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A NEW SHIFT ESTIMATION ALGORITHM FOR BARCODE SUPER RESOLUTION

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ABSTRACT

In this paper we propose a novel way of estimating the rotation angle (shifts between consecutive scan lines) of bar codes in 2D images. The proposed method is compared to a well-established method, and results with real and simulated image data are presented.

Index Terms— super resolution, bar code, shift estimation, rotation estimation, registration

I. INTRODUCTION

In the literature two decades ago an interesting field in image processing emerged called super resolution [1], which has been extensively studied since then (see [2], [3], [4] and references therein). Super resolution (in the context of information gain) in general uses different information sources which have overlapping but not identical content. The task of super resolution is to combine this information in an intelligent manner to create a single result with more information as each individual low-resolution source. In the context of image super resolution this could mean to take several undersampled, degraded and shifted source images and combine them to a single high resolution image [5], [6].

In this paper we consider the super resolution of bar code images. In contrast to 2D image super resolution, where often a third dimension (several images) is needed to complete the task, undersampled bar-code images most likely already contain enough information to extract the code information. Bar codes are presented to us as 2D images but only contain 1D information so that we have the extra dimension needed for super resolution. The base idea of bar code enhancing through super resolution is not new and has been published by several authors ([7], [8], [9]). In this paper we show a superior method of scan-line shift estimation which can be combined with any fusion technique available. For information fusion we use the one described in [7] and compare our method of registration to the method in the same paper.

In the next section we introduce the image model which describes the 2D image generation from a 1D function. Section 3 introduces our shift estimation method. Section 4 gives a short introduction into image fusion and a quality measure for bar codes. Results are presented in Section 5 and we conclude with Section 6.

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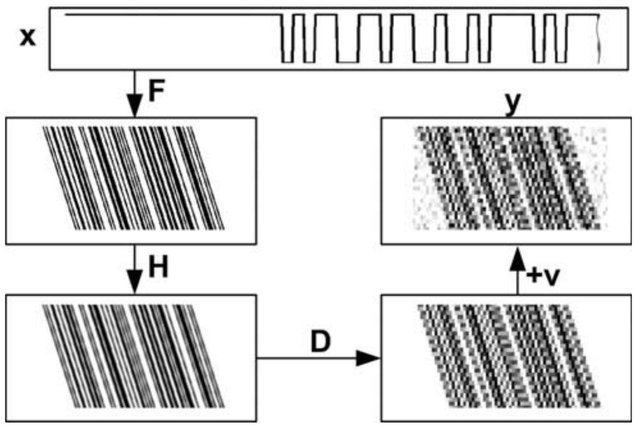

Fig. 1. Image Model

II. IMAGE MODEL

Given a rendered 1D bar code $\mathbf{x}$ with $x_i \in \{0, 1\}$ and $i = 1, 2, \ldots, N$. An image[1] $\mathbf{y}$ is then generated by

$$\mathbf{y} = \mathbf{DHFx} + \mathbf{v}, \quad (1)$$

where the matrix $\mathbf{F}$ creates a 2D image by stacking M 1D functions one below another where each function is a copy of $\mathbf{x}$ shifted by $m \cdot \hat{d}$ pixel with $m = [0, 1, \ldots, M-1]$. This operation results in a 2D image with dimension $[M, N]$. Due to the stacking of shifted 1D function the 2D image seems to be rotated by an angle of $\alpha = \arctan(d)$. Matrix $\mathbf{H}$ models the blurring introduced by the camera systems optic and sampling process. $\mathbf{D}$ is the downsampling matrix with dimension $[L \cdot K \times M \cdot N]$, and $\mathbf{v}$ is a white Gaussian noise vector. In the resulting image $\mathbf{y}$ each scan line is shifted to its predecessor by $d = \hat{d}\frac{K}{N}$ pixel because of the downsampling process. The modeling of a 2D bar-code image according to (1) is visualized in Fig. 1.

[1] All images in this work are represented by column wise lexicographic ordered vectors.

