ITERATIVE OPTIMIZATION OF QUARTER SAMPLING MASKS FOR NON-REGULAR SAMPLING SENSORS

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ABSTRACT

Non-regular sampling can reduce aliasing at the expense of noise. Recently, it has been shown that non-regular sampling can be carried out using a conventional regular imaging sensor when the surface of its individual pixels is partially covered. This technique is called quarter sampling (also 1/4 sampling), since only one quarter of each pixel is sensitive to light. For this purpose, the choice of a proper sampling mask is crucial to achieve a high reconstruction quality. In the scope of this work, we present an iterative algorithm to improve an arbitrary quarter sampling mask which results in a continuous increase of the reconstruction quality. In terms of the reconstruction algorithms, we test two simple algorithms, namely, linear interpolation and nearest neighbor interpolation, as well as two more sophisticated algorithms, namely, steering kernel regression and frequency selective extrapolation. Besides PSNR gains of +0.31 dB to +0.68 dB relative to a random quarter sampling mask resulting from our optimized mask, visually noticeable enhancements are perceptible.

Index Terms— Non-Regular Sampling, Image reconstruction

1. INTRODUCTION

Non-regular sampling of images can be used to reduce aliasing conventionally occurring from regular sampling [1,2,3]. Additionally, it has been suggested to use non-regular sampling to enhance the spatial resolution of an imaging sensor [4]. This so called quarter sampling (1/4 sampling) can increase the resolution of an image by physically masking three quarters of each pixel of a low resolution sensor. While the same amount of energy, cost and data bandwidth is needed as for the low resolution sensor, the higher resolution is achieved at the expense of an additional post-processing step performing the extrapolation on the high resolution grid which features twice the resolution in both dimensions.

Figure 1 depicts the concept behind quarter sampling: Fig.1(a) shows a high resolution test image taken with a high resolution sensor with twice the resolution of our presumed low resolution sensor. In a simplified model, the low resolution sensor measures a downsampled version of that image by averaging 2×2 pixels at a time. A simulated measurement of the low resolution sensor is shown in Fig.1(b). Conversely, when quarter sampling is used three quarters of each pixel of the low resolution sensor are covered. Figure 1(c) shows a random quarter sampling mask. Each of these pixels is covered by three quarters (black) and only one quarter of the pixel surface is transparent such that the measurement can be described as a sub-sampling of the image in Fig.1(a). The sub-sampled image is depicted in Fig.1(d). Finally, the missing pixels on the high resolution grid need to be reconstructed yielding an image as in Fig.1(e). It is important to note that the complete high resolution data is not present in an actual hardware implementation of the sensor because only the data depicted in Fig.1(d) is measured and used for the reconstruction. Therefore, Fig.1(b) and Fig.1(e) have the same number of sampling data points but placing them non-regularly leads to higher image quality.

It turns out that the resulting image quality depends on the chosen quarter sampling mask. For example, a regular quarter sampling mask, which contains the transparent area in the same corner for each low resolution pixel, is disadvantageous since it leads to aliasing again. On the other hand, random quarter sampling masks are expected to be non-optimal since they may contain large covered areas which are in turn harder to reconstruct.

In terms of the reconstruction algorithm we investigate linear interpolation and nearest neighbor interpolation, as well as two more sophisticated algorithms, namely, steering kernel regression (SKR) [5] and frequency selective reconstruction (FSR) [6]. FSR has shown to be a successful reconstruction scheme for various inpainting and extrapolation tasks [7,8,9] and showed best results for non-regular sampling and quarter sampling in [4,6].

This work is organized as follows: Section 2 summarizes existing optimization strategies for quarter sampling masks. In Section 3, we identify properties of a good quarter sampling mask and use these properties to propose an algorithm which iteratively improves the quality of an arbitrary quarter sampling mask. This leads to high quality masks of size 8×8 and 32×32. In Section 4, the reconstruction quality using these masks is evaluated. Therein, visual comparisons are presented as well.

2. EXISTING MASK OPTIMIZATION STRATEGIES

In order to find an optimal quarter sampling mask, Jonscher et al. suggest to use a brute force method [10]. They suggest to randomly generate quarter sampling masks of size b×b, b ∈ {2, 4, 8, 16, ...}
and repeat them periodically to match the image size on the high resolution grid. The masks are then applied to a set of test images. Afterwards, high resolution images are reconstructed from the sub-sampled data and the PSNR can be calculated. The mask yielding to the highest average PSNR for a given reconstruction algorithm is chosen for future sampling tasks. Of course, care has to be taken when choosing the test images as these need to be representative.

Unfortunately, there is a serious downside with this approach. For each of the \((b/2)^2\) low resolution pixels on a quarter sampling masks of size \(b\times b\), there are four possible choice to place the transparent pixel. Therefore, the number of possible masks is \(N_b = b^2/4\) and thus scales exponentially with the number of pixels. The actual values are \(N_2 = 4, N_3 = 256, N_4 = 4 \times 10^9, N_6 \approx 3 \times 10^{38} \ldots\). For large masks \(b \geq 8\), the number of all possible masks makes it computationally infeasible to generate all possible masks and perform the reconstruction on several sub-sampled test images.

