Genetic method to optimize binary dithering technique for high-quality fringe generation

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The recently proposed dithering techniques could substantially improve measurement quality when fringes are wide, but offer limited improvement when fringes are narrow. This Letter presents a genetic algorithm to optimize the dithering technique for sinusoidal structured pattern representation. We believe both simulation and experimental results show that this proposed algorithm can substantially improve fringe quality for both narrow and wide fringe patterns.

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Digital fringe projection (DFP) techniques have been increasingly employed due to their flexibility and speed [1]. A DFP system uses a computer to generate sinusoidal fringe patterns that are projected on to an object by a projector. A camera captures the fringe patterns distorted by the object surface geometry, and a fringe analysis algorithm is used to reconstruct a three-dimensional (3D) shape. However, since it requires 8 bits to represent sinusoidal patterns, the measurement speed is typically limited to 120 Hz, which is the video projector refresh rate.

The squared binary defocusing technique can achieve tens of kHz since it only requires 1-bit structured patterns [2]. However, its measurement quality is not as high as the DFP technique due to the influences of high-frequency harmonics. Pulse width modulation (PWM) techniques [3,4] could substantially enhance the binary defocusing technique when fringe stripes are narrow. Yet, the improvements are limited when fringe stripes are wide because the PWM techniques are one-dimensional in nature, and cannot fully use the two-dimensional information of the structured patterns.

The area-modulation technique developed by Xian and Su [5] could generate high-quality fringe patterns, yet is difficult to realize in a DFP system because of the need for highly dense pixels. Locally modulating the 1s and 0s ratios could result in patterns better for the defocusing technique [6]. However, it also is difficult for these techniques to achieve high-quality wide fringes.

Since the 1960s [7], researchers have been developing methods to represent grayscale images with binary images for printing. The technique developed was called halftoning or dithering. Numerous dithering techniques have been developed that include random dithering [8], ordered dithering [9], and error-diffusion dithering [10]. Our previous study [11] showed that these techniques could substantially enhance 3D shape measurement quality when fringe stripes are wide, but offered limited improvement when fringes are narrow. All these dithering techniques were simply applying a single matrix to convert an 8 bit grayscale image to a 1 bit binary image, ignoring the inherent image structures. Since the required fringe patterns have sinusoidal structures, there should be great room for drastically improving their quality.

Some genetic algorithms have been developed to improve dithering techniques [12,13] and they have shown drastic improvement over the conventional dithering technique. However, they were developed to improve dithering techniques in general, which may not be optimal for structured patterns. This Letter presents a genetic algorithm to specifically optimize the dithering technique for sinusoidal structured pattern generation. The proposed genetic algorithm takes full advantage of the inherent sinusoidal structures of the desired patterns, and optimizes 1s and 0s distributions so better sinusoids can be generated. The proposed method is a genetic algorithm that produces better genes through mutations and crossovers from the dithered patterns.

Among all existing dithering techniques, the error-diffusion dithering techniques have been most extensively adopted because they are more accurate. In this method, the pixels are quantized in a specific order by applying a diffusion kernel $h(x,y)$, and the quantization error for the current pixel is propagated to unprocessed pixels. The process of modifying an input pixel can be described as,

$$\tilde{f}(i,j) = f(i,j) + \sum_{k,l \in S} h(k,l)e(i-k,j-l). \qquad (1)$$

Here, $f(i,j)$ is the original image, and error $e(i,j) = \tilde{f}(i,j) - b(i,j)$ is the difference between the quantized image $b(i,j)$ and the diffused image including the prior processed pixel influences. The quantization error $e(i,j)$ is further diffused to unprocessed pixels through the diffusion kernel $h(i,j)$. There are numerous diffusion kernel selections, and we used the kernel proposed by Floyd–Steinberg [14]:

$$\frac{1}{16}\begin{bmatrix} - & * & 7 \\ 3 & 5 & 1 \end{bmatrix}. \qquad (2)$$

Here, $-$ represents the previously processed pixels, and $*$ the pixel in processing. One may notice that the kernel coefficients sum to one, and thus this operation preserves the local average value of the original image.