III. SCAN LINE SHIFT ESTIMATION

Suppose we extract P consecutive horizontal scan lines $\mathbf{s}_i$ (each holding at least the whole code length) from the image $\mathbf{y}$ and stack them into a scan line matrix $\mathbf{S}$ with dimension $[P, K]$:

$$\mathbf{S} = [\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_P]^T = \mathbf{By}, \tag{2}$$

with $\mathbf{B}$ being the scanning matrix. We assume that the scan lines in $\mathbf{S}$ are shifted by d pixels to its predecessor with $0 < d < 1$. Further we assume the presence of aliasing. The task of shift estimation is to extract d from $\mathbf{S}$.

Because the rows of $\mathbf{S}$ are degraded and shifted versions of one single 1D function we use a correlation approach. For that we define

$$\mathbf{c}_{i,j} = [c_{1,i,j}, c_{2,i,j}, \ldots, c_{2K-1,i,j}]^T = \mathbf{s}'_i \otimes \mathbf{s}_j, \tag{3}$$

where $\otimes$ is the correlation operator and $\mathbf{s}'_i$ is the unbiased i-th row of $\mathbf{S}$. Further we define the matrix

$$\mathbf{C}_i = [\mathbf{c}_{i,1}, \mathbf{c}_{i,2}, \ldots, \mathbf{c}_{i,P}]^T, \tag{4}$$

which holds the correlation results with respect to the i-th row of $\mathbf{S}$. Now we take from $\mathbf{C}_i$ in each row the maximum value which holds the maximum correlation result between the i-th and the respective rows scan line:

$$\mathbf{u}_i = [u_{1,i}, u_{2,i}, \ldots, u_{P,i}] = \underbrace{\max\left(\mathbf{C}_\mathrm{i}\right)}_{\text{over rows}}, \tag{5}$$

It is obious to see that $u_{j,i}$ is a local maximum in $\mathbf{u}_i$, where the i-th and the j-th row of $\mathbf{S}$ have the same aliasing components and therefore are shifted by an integer number of pixels. That makes $\mathbf{u}_i$ a periodic signal which is best analyzed with the FFT. Taking the maximum non-DC component of the FFT result reveals the dominant frequency and therefore the number of columns needed for a shift of one pixel. To rise FFT resolution $\mathbf{u}_i$ is zero padded to a total length of N (with $N > P$) and named $\hat{\mathbf{u}}_i$.

$$\mathbf{U}_i = [U_{1,i}, U_{2,i}, \ldots, U_{N,i}] = FFT(\hat{\mathbf{u}}_i) \tag{6}$$

$$r_i = \arg\max_n U_{n,i} \;\; \forall n > 1 \text{ and } \mathrm{n} \leqslant \frac{\mathrm{N}}{2} \tag{7}$$

$$\kappa_i = \frac{N}{r_i - 1}, \tag{8}$$

where r_i is the index in the FFT result that contributes (beside the DC-Term) the most energy, and κ_i is the period length of the dominant frequency in $\mathbf{u}_i$ (see Fig. 2). κ_i directly corresponds with the shift of the scanlines in $\mathbf{S}$:

$$d_i = \frac{1}{\kappa_i}, \tag{9}$$

where d_i is the shift in pixels from one scan line to the next in $\mathbf{S}$. It will be shown in the result section that this procedure is very robust against noise to a certain level. Above that level outliers occur. To reduce them it is useful to not only calculate one d_i but a set of them and take the median value:

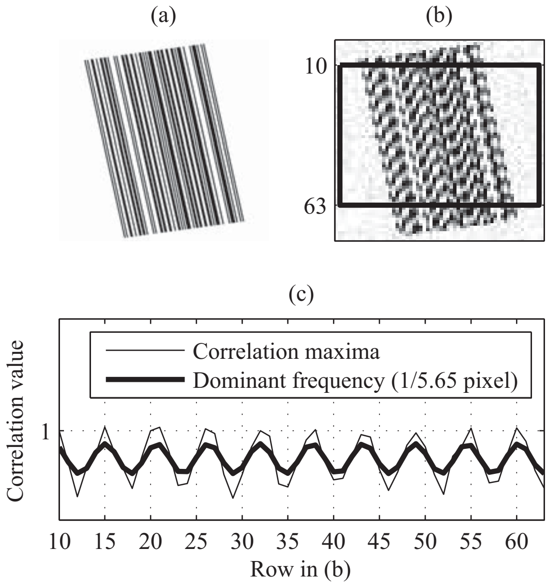

Fig. 2. Scan line correlation and its fourier analyzation. (a): Original high resolution bar code rotated by 10°. (b): Low resolution bar code with black bordered scanning window. (c): Normalized correlation result ($\mathbf{u}_i$ in (5)) and dominant frequency.

$$d_{med} = \mathrm{median}(d_i) \;\; \text{with i} \in \mathcal{I}, \tag{10}$$

where $\mathcal{I}$ is the set of all reference lines. Another benefit of this procedure is the robustness against other types of noise like scratches on the bar code. The drawback, of course, is the linear increase of computing costs.

