Optimal Decoding of Stripe Patterns with Window Uniqueness Constraint

Shuntaro Yamazaki and Masaaki Mochimaru

Digital Human Research Center
National Institute of Advanced Industrial Science and Technology
{shun-yamazaki,m-mochimaru}@aist.go.jp

Abstract. We propose an optimal algorithm for solving correspondences problem in one-shot depth acquisition using color stripe patterns composed of pseudo-random sequence (PRS). Our algorithm solves one-dimensional matching in a globally optimal manner, imposing the uniqueness of subsequences in the PRS as a hard constraint. The proposed algorithm has linear time complexity with respect to the size of image, which is of the same order as conventional dynamic programming matching. Experimental results are presented to demonstrate the performance of the algorithm using real data, for several color stripes that have been proposed in this field.

1 Introduction

Rapid depth acquisition is the fundamental task for many applications including recognition, tracking, and geometric modeling. A number of different approaches to this problem are proposed, such as, real-time laser scanning [1], time-of-flight camera [2], and stereo vision systems [3]. Coded light is a variant of active stereo methods where one of cameras is replaced by a projector, and has been widely adopted in many practical applications for its accuracy and capability of rapid depth acquisition.

When moving and/or deforming objects are captured, the speed of image acquisition is crucial for active vision systems that use *temporally-coded light*. Rusinkiewicz et al. proposed an interactive system for in-hand modeling of static objects, using a synchronized pair of projector and camera [4]. Weise et al. extended the system to a multiple camera setup [5]. For even faster objects, Narasimhan et al. proposed a high-speed projector-camera system that acquires images at more than 1kHz [6]. These high-performance systems have advantages in accuracy and reliability. The special hardware requirements, however, restrict the scope of the application.

Spatially-coded light is an alternative approach to rapid depth acquisition. The spatial distribution of illumination intensities allows the algorithms to estimate the correspondences from a small number of images, typically one. The illumination patterns are designed so that, each point is uniquely colored [7], each neighborhood has unique pattern [8–10], or the pattern has distinctive sparse structures [11, 12]. To cope with the fundamental tradeoff between resolution and robustness, the decoding algorithms involve with numerical optimization techniques that are computationally expensive and unstable.

In this paper, we propose an algorithm of optimally decoding stripe patterns generated from pseudo-random sequence (PRS) in a computationally efficient manner. PRS has the *window uniqueness property* — each subsequence of a certain length occurs at most once — and therefore allows the algorithm to determine the correspondences uniquely from its partial observations. Our method can find the globally optimal correspondence, on a practical assumption of the monotonicity of observed stripes along epipolar lines. The algorithm is independent of the underlying PRS, and therefore can be applied to many different types of stripe patterns. To demonstrate the capability of this method, we have recovered correspondences using several patterns generated from: de Bruijn, XOR-ed de Bruijn, non-recurring de Bruijn, and Hamming color sequences. The experiments show that our method achieves substantial improvements in reconstruction accuracy and robustness.

2 Color Stripes for One-shot Depth Acquisition

The strategies of coded light are comprehensively surveyed and systematized by Salvi et al.[13] Among other techniques of spatially-coded light for one-shot depth acquisition, stripe-based approach has a great advantage that spatial resolution is lost in only one dimension. Due to the simple structure of the pattern, the reconstruction algorithm can be simple; Near-realtime implementations have also been possible [14, 15]. In this section, we briefly describes existing techniques of spatially-coded light using stripe patterns generated from PRS.

2.1 Pseudo-Random Sequences

De Bruijn Sequence is a cyclic sequence for which every possible subsequence of a certain length appears as a sequence of consecutive characters exactly once. Hügli and Maître propose sparse color stripes generated from the de Bruijn sequence of 3-bit alphabets [16]. Zhang et al. propose a method of encoding the sequence into the transition of color stripes, allowing the detection algorithm to localize the pattern with sub-pixel accuracy. In these methods, one-dimensional correspondence problem is solved efficiently via one-dimensional pattern matching by dynamic programming [8].

Robustness: De Bruijn sequence has several drawbacks for the use of coded light. One of them is recurrence of sample alphabets, which makes it difficult to detect individual stripes correctly. Pages et al. solved the problem by inserting dark separators into every other stripes. Lim proposed non-recurring de Bruijn sequence that can be embedded densely into a projection pattern for a stereo system with active illumination [9]. Another issue of the robustness to imaging error and occlusion is addressed by Yamazaki et al in [10]. They introduce a

variant of de Bruijn sequence that by construction does not yield fake colors between adjacent stripes due to local color blending.
Error-correction: Forster proposes a color stripe pattern that has error detection and correction capabilities as well as window property [14]. He first define a list of requirements that the code should satisfy, and generate one of such sequences by a randomized algorithm. They also describe a technique of robust stripe detection on colored surfaces, under unknown ambient illumination.

