Edge-Directed Interpolation in a Bayesian Framework

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The problem of image interpolation is one of the most thoroughly developed in the area of multimedia processing. Linear interpolation methods suffer from aliasing and Hibbs effect, and they fail to provide artifacts-free enlargement of edges. This has led to a plethora of edge-oriented upscaling techniques aimed at providing superior edge processing quality. However, Edge-Directed Interpolation (EDI) of textured areas results in strong artifacts, making the discrimination between edges and texture an important task as well.

Non-linear image enlargement techniques can be divided into two groups according to the edge processing strategy which can be implicit or explicit. Implicit EDI methods are constructed in such a way that their inner parameters adaptively change depending on the local image structure. Therefore, the interpolation is performed along an edge if it is present [2, 4, 6, 8]. Unlike local implicit EDI methods mentioned above, global implicit methods impose constraints on the whole resulting image [1, 7]. Following the opposite approach, an explicit EDI algorithm can be subdivided into two blocks: edge detection and edge-oriented interpolation. Such methods often limit the set of possible edge directions, aiming at speed-up and robustness [3, 5, 9].

We suggest applying a pixelwise Bayesian reasoning for the *simultaneous* HR pixel type detection and its intensity interpolation. The pixel type can be either an index of one of the pre-defined edge orientations or "non-edge". The former is for the pixels lying on edges; the number of allowed orientations in the range $[0°; 180°]$ is an algorithm parameter. The latter stands for the pixels belonging to uniform areas, areas of texture and clutter. In the general case we introduce an iterative upscaling process, at each iteration n considering MAP estimates of each HR pixel j type $t^n(j)$ and intensity $I^n(j)$ given types and intensities calculated at the previous iteration $(n-1)$:

$$\left\{\widetilde{t^n}(j), \widetilde{I^n}(j)\right\} = \arg\max_{t^n(j), I^n(j)} P\left(t^n(j), I^n(j) \,\middle|\, \left\{t^{n-1}(k), I^{n-1}(k)\right\}_{k\in\Theta}\right) \forall j. \quad (1)$$

Here Θ stands for a spatial neighbourhood of pixel j. According to the Bayes rule and omitting obvious transformations, MAP estimates (1) can be rewritten as:

$$\left\{\widetilde{t^n}(j), \widetilde{I^n}(j)\right\} = \arg\max_{t^n(j), I^n(j)} \left(P_1 \cdot P_2 \cdot P_3\right), \quad (2)$$

where $P_1 = P\left(I^n(j) \,\middle|\, t^n(j), \{I^{n-1}(k)\}_{k\in\Theta}\right)$ denotes the likelihood of an intensity value $I^n(j)$ given the pixel type $t^n(j)$ and neighbourhood intensities $\left\{I^{n-1}(k)\right\}_{k\in\Theta}$ calculated at the previous iteration. In other words, P_1 reflects how good the new pixel intensity fits the local image structure while the new pixel type is being fixed. $P_2 = P\left(\left\{I^{n-1}(k)\right\}_{k\in\Theta} | t^n(j)\right)$ expresses how likely the intensities $\left\{I^{n-1}(k)\right\}_{k\in\Theta}$ are if the j-th pixel has type $t^n(j)$. Thus P_2 measures how the pixel type impacts its neighbourhood intensities. Finally, $P_3 = P\left(t^n(j) \,\middle|\, \left\{t^{n-1}(k)\right\}_{k\in\Theta}\right)$ expresses the relation between the new pixel type $t^n(j)$ and the old neighbourhood configuration $\left\{t^{n-1}(k)\right\}_{k\in\Theta}$. In a general case the optimum search is performed over all possible pairs $\{t^n(j), I^n(j)\}$.

In the framework implementation we used, the following major assumptions were made:

- The intensities of pixels lying next to an edge are distributed as a mixture of gaussians with means corresponding to different sides of the edge.
- The intensities of non-edge pixels are considered uniformly distributed.

Then the interpolation problem takes the form of a minimization of simple (from the computational point of view) function calculated over a local window. Like in [3], the minimization is performed over a reduced candidate set.

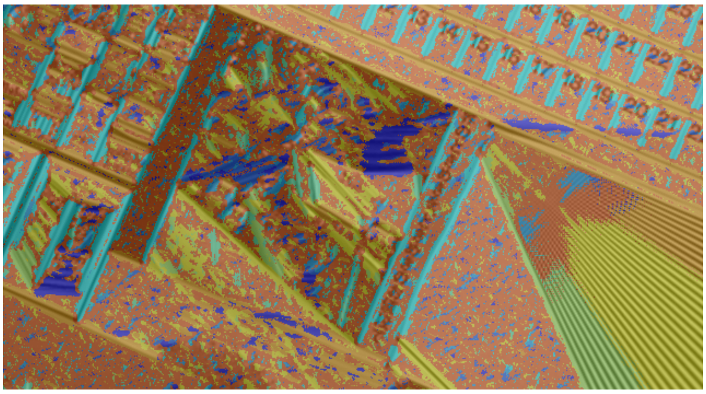
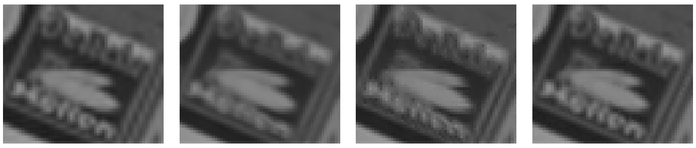


Figure 1: Pixel type map for a fragment of *Spincalendar* test image, superimposed on the image. Different pixel types are shown with different colours.



Bicubic SKR[8] NEDI[4] Proposed

Figure 2: Visual quality comparison on a fragment of *Spincalendar* test image.

As the objective and subjective comparisons show, the proposed algorithm outperforms conventional edge-oriented upscaling methods, combining high-quality edge interpolation with artifacts-free texture handling. As it is local, computationally simple, and parallelizable, the method suits well for the hardware implementation, particularly on massively parallel systems, *e.g.* modern GPUs.

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