IV. SCAN LINE FUSION AND QUALITY MEASURE

To be able to measure the overall performance we use the fusion method proposed in [7] without the deblurring procedure also proposed. Given P 1D scan lines with length K each shifted to its predecessor by d pixel (where $0 < d < 1$) and a upscaling factor L. A new high resolution scan line of length LK is generated by taking the gray values from the low resolution scan lines. The gray value of scan line i at position n_l is used to fill the position $n_h = \lfloor L(i \cdot d + n_l) \rfloor$ is the high resolution result. The reconstructed scan line is thresholded to only provide white/black or $1/0$ values.

To measure the quality of a given reconstructed scan line $\mathbf{x}$ it was chosen not to use a decoder because its noise reduction and prior knowledge could have influenced the results. Therefore we analyze the bar code at a lower level of the decoding process. Each bar code consists of bars with a width which is a multiple (1, 2, 3, and 4) of a base length (*b*). Doing a run length encoding on the vector $\mathbf{x}$ reveals the bar width information:

$$\mathbf{r}_x = \text{RunLengthEncoding}(\mathbf{x}) \tag{11}$$

The first and last element of $\mathbf{r}_x$ is without meaning since they do not belong to the bar code itself. A histogram on $\mathbf{r}_x$, without first and last element, reveals the distribution of the bar width in the code and deliver therefore the basis to estimate the quality (q):

$$q = \frac{\text{Sum of good bars}}{\text{Sum of all bars}}, \tag{12}$$

where we define a bar to be "good" if its length (l) is within $n \cdot b - \frac{b}{4} < l < n \cdot b + \frac{b}{4}$ with $n = [1, 2, 3, 4]$.

V. RESULTS

In this section we compare our proposed shift estimation method with the method in [7]. For that we set up experiments using modeled data according to (1) and real data taken with a gray-scale CCD camera from a printed bar code. If not otherwise mentioned our method is used by taking only one reference scan line for shift estimation (see (10)).

V-A. Model Data

In the first experiment we show the noise propagation and accuracy of both methods. According to (1) we generated an undersampled 2D image from a EAN-13 bar code with base length of 3 pixel and undersampling factor of 4. We chose Matrix $\mathbf{D}$ to provide an undersampled baselength of $3/4 = 0.75$ pixel and matrix $\mathbf{F}$ to do a rotation of $5°$. Blurring ($\mathbf{H}$) was done with a Gaussian kernel with standard deviation of 0.9 pixel. The noise level was raised from $\sigma^2 = 0$ to $\sigma^2 = 0.5$. For both methods we took the same 70 scan lines into consideration. At each noise level we took 500 outcomes and averaged over the measured angle. Fig. 3 shows the results. At low noise levels ($\sigma^2 < 0.05$) both methods measure the correct angle (Fig. 3(a)), although our method provides more stable results (Fig. 3(b)). Above a noise level of about 0.05 the method in [7] looses stability, while our method still provides good results. At higher noise levels ($\sigma^2 > 0.45$) our method also gets unstable but still delivers better mean results.

In the second experiment we were interested in the overall performance including reconstruction of the the actual 1D bar-code function. The quality was measured according to (12). We took the same images as in the first experiment, reconstructed the 1D function with the respective registration results and calculated the quality. The result can be seen in Fig. 4. Up to a noise level of about 0.05 both methods provide the same overall quality. With rising noise level the reconstruction quality drops down but our method always provides better results.