Our reconstruction algorithm is independent of the underlying PRS from which color stripes are generated, and therefore can be used to decode the above-mentioned patterns.

2.2 Decoding Algorithms

Semi-global methods try to solve the correspondence problem by iteratively applying local optimization. Many existing techniques of one-shot depth acquisition rely on one-dimensional pattern matching by dynamic programming [16, 8, 10]. This method yields a globally optimal solution in a computationally efficient manner, but often results in inconsistency between adjacent lines. To address the problem, Forster proposes to propagate the result of adjacent reconstruction to improve the coherence between lines [14]. Christoph and Angelopoulou propose an incremental method where local reconstructions are iteratively concatenated, and report that their semi-global method outperformed a global method due to the high complexity of the problem [15].
Global methods: If the cost function is properly define, global optimization methods may achieve the best reconstruction. Among many different techniques, belief propagation [17], graph cut [15], and optimization via linear system [18] have been effectively utilized. The drawback of these approaches is their high computational cost. They typically take one to several seconds, making it difficult to integrate the scanning component into interactive systems.

Our goal is to propose a new algorithm of optimally decoding existing color stripe patterns and achieves reliable reconstruction without increasing computational cost.

3 Solving Optimal Correspondence

In the rest of this paper, we assume that the projector and camera are geometrically calibrated and the images are rectified so that, each line of acquired images has one-to-one correspond to a one-dimensional color stripe pattern.

3.1 Dynamic Programming Matching — Review

The problem of depth recovery for each image line is equivalent to a one-dimensional matching between a stripe pattern and the line. And hence, it can be solved efficiently by dynamic programming matching (DPM), on a practical assumption of the monotonicity of observed stripes along epipolar lines. The correspondence problem is solved independently for each line, using a two-dimensional

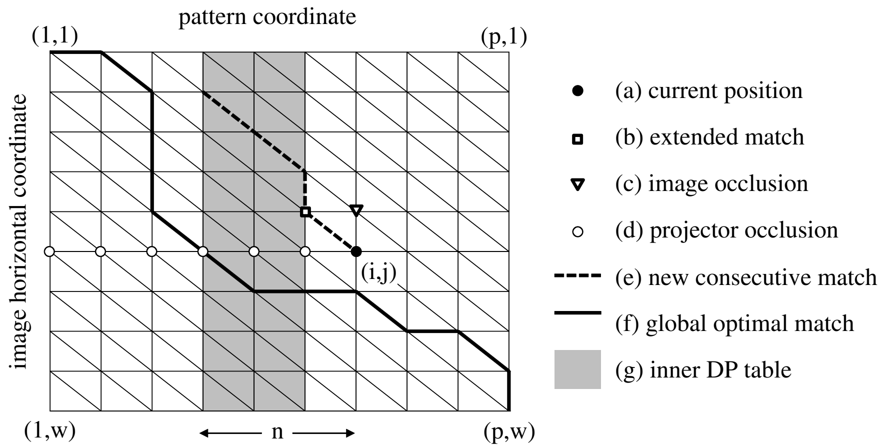


Fig. 1. A diagram of dynamic programming matching (DPM) for a single image line. In conventional DPM, the optimal correspondence at a grid point (a) is estimated from the score at (a), and the previous results obtained at (b), (c), and (d). In our dual DPM, the matching cost (b) is replaced with the optimal consecutive matches denoted by (e), which is obtained by solving another DPM using a table denoted by (g).

table illustrated in Fig. 1. For the detail of DPM, please refer to prior work [19, 8].

DPM algorithm uses a two-dimensional table on which subproblems are solved recursively. The horizontal and vertical axes respectively correspond pattern coordinates ($i \in [1, p]$) and image line coordinates ($j \in [1, w]$). The matching score $c(i, j)$ of the matching between a pattern color at i and an image color at j is stored at a grid point (i, j). The algorithm visits the grid points once for each, proceeding from top-left to bottom-right. That is, the algorithm recursively solve the correspondence by choosing the best solution to the previous subproblems: $M(i, j) = \max\{M_1(i, j), M_2(i, j), M_3(i, j)\}$ where

$$M_1(i, j) = M(i-1, j-1) + c(i, j) \tag{1}$$

$$M_2(i, j) = M(i, j-1) \tag{2}$$

$$M_3(i, j) = \max_{i' < i} M(i', j) + \epsilon_h \tag{3}$$

ϵ_h is the penalty terms of skipping pattern stripes. In our experiments, $\epsilon_h = -1.1$ is used when the score is defined as $c \in [-1, 1]$. The matching for the entire sequences is obtained by backtracking the best path found at (p, w).

