | LCID [3] | AWSD [4] | FDIF [5] | Proposed1 | Proposed2 (2) |
|---|---|---|---|---|---|---|---|---|
| Lena | 37.640 | 37.891 | 37.984 | 37.853 | 37.860 | 38.192 | 37.965 | **38.088** |
| Baboon | 23.936 | 23.944 | 23.956 | 23.973 | 23.980 | 23.410 | 24.325 | **24.439** |
| Splash | 38.895 | 39.286 | 39.188 | 39.103 | 39.187 | 39.214 | 39.241 | **39.356** |
| Peppers | 33.763 | 34.207 | 33.699 | 34.221 | 34.043 | 33.710 | 34.718 | **34.856** |
| Aeroplane | 34.236 | 34.119 | 34.325 | 34.626 | 34.323 | 34.701 | 34.302 | **34.363** |
| Boat | 35.375 | 35.287 | 35.635 | 35.024 | 35.445 | **36.171** | 35.490 | 35.572 |
| Akiyo | 40.364 | 40.216 | 40.456 | 39.894 | 40.236 | 40.612 | 40.693 | **40.842** |
| News | 33.657 | 33.548 | 33.843 | 33.353 | 33.719 | 34.905 | 34.927 | **35.063** |
| **Average** | 34.733 | 34.811 | 34.885 | 34.756 | 34.848 | 35.114 | 35.208 | **35.332** |

block size $16 \times 32$ ($m$=16) gives the most efficient approximated pixels $I_{Obs}$. The linear predictor for block $i$ is defined as

$$f(I_{Obs}, w) = \vec{W}^T \vec{\phi}(I) = \sum_{v=1}^{6} W_v \phi_v(I) \tag{5}$$

where $\vec{W}$ is the 6-dimensional weight vector and $\vec{\phi}(I) = (\phi_1, ..., \phi_6) \in \mathrm{R}^{6\times 1}$ is the basis function vector containing the neighboring 6 pixels in a $3 \times 3$ window, as shown by the cyan circles in Fig. 1. In our algorithm, we estimate the least squares formulated optimized parameter for block $i$ by minimizing the following kernel ridge regression (cost function):

$$J(\vec{W}) = \sum_{v=1}^{M(i)} (I_v - \vec{W}^T \vec{\phi}(I_v))^2 + \beta ||\vec{W}||^2 \tag{6}$$

Here $I_v \in \text{block}\,(i)$ and $M(i)$ are the total no. of pixels in block $i$ ($m \times 2m$). In (6), $\beta \geq 0$ is a parameter controlling regularization, which forces the regression coefficients ($\vec{W}$) to be close to zero and each other. This prevents the large, mutually canceling coefficients that can arise in normal (non-regularized) regression. As suggested in [10], optimal $\beta$ can be chosen from (0,1). Hence in the experiments, $\beta$ has been choses to be 0.5.

$$\vec{W}^* = \min_{W} \quad J(\vec{W}) \tag{7}$$

The closed form solution of the kernel ridge regression (KKR) is given as

$$\vec{W}^* = (\vec{\Phi}^T \vec{\Phi} + \beta J)^{-1} \vec{\Phi}^T \vec{y} \tag{8}$$

Here, $J$ is the identity matrix, $\vec{\Phi}(I)$=[$\vec{\phi}_1\ \vec{\phi}_2\ \vec{\phi}_v\ .\ .\ .\ \vec{\phi}_{M(i)}]^T$ and $\vec{y}$=[$\vec{I}_1\ \vec{I}_2\ \vec{I}_v\ .\ .\ .\ \vec{I}_{M(i)}]^T$. After estimating the KRR based parameters, these parameters are used to approximate ($I_{Obs}$) the missing pixels of the corresponding block of size $2m \times 2m$ of the deinterlaced image of size $2M \times 2N$ by the weighted sum of the neighboring 6 pixels in a $3 \times 3$ window, as given in (9).

$$\begin{aligned} I_{Obs}\,(v) \quad &= w_1 I_1 + w_2 I_2 + w_3 I_3 \\ &+ w_4 I_4 + w_5 I_5 + w_6 I_6 \end{aligned} \tag{9}$$

Our proposed deinterlacing algorithm requires estimating $((M \times 2N)/(m \times 2m))$ the number of kernel ridge regression based optimized parameters to approximate the $I$ as $I_{Obs}$. One might argue that the block based least squares optimization using kernel ridge regression is susceptible to noise and not able to alleviate the effect of outliers. Fortunately, in the proposed algorithm the approximated image $I_{Obs}$ is not used directly for the deinterlacing. However, the approximated image $I_{Obs}$ is used to estimated the weights $w_k$ (4) of the bilateral filter, and it is well known that the bilateral filter [9]-[10] is not sensitive to the outliers. So, it is prompt to approximate the $I$ as $I_{Obj}$ using the least squares based optimization using the kernel ridge regression. Hence, our proposed algorithm is able to deinterlace the frames in the presence of noise and alleviate the effect of outliers [10].

## 3. SIMULATION RESULTS

The proposed intra-frame deinterlacing algorithm using the observation model based bilateral filter (OBF) was implemented, and it's performance for deinterlaced a image/frame was compared with the existing LA [14], MELA [1], FDD [2], LCID [3], AWSD [4] and FDIF [5] algorithms. In order to show the accuracy of the proposed incorporation of the observation model with the bilateral filter, we have shown the results of the proposed algorithm using, bilateral filter without and with the observation model, respectively in the last two column of Table 1. It can be observed that the proposed algorithm with the observation model achieves an average 0.124 $dB$ better PSNR as compared to the proposed algorithm without the observation model.