Since the error-diffusion pattern is simply applying a matrix to the image, it is far from optimal. Therefore, this Letter proposes a genetic algorithm to optimize the dithering technique to generate better sinusoids. The genetic algorithm starts with the dithered patterns using the error-diffusion algorithm. Since the error-diffusion

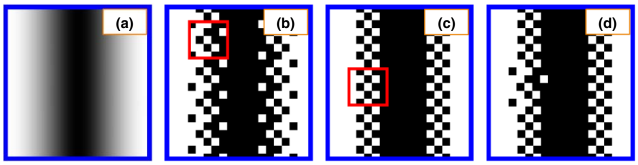

Fig. 1. (Color online) Crossover example. (a) Ideal pattern, (b) parent 1, (c) parent 2, (d) crossover from (b) to (c).

algorithm is path and origin dependent, different variations (genes) can be generated. Figures 1(b) and 1(c) shows two variations with one starting from the top left corner and diffusing, and the other starting from bottom left and bottom corner and diffusing. The diversity of variations within genes will speed up the optimization process. The proposed genetic algorithm was designed to have a population of 20 patterns for each generation, and individuals within each generation were evaluated using a fitness function. The probability of choosing one individual as the parent of next generation was calculated using the rank selection method discussed in [15].

To emulate a projector defocusing effect, the pattern was first blurred by a small Gaussian filter (e.g., 5×5 with a standard deviation of $5/3$ pixels). Then, the intensity of this blurred image at each pixel was compared to the ideal image. The difference between the two was defined as the fitness function to be minimized. The proposed genetic algorithm used two major techniques: crossover and mutation.

Crossover is a technique that copies a block of one pattern to the other. This happens when two parents are chosen for recombination: a random rectangle from the first parent with a random starting location, and random width and height with both width and height less than the fringe period. The random starting location from the second parent is chosen with a constraint of ensuring the same phase. To improve the efficiency of the crossover process, the rectangle was chosen to lie in a region that had a higher error for about 50% of the time to ensure that the algorithm will avoid wasting too much time on areas already optimized. Figures 1(b)–1(d) illustrate one crossover (inside the red rectangle) from Fig. 1(b) to Fig. 1(c).

While crossover was the primary driver, with approximately 80% of children having crossover from two parents, the importance of mutations cannot be overlooked. In fact, according to Spears [16], “Mutation serves to create random diversity in the population, while crossover serves as an accelerator that promotes emergent behavior from its components.” This research employed a few different strategies.

The primary method of mutation was bit-flip: changing 1s to 0s or 0s to 1s. We also adopted bit-switching: switching pixels within 4×4 pixels region. High-error (or low-fitness) bits were more likely to undergo recombination or be flipped. Similar to crossover, about 50% of mutations occur on bits with a larger errors to speed up the whole process.

Due to the fast speed of computing the genome fitness value, no more than one mutation would occur for any child. If we assume the probability $p_s < 1$ that any mutation will be successful, then the probability of two mutations far apart both being successful will be less than

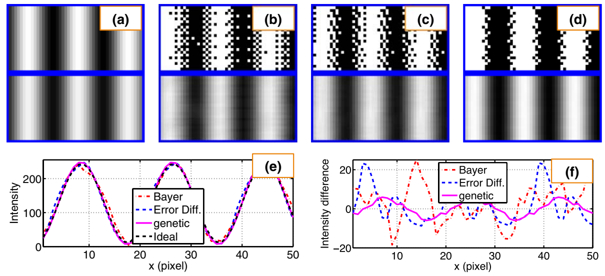

Fig. 2. (Color online) Patterns with different techniques: (a) ideal sinusoidal, (b) Bayer dithering, (c) error-diffusion dithering, (d) genetic optimized, (e) cross sections, and (f) cross sections of intensity difference maps.

the probability of only one mutation being successful (i.e., $p_s^2 < p_s$). If we remove the restriction that the two pixels will be far apart, and instead only consider when the pixels are close, then we have two cases: (1) The pixels have the same value, in which case it is far more likely that one flip would be successful rather than two; and (2) the pixels have differing values, in which case they could still be bit-switched.

Although allowing the algorithm to run for as long as possible would yield the patterns with the lowest fitness function, a stopping criterion was used to balance the processing time and fitness value. The algorithm was stopped when the fitness of the best individual did not improve after 100 iterations. The results presented in this Letter were generated by roughly 10,000 iterations.