DPM has several advantages including linear time complexity and global optimality. However, a naïve DPM algorithm tries to match as many pixels as possible to obtain the highest matching score, resulting in discontinuous matching that is unlikely correct correspondence. To penalize such undesirable results, a variety of weighting schemes have been proposed. For instance, Mei et al. propose a real-time stereo algorithm using a semi-global optimization similar in spirit to DPM, and demonstrated an efficient implementation on graphics processing unit (GPU) [20]. In general, however, these weighting are unreliable, and therefore we propose a more structured way to obtain likely correspondence.

3.2 Global Optimization with Window Uniqueness Constraint

We propose a variant of DPM for solving correspondences where the window uniqueness property of a stripe pattern is considered as a hard constraint, without losing the capability of global optimization and computational efficiency that the original DPM holds. Specifically, we propose an algorithm that guarantees the following properties in the solution:

- The solution is globally optimal with respect to a matching consistency.
- The matching consists of consecutive subsequences of at least length n in the pattern coordinates.

n is the size of window uniqueness of the underlying PRS. The second property is crucial for our algorithm, because otherwise the algorithm tries to maximize the objective function by corresponding as many pairs as possible, potentially resulting in numerous isolated correspondences. Since our pattern is ambiguous if the length of subsequences is less than n, any matching that has less than n correspondences shall be discarded.

3.3 Dual Dynamic Programming Matching

To guarantee the minimum length of consecutive matches, we propose a dual dynamic programming matching (dual DPM) where an inner DPM is solved for each to evaluate the accumulated scores for consecutive matches. In this algorithm, we replace accumulated score of a single matching M_1 with that of the best n-consecutive matching M_1' at each grid point (i, j). M_1' is computed using an internal DPM of size $n \times w$, as shown in a dark color in Fig. 1. When solving the inner DPM, skipping pattern pixel, or equivalently, vertical transition in the table is prohibited to guarantee consecutive matching. Then, the best correspondence is chosen among $\{M_1', M_2, M_3\}$ in the same manner as the conventional DPM. The algorithm described above is summarized in Algorithm 1.

The computational complexity of the dual DPM is $O(p^2 w)$ where p is the length of a color pattern and w is the length of an image line. This complexity is same as that of the conventional DPM with occlusion handling [19], despite an inner DPM which requires an additional iteration for each column. The inner DPM of size $n \times w$ is solved only once for each column, i.e., in $O(nw)$ times, where n is the size of window uniqueness of PRS, and much smaller than p. The new consecutive match (e) in Fig. 1 at each grid point (i, j) is determined in a constant time, by referring to the precomputed table for the inner DPM.

Algorithm 1 Dual Dynamic Programming Matching

input: Matching score $c(i,j)$ for $i \in [1,p]$ and $j \in [1,w]$
output: Optimal path $L_{(1,1)\to(p,w)} \leftarrow \underset{L}{\operatorname{argmax}} \sum c(i,j)$