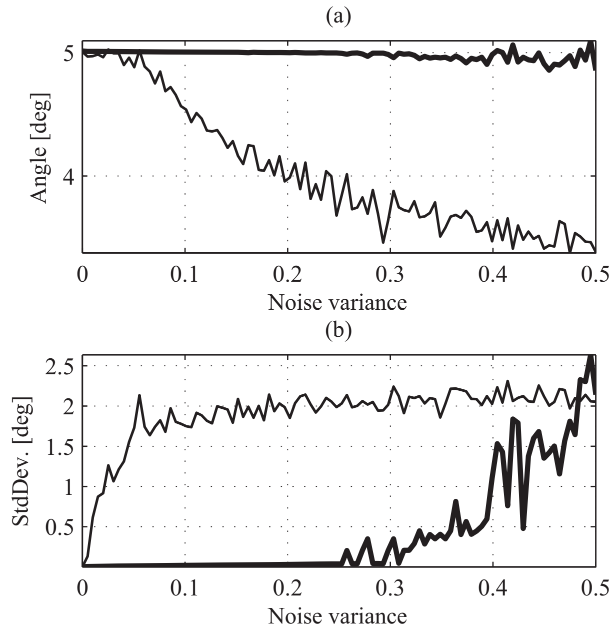

Fig. 3. Noise propagation and accuracy of the proposed method (thick lines) and the method in [7] (thin lines). The input bar code image has been generated with a rotation angle of $5°$, undersampling of 4 and varying noise. The measurements were repeated 500 times at one noise level. (a): Accuracy. (b): Noise propagation.

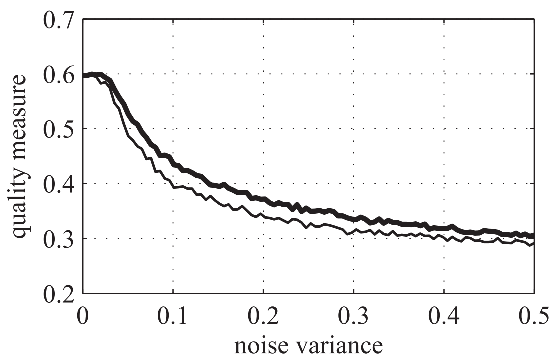

Fig. 4. Quality of reconstruction over noise variance of proposed method (thick line) and method in [7] (thin line).

V-B. Real Data

In this subsection we analyze the behavior of the proposed method and the method in [7] on real data. The third experiment is called *sliding window* since the estimation is done on a small window upon a given bar code image (Fig. 5(a)). Because the orientation of the bars in each window approximately keeps the same, the algorithms are expected to deliver a stable result no matter where the window is. Fig. 5(b) shows the result. In this experiment our method used a set of 20 reference scan lines (see (10)). Obviously the photographed bar-code image has some spatial distortions due to either the printing or capturing process, since both methods provide roughly the same deviation over the window start positions. But our method provides a more stable result at a given window start position and its surroundings. The overall mean of both methods is very similar (3.09 and 3.08 for our method and the method in [7] respectively) but the overall standard deviation of our method is roughly 2 times better (0.0183 vs. 0.0328).

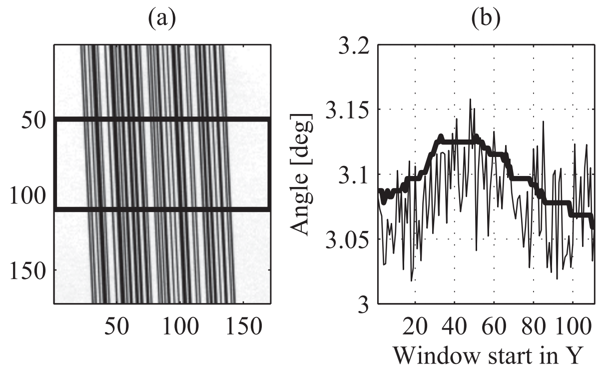

Fig. 5. Sliding window with window height of 60 pixel. (a): Original bar code taken with a camera and the window start position in Y exemplary at position 50. (b): Angle estimation. Thick line: Proposed method (3.09, stddev: 0.0183), Thin line: Method in [7] (3.08, stddev: 0.0328).

VI. CONCLUSION AND OUTLOOK

In this paper we presented a new method for bar-code shift estimation in undersampled 2D images to reconstruct the underlying information. A model was presented and the proposed method was tested on generated and real images against a well known method and its superiority was shown.

The model presented in this paper only covers rotation as spatial distortion. But since bar codes are often photographed with perspective distortion this has to be taken into account in future researches. Also the fusion of such distorted bar codes has to be improved and is subject to ongoing investigations.

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