We firstly performed some simulations with a wide range of fringe breadths. Figure 2 shows the example when fringe is dense (period of 18 pixels). Figures 2(b)–2(d) top half images show the dithered patterns, and the bottom images show the smoothed patterns with a Gaussian filter (5×5 with a standard deviation of $5/3$ pixels). The cross sections of these smoothed patterns were plotted in Fig. 2(e). Figure 2(f) shows the differences between these patterns and the ideal sinusoidal pattern. This figure shows that the genetic optimized pattern is closer to the ideal pattern.

Since the phase quality determines the measurement quality, the phase was also calculated using a three-step, phase-shifting algorithm and a temporal phase unwrapping framework [17]. The phase errors were calculated by comparing them with the phase obtained from ideal sinusoidal patterns. Figures 3(a) and 3(b) show the comparison of the phase root-mean-square errors for different techniques

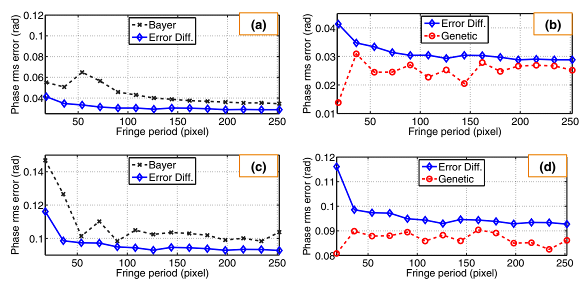

Fig. 3. (Color online) Results with different dithering techniques. (a) and (b) Simulation results; (c) and (d) experimental results.

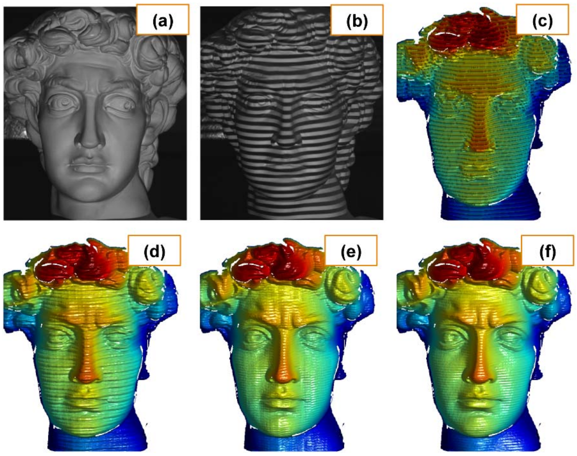

Fig. 4. (Color online) Measurement results of 3D statue using different techniques. (a) Photo of the object. (b) One of the squared binary patterns. (c)–(f) 3D results using the squared binary, the Bayer dithered, the error-diffusion dithered, and the genetic optimized dithered patterns.

with different fringe periods. This clearly shows that the proposed genetic algorithm works the best while the error-diffusion technique works better than the Bayer diffusion technique. Notice that both the Bayer and error-diffusing dithering techniques showed larger errors when fringes are dense, while the genetic optimization method performed well even when fringe stripes were very dense.

The proposed technique also was verified with a previously developed 3D shape measurement system that includes a digital light processing projector (Samsung SP-P310MEMX) and a CCD camera (Jai Pulnix TM-6740CL). The camera was attached a 16 mm focal length megapixel lens (Computar M1614-MP). The projector and the camera remained untouched for these experiments.

We experimentally verified the simulation results by measuring a flat white surface using all these fringe patterns. Figures 3(c) and 3(d) show the results. The phase errors were calculated by taking the difference between the phase recovered from the ideal sinusoidal fringe patterns with that from the dithered patterns. Again, the genetic optimized algorithm generated the best results while the Bayer dithering performed the worst.

A more complex 3D statue, the David head shown in Fig. 4(a), was also measured to compare these methods. Figure 4 compares all the results. The captured squared binary pattern, shown in Fig. 4(b) clearly shows that the projector was nearly focused. The fringe period used was very small (18 pixels), and the phase was converted to depth using the simple reference-plane-based method [2]. This figure showed that the squared-binary technique could not generate reasonable quality measurement when projector is nearly focused, as indicated in Fig. 4(c). Figures 4(d)–4(f), respectively, shows the result with the Bayer dithering, error-diffusion dithering, and the genetically optimized dithering technique. All these were better than Fig. 4(c) with the proposed method performing the best. It is important to note that all these 3D data were smoothed by a 5×5 Gaussian filter to reduce some random noise.

We have presented a genetic algorithm to optimize the dithering technique. Both simulation and experiments have demonstrated the proposed technique can substantially improve fringe quality for both narrow and wide fringes.

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