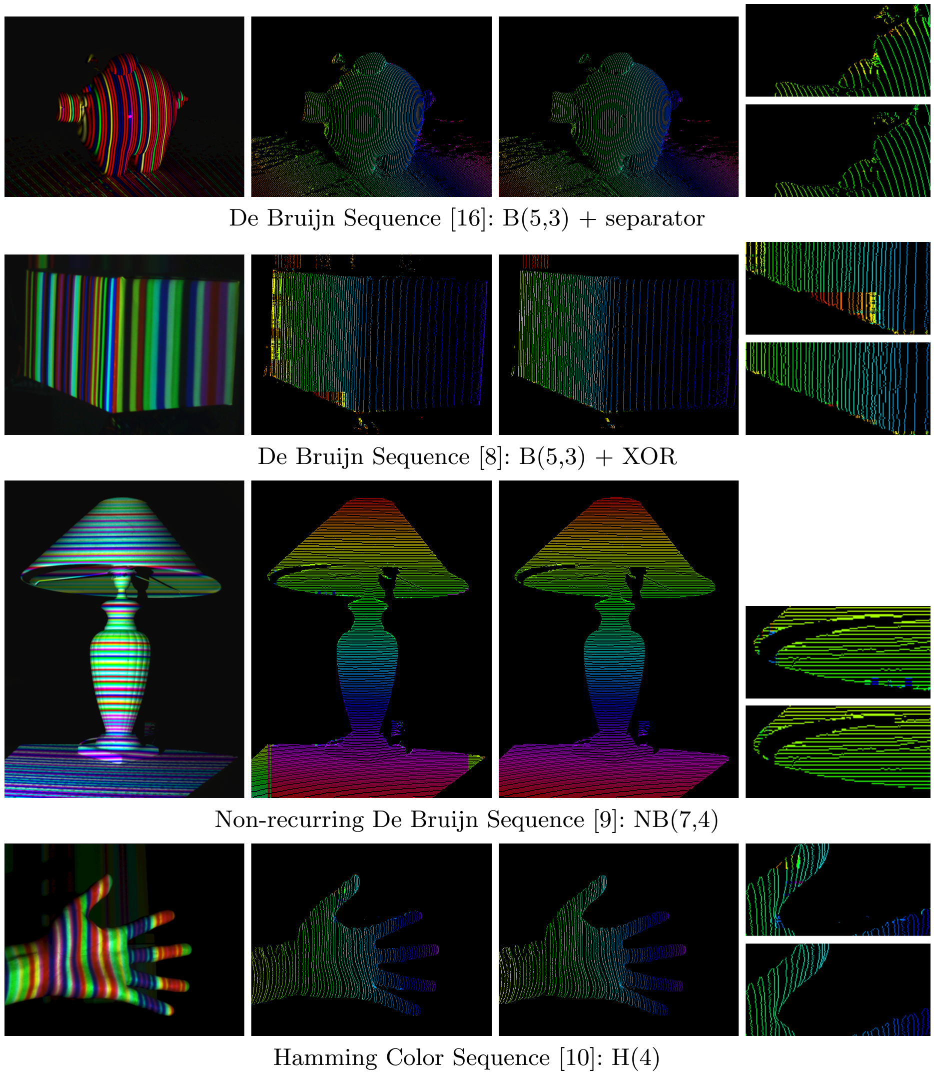
foreach $(i,j) : i \in [-1, n-1]$ or $j \leftarrow -1$ /* initialize DPM */
  $M(i,j) \leftarrow 0$
foreach $i \in [1,p]$
  foreach $(i',j') : i' \leftarrow i-n$ or $j' \leftarrow -1$ /* initialize inner DPM */
    $N(i',j') \leftarrow M(i',j')$
  foreach $i' \in [i-n+1, i-1]$ /* solve inner DPM */
    foreach $j' \in [1,w]$
      $N(i',j') \leftarrow \max\{N(i'-1,j'-1) + c(i',j'), N(i',j'-1)\}$
  foreach $j \in [1,w]$
    $M_1' \leftarrow N(i-1,j-1) + c(i,j)$ /* (1) n-consecutive match */
    $M_2 \leftarrow M(i,j-1)$ /* (2) image pixel skipped */
    $M_3 \leftarrow \max_{1 \le i' < i} M(i',j) + \epsilon_h$ /* (3) pattern pixel skipped */
    $M(i,j) \leftarrow \max\{M_1', M_2, M_3\}$
$L \leftarrow$ Backtrack(l,w) /* retrieve optimal correspondence */

4 Results

We have applied our method to four state-of-the-art techniques of color stripes: De Bruijn Sequence B(5,3) with black separators [16], De Bruijn Sequence B(5,3) encoded in color transition by XOR operator [8], Non-recurring De Bruijn Sequence NB(7,4) [9], Hamming Color Sequence H(4) [10]. The matching score $c(i,j)$ is defined in the same way as proposed in the original papers, and then normalized into $[-1,1]$. Fig. 2 summarizes the experiment results. The acquired images are presented in (a). The correspondences recovered by conventional DPM and our dual DPM are presented in respectively (b) and (c), where one-dimensional coordinates are encoded in hue. The close-up of the differences between two results are presented in (d). The conventional DPM algorithm tends to yield contiguous incorrect matches, as it attempts to maximize the number of correspondence with non-negative consistencies. This issue can be successfully resolved in our dual DPM algorithm where such incorrect matches are avoided by enforcing window uniqueness constraint.