**Table 2**. Comparison of required CPU processing time in seconds. Here Proposed1 and Proposed2 represents the proposed algorithm using bilateral filter without and with observation model respectively.

| Method/Image | LA [14] | MELA [1] | FDD [2] | LCID [3] | AWSD [4] | FDIF [5] | Proposed1 | Proposed2 (2) |
|---|---|---|---|---|---|---|---|---|
| Lena | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Baboon | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Splash | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Peppers | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Aeroplane | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Boat | 0.065 | 0.263 | 1.927 | 0.327 | 0.391 | 0.397 | 1.268 | 1.492 |
| Akiyo | 0.042 | 0.136 | 0.294 | 0.127 | 0.251 | 0.242 | 0.628 | 0.791 |
| News | 0.042 | 0.136 | 0.294 | 0.127 | 0.251 | 0.242 | 0.628 | 0.791 |
| **Average** | 0.059 | 0.231 | 1.519 | 0.277 | 0.324 | 0.358 | 1.108 | 1.317 |

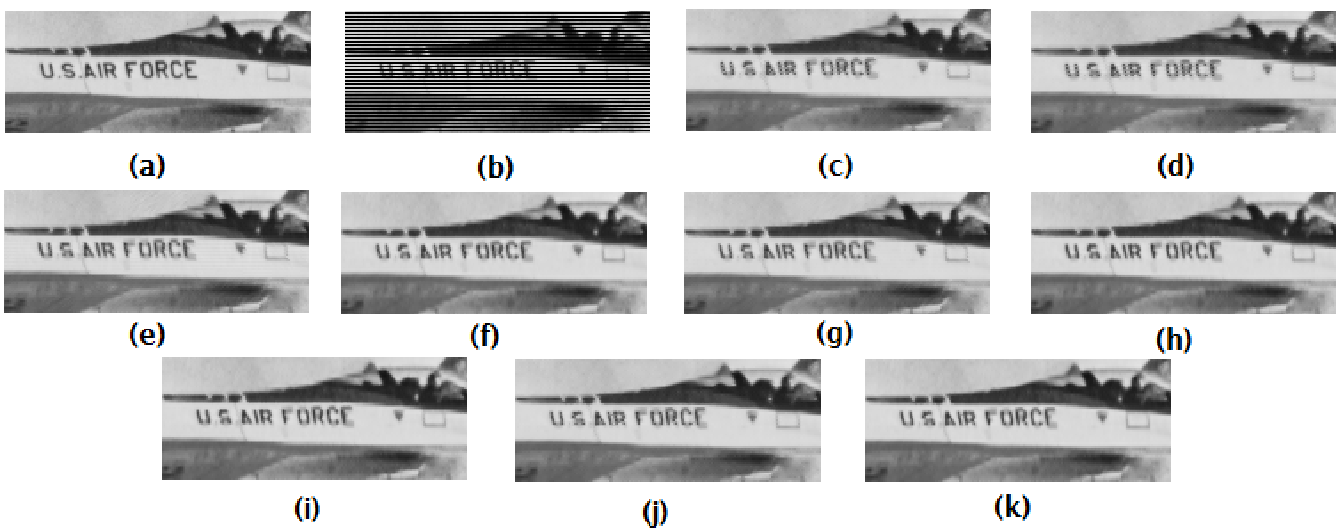


**Fig. 2**. Comparison of subjective quality for deinterlaced cropped aeroplane image (a). Original image (b). Interlaced image (c). LA [14] (d). MELA [1] (e). FDD [2] (f). LCID [3] (g). AWSD [4] (h). FDIF [5] (i). LS (9) (j). Prop1 (k). Prop2 (2).

From Table 1 it can be observed that the FDIF [5] algorithm produces better results as compared to the existing algorithms. On the other hand proposed deinterlacing algorithm (2) achieves 0.559, 0.521, 0.447, 0.576, 0.484 and 0.218 $dB$ better PSNR as compared to LA[14], MELA [1], FDD [2], LCID [3], AWSD [4] and FDIF [5] respectively. Table 2 shows the comparison of the required CPU processing time of the proposed deinterlacing algorithm with the existing algorithms [1-5], [14]. The simulations were conducted on a computer with a 2.53 GHz intel(R) core (TM) i5 CPU using the Matlab environment. From Table 2, it can be concluded that the proposed deinterlacing algorithm is not computationally expensive and has comparable required CPU processing time for deinterlacing a frame.

Figure 2 shows the subjective quality comparison of the proposed algorithm with the existing algorithms [1]-[5], [14] and it can be observed that the proposed algorithm has a very good edge preservation capability for the deinterlaced image.

## 4. CONCLUSIONS

In this paper, we have proposed a fast and efficient intra-frame deinterlacing algorithm using an observation based bilateral filter. Our proposed algorithm is able to merge both observation (likelihood) and the bilateral filter (prior). Our proposed algorithm has also used approximated horizontal pixels for prediction, which is able to efficiently adapt in the presence of edges, and is able to do better prediction. From a performance evaluation, we found that our algorithm is significantly better in terms of both objective and subjective quality as compared to some of the recently developed deinterlacing methods.

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