Robust Image/Video Super-resolution Display

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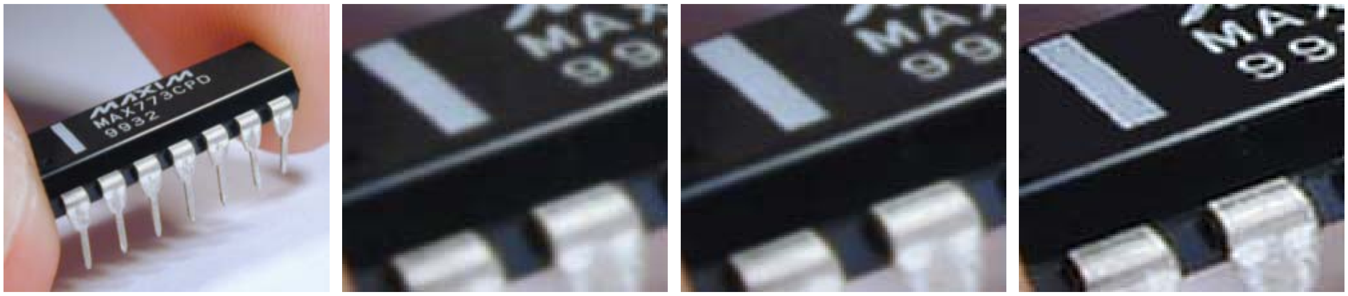

Figure 1: *Low-Resolution image, Bicubic Result , Shen's Result and Our Result (from left to right).*

Abstract

This paper describes a new method to reconstruct high-resolution video sequences from several observed low-resolution images based on an adaptive Mumford-shah model which is extended by using nonlocal information and low-rank representation. In our regularization framework, joint image restoration and motion estimation are first implemented and then detailed information can be recovered by incorporating new model as a prior term.

1 Adaptive Mumford-Shah Model (AMS)

The nonlocal differential operators can be utilized to conclude the regularizing function. Let w be a symmetric weight function. The general form of nonlocal functional introduced is as follows:

$$\Psi(u) = \int_\Omega \phi(|\nabla_w u|^2)dx$$

the rank distribution of degraded image differs drastically from the one of clean image and validates this prior for image enhancing task. The local patch rank implicitly characterizes the variation pattern of data redundancy in textural structure. The following generalized Logistic function is used for controlling the structural preservation as a prior:

$$\mathrm{r(g)}=1+\frac{12.4}{(1+0.72\mathrm{e}^{-0.51(\mathrm{g}-8)})^{1/0.72}}$$

the AMS model can obtain and preserve the deformable contours. To adapt the non-smooth data, the nonlocal information and low-rank prior are respectively incorporated in the AMS.

$$\Psi^{AMS}(u,v) = \beta\int_\Omega v^2\|\nabla_w u\|^2 dx + \alpha\int_\Omega (\varepsilon|\nabla v|^2 + \frac{(v-1)^2}{4\varepsilon})dx + r(g(u,v))$$

where $0 \le v(x) \le 1$ represents the edges. ε is a small positive constant and α , β are positive weights.

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2 Image/Video Reconstruction Method

At the first stage, input videos are enhanced and simultaneously the motion flow are estimated. An object moves with speed v in front of a still background $f_b : \Omega \to \mathbb{R}$. The formula for the theoretically observed motion blur at time t_i is as follows.

$$G_i[v, f_o, f_b](x) = ((f_o\chi_o)*h_v)(x - t_i v) + f_b(1-(\chi_o * h_v)(x - t_i v))$$

the AMS model acting as the penalty term is suitable to recover the blurred image and estimate the velocity flow simultaneously. the energy function can be obtained as.

$$\varepsilon[v, f_o] = \sum_{i=1}^{N}\int_\Omega (G_i[v, f_o, f_b] - g_i)^2 dx + \Psi^{AMS}(u,v)$$

where N is the number of neighbor frames. Once the minimum is known, the deblurred image f_0 and v can be solved. The reconstruction video $\widehat{X}_o$ can be solved by minimizing the following function:

$$\widehat{X}_o = \arg\min(\sum_{k=1}^{N}\|D_k H_k F_k \underline{X}_o - \underline{Y}_k\|_2^2) + \lambda(\underline{X}_o)\Psi^{MS}(\underline{X}_o)$$

the information of iterative errors is fully used in the first stage. Based on the errors, an optimization function is designed to select the initial value and is defined by

$$\lambda_i = \sqrt{(G_i[v, f_o, f_b] - g_i)^2 / \sum_{i=i}^{N}(G_i[v, f_o, f_b] - g_i)^2 + \mu}$$

3 Results

According to the PSNR results of state-of-the-art methods, our method is more robust than other methods. The subjective comparison results are shown in the upper figures. Our method achieves best quality with high contrast and minimal artifacts.

References

SHEN, C.T., LIU, H.H., YANG M.H. AND HUNG Y.P. 2015. Viewing-distance aware super-resolution for high-definition display. *IEEE Trans. Image Process.*, 24, 403-418.