5 Conclusion

We have proposed the optimal method of solving correspondences between color stripe patterns generated from maximum length sequence (MLS) and its partial observation by dual DPM algorithm. The computational complexity of the proposed algorithm is pseudo-linear, which is equivalent to that of the conventional DPM and substantially lower than other global methods. Several existing stripe patterns have been used in our experiments to demonstrate the performance of our proposed method. The algorithm is easy to implement. The limitation of our current technique is that the coherence between image lines are not considered. While the proposed DPM yields the globally optimal solution to the correspondence for each image line, it is important to consider the coherence between lines to obtain reliable correspondences. We are currently implementing the dual DPM algorithm on graphics processing unit (GPU), based on our



(a) input (b) DPM (c) Dual DPM (d) close-up

Fig. 2. Results of correspondence recovery

previous work on parallel DPM on GPU [10], to achieve robust one-shot shape recovery in real-time.

References

1. Livingstone, F.R., King, L., Beraldin, J.A., Rioux, M.: Development of a real-time laser scanning system for object recognition, inspection, and robot control. In: Telemanipulator Technology and Space Telerobotics. (1993) 454–461

2. Iddan, G.J., Yahav, G.: Three-dimensional imaging in the studio and elsewhere. In: SPIE Conference. Volume 4298. (2001) 48–55
3. Scharstein, D., Szeliski, R.: A taxonomy and evaluation of dense two-frame stereo correspondence algorithms. International Journal of Computer Vision **47** (2002) 7–42
4. Rusinkiewicz, S., Hall-Holt, O., Levoy, M.: Real-time 3D model acquisition. In: SIGGRAPH. (2002) 438–446
5. Weise, T., Leibe, B., Gool, L.V.: Fast 3D scanning with automatic motion compensation. In: Computer Vision and Pattern Recognition. (2007) 1–8
6. Narasimhan, S.G., Koppal, S.J., Yamazaki, S.: Temporal dithering of illumination for fast active vision. In: Lecture Notes in Computer Science (European Conference on Computer Vision). Volume 5305. (2008) 830–844
7. Tajima, J., Iwakawa, M.: 3D data acquisition by rainbow range finder. In: International Conference on Pattern Recognition. (1990) 309–313
8. Zhang, L., Curless, B., Seitz, S.M.: Rapid shape acquisition using color structured light and multi-pass dynamic programming. In: the 1st International Symposium on 3D Data Processing, Visualization, and Transmission. (2002) 24–36
9. Lim, J.: Optimized projection pattern supplementing stereo systems. In: International Conference on Robotics and Automation. (2009) 2823–2829
10. Yamazaki, S., Nukada, A., Mochimaru, M.: Hamming color code for dense and robust one-shot 3D scanning. In: British Machine Vision Conference 2011. (2011) 96.1–96.9
11. Koninckx, T.P., Gool, L.V.: Real-time range acquisition by adaptive structured light. IEEE Transactions on Pattern Analysis and Machine Intelligence **28**(3) (march 2006) 432–445
12. Furukawa, R., Kawasaki, H.: Geometrical constraint based 3D reconstruction using implicit coplanarities. In: British Machine Vision Conference. (2007) 780–789
13. Salvi, J., Pages, J., Batlle, J.: Pattern codification strategies in structured light systems. Pattern Recognition **37**(4) (2004) 827–849
14. Forster, F.: A high-resolution and high accuracy real-time 3D sensor based on structured light. In: 3D Data Processing, Visualization, and Transmission. (2006) 208–215
15. Schmalz, C., Angelopoulou, E.: A graph-based approach for robust single-shot structured light. In: Projector-Camera Systems. (2010) 80–87
16. Hügli, H., Maître, G.: Generation and use of color pseudo random sequences for coding structured light in active ranging. In: Industrial Inspection. Volume 1010. (1989) 75–82
17. Ulusoy, A.O., Calakli, F., Taubin, G.: Robust one-shot 3D scanning using loopy belief propagation. In: CVPR Workshop on Applications of Computer Vision in Archaeology. (2010) 15–22
18. Sagawa, R., Ohta, Y., Yagi, Y., Furukawa, R., Asada, N., Kawasaki, H.: Dense 3D reconstruction method using a single pattern for fast moving object. In: International Conference on Computer Vision. (2009) 1779–1786
19. Intille, S.S., Bobick, A.F.: Disparity-space images and large occlusion stereo. In: ECCV94. Volume 1., Springer-Verlag (May 1994)
20. Mei, X., Sun, X., Zhou, M., Jiao, S., Wang, H., Zhang, X.: On building an accurate stereo matching system on graphics hardware. In: ICCV Workshop on GPU in Computer Vision Applications. (2011) 467–474