Jonscher et al. incorporate this issue by choosing 256 randomly selected quarter sampling masks for each \(b \geq 4\). This means, that only a small subset of all possible masks is tested for \(b \geq 8\). Then, they evaluate all chosen masks on a set of test images and find the mask with the best average PSNR for each \(b\) and each investigated reconstruction algorithm. For example, for the FSR their best mask found is of size \(b = 8\). Even though their brute force method theoretically works, it is practically unsatisfactory, because only a small subset of masks is tested for \(b \geq 8\). Since all masks of size \(b\) are included in the set of all masks of size \(b' = 2 \cdot b\), the reconstruction quality cannot decrease for larger masks, if all possible masks are taken into account.

To overcome the problems with this brute force method, we propose an optimization strategy in the next section. We circumvent calculating all possible masks and additionally do not need to perform any reconstruction during the mask optimization. It is not our goal to find the one and only best mask for a given reconstruction algorithm but rather to provide a method to find a very good mask based on reasonable heuristic assumptions.

3. PROPOSED MASK OPTIMIZATION

3.1. Properties of a good mask

Before being able to optimize a quarter sampling mask, we need to identify properties to distinguish favorable and unfavorable masks.

We claim that two properties are favorable for a good quarter sampling mask: (A) low regularity and (B) uniformity. (A) Regularity leads to high peaks in the spectrum of the masking function. As an immediate consequence, aliasing occurs. This is unfavorable since information about the image is irretrievably lost. In order to achieve a low regularity, a random quarter sampling mask could be chosen. (B) Uniformity is the second desired property. Within an image, details consisting of very few pixels can be anywhere with the same probability and should be captured independent of their location. This condition implies that the mask should be as uniform as possible. While a regular mask means high uniformity, a random mask means low uniformity. Putting these two properties together, both the random mask and the regular masks are extreme cases complying only with one of the properties.

3.2. Proposed optimization strategy

An optimized mask should combine both properties, i.e., it should be both non-regular and uniform. To achieve this, we propose that an arbitrary quarter sampling mask can be improved by reducing the occurrences of the following structures (see also Fig. 2):

- 2-spx: horizontal/vertical pair of transparent pixels forming a superpixel (spx).
- 4-spx: pair of two 2-spx forming a transparent \(2\times2\) superpixel, already mentioned in [10].
- 8-void: \(2\times4\) or \(4\times2\) block of masked pixels forming a large unknown area.
- 3-regular: three transparent pixels in a horizontal/vertical line, spaced with two masked pixels.
- 3-diag: three neighboring pixels lying on a diagonal.
- 5-zigzag: five pixels in a horizontal/vertical zigzag assembly.

Removing the superpixel structures (2-spx, 4-spx) and the void structure (8-void) results in a more uniform mask, while the removal of the regular structures (3-regular, 3-diag and 5-zigzag) makes the mask less regular.

To produce masks with a reduced number of these structures from an arbitrary quarter sampling mask, we propose an iterative algorithm consisting of four core steps (A–D) to remove the structures. A flow graph illustrating the whole algorithm is depicted in Fig. 3.

The steps are exemplarily shown for the removal of a 4-spx and a 8-void structure in Fig. 4 and can be described as follows:

(A) First, one randomly selected structure of those depicted in Fig. 2 is selected to be removed.

(B) Then, one of the pixels contributing to this structure is randomly selected (marked with an asterisk in Fig. 4).

(C) Temporarily, mask all four pixels of the quarter block corresponding to this pixel.

(D) Unmask one randomly chosen pixel of this quarter block.

Fig. 3. Flow graph of the proposed mask optimization algorithm.
The steps (A)-(D) are repeated over and over again. With this algorithm, the structures are removed most of the time while it actually allows to reproduce them. Furthermore, the algorithm potentially creates structures of a different type that were not present before. Nevertheless, the total number of structures is expected to decrease in average. During the search and the removal of the structures periodic boundary conditions have to be taken into account, since masks are structure-free and have a uniform appearance while still being non-regular.

Now, our goal is to generate a quarter sampling mask without any structures to reach a high quality of uniformity and non-regularity. In terms of the desired size of the quarter sampling masks, we will restrict ourselves to sizes up to $8 \times 8$ pixels. This simplification can be made because all investigated reconstruction algorithms act locally, i.e., the masked data is reconstructed from its immediate vicinity. However, our algorithm is capable of creating larger masks, if necessary. As a side effect, the periodicity of the masks may allow for a simpler manufacturing process of the actual quarter sampling sensor.

To generate a quarter sampling mask without any structures, a $32 \times 32$ random quarter sampling mask is used as initial mask and optimized using the just described algorithm. In the beginning, the number of remaining structures goes down quickly because removing one structure might even remove another structure simultaneously. Conversely, removing the last remaining structures is more difficult, because with every removal new structures may be generated. Later, these new structures need to be removed in addition to the remaining ones. The optimization is stopped, after all structures have been removed. Finally, a $32 \times 32$ quarter sampling mask without any structures is found. Similarly, we created a additional quarter sampling mask of size $8 \times 8$ without any structures.

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