Abstract

Accurate depth map at high resolution is required in many 3D video concepts. Given a low-resolution depth map, this paper studies how to enhance its resolution with a registered high-resolution color image. The idea of the proposed approach is that pixels with similar color values and small distances should have similar depth values, while color discontinuities indicate sharp depth changes at object edges. Therefore, the known depth values in input depth map can be propagated to estimate the unknown depth values of their neighboring pixels with similar color values and small distances in high-resolution depth map. Different from conventional approaches, the proposed approach utilizes the ant colony optimization (ACO) technique to dispatch artificial ants moving on a coupled graph, which consists of a depth map and a color image, and propagate the known depth information from the observed low-resolution depth map to its up-sampled counterpart. Experimental results show that the proposed approach achieves high-resolution depth maps at more desirable quality than that of conventional approaches.

1 Introduction

Many recent 3D video concepts, such as free viewpoint TV (FTV) and 3-Dimensional television (3DTV), are able to provide a more immersive vision experience and allow a higher level of interaction between the user and the service provider. For example, a popular 3DTV format, known as video-plus-depth, typically down-samples depth maps at the encoder before compression to save network bandwidth. However, the down-sampled depth map is required to be up-sampled at the decoder to provide accurate depth information for synthesizing the viewpoint video for 3D TV [10].

This paper hence focuses on enhancing the resolution of a given non-ideal low-resolution depth map. For that, various depth map up-sampling approaches have been proposed in the literature such as edge-adaptive image interpolation methods [2, 4–6, 18]. Their results contain lots of errors around object boundaries, since they interpolate depth values without the consideration of color discontinuities. In view of this, many techniques have been developed to combine the low-resolution depth map with the registered high-resolution image. Diebel and Thrun [1] proposed an interpolation method using the Markov random field (MRF) and designed a weighting function that is adaptive according to the color image gradient. Yang et al. [17] refined the input low-resolution depth map using an iterative joint bilateral filtering scheme, where depth values are calculated using weights based on pixel distance and color difference. In addition, several edge-preserving functions have been proposed in [7, 15, 16], instead of using a quadratic function in the energy function.

This paper proposes a new depth map up-sampling approach based on the observation that the pixels with similar color values and small distances should have similar depth values. Meanwhile, color discontinuities usually indicate sharp depth changes at object boundaries. The proposed approach has two components: (i) a coupled graphical representation that consists of a depth map and a color image, and (ii) an automatic way using the ant colony optimization (ACO) technique to propagate the known depth values in input low-resolution depth map to estimate the unknown depth values of the neighboring pixels that have similar color values and small distances. ACO is an optimization algorithm [8, 9, 11–14] motivated by the natural collective foraging behavior of real-world ant colonies. The readers are
referred to [3] for fundamentals of the ACO algorithm
due to the limited space of this conference paper.

The rest of this paper is organized as follows. The
proposed depth map up-sampling approach is presented
in Section 2. Experimental results are presented in Sec-
tion 3. Finally, Section 4 concludes this paper.

2 Proposed depth map up-sampling ap-
proach

The proposed approach consists of a coupled graph
representation to model the depth map and its regis-
tered color image, and an ACO algorithm to automatic-
ly propagate the known depth information from the
observed low-resolution depth map to its up-sampled
counterpart. These two components are presented in
next two subsections, respectively.

2.1 Coupled graph representation

The proposed graph, as illustrated in Figure 1), is
defined as $G(V_d, V_i, E)$, where $V_d$ and $V_i$ are sets of
vertices or nodes and $E$ is the set of edges. The vertices
(nodes), $v_d \in V_d$, are pixels in depth map (black/white
pixels in Figure 1), and the vertices (nodes), $v_i \in V_i$, are
pixels in color image (gray pixels in Figure 1), while
the edges, $e \in E$ represent the connection between
the nodes. The links among nodes are determined by
the 4-neighborhood structure used in images. In addi-
tion, each pixel of the depth map is linked to the corre-
sponding pixel in the color image. Based on this formu-
lation, our objective is to automatically propagate the
known depth information (black pixels in Figure 1) on
this coupled graph to estimate those unknown depth val-
ues (white pixels in Figure 1).

2.2 Depth map up-sampling using ACO

The idea of the proposed approach is to dispatch a
number of artificial ants on the pixels (black pixels in
Figure 1), where depth values at available. Then, these
artificial ants carry the depth values, move on the grid of
the enlarged depth map, and deposit these color values
on the pixel positions (white pixels in Figure 1) where
no depth value is available. The movements of these
artificial ants are steered by local statistics of color im-
age; they tend to moving towards neighboring pixels
that have similar color values and small distances. For
each pixel with unknown depth value, it can be visited
by few artificial ants, we record the frequency of it is
visited by other artificial ants. Finally, its depth value is
copied from the that carried by the artificial ant visiting
this pixel most frequently.

The procedure of the proposed approach is described
in details as follows. It utilizes a number (say, $K$) of
artificial ants to move on a graph for constructing a
pheromone matrix, each entry of which represents the
frequency of artificial ants visiting each pixel. The pro-
posed approach starts from assigning one artificial ant
on each node of the observed depth map (i.e., black
nodes in Figure 1). Furthermore, the initial value of
each component of the pheromone matrix $f^{(k,0)}$, $k \in
[1, K]$ is set to be a constant 1. Then the proposed algo-
rithm runs for $N$ iterations, in each iteration, each ant
moves to neighboring nodes and the pheromone content
of the coefficient on the ant’s path is updated. Finally,
for each pixel that has unknown depth value, its depth
value is copied from that of the artificial ant that visiting
this pixel most frequently.

More specifically, at the $n$-th iteration, the $k$-th artifi-
cial ant is selected. Then, this artificial ant moves from
the node $(i, j)$ to its linked neighboring node $(l, m)$ ac-
cording to a transition probability that is defined as

$$P^{(n)}_{(i,j),(l,m)} = \frac{\left( f^{(n-1)}_{l,m} \right)^{\alpha} (\eta_{l,m})^{\beta}}{\sum_{(l,m) \in \Omega_{i,j}} \left( f^{(n-1)}_{l,m} \right)^{\alpha} (\eta_{l,m})^{\beta}},$$

(1)

where $f^{(n-1)}_{l,m}$ is the pheromone value of the node
$(l, m)$; $\Omega_{i,j}$ is the neighboring nodes of the node
$(i, j)$; the constants $\alpha$ and $\beta$ represent the influence
of the pheromone matrix and the heuristic matrix, re-
spectively; the heuristic information $\eta_{i,j}$ in (1) is determined
by the local statistics of the position $(i, j)$ as

$$\eta_{i,j} = |I_{i-2,j-1} - I_{i+2,j+1}| + |I_{i-2,j+1} - I_{i+2,j-1}|
+ |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j+1} - I_{i+1,j+1}|
+ |I_{i+1,j-1} - I_{i+1,j+1}|
+ |I_{i-1,j-2} - I_{i+1,j+2}| + |I_{i-1,j+1} - I_{i+1,j+1}|,$$

(2)

where $I_{i,j}$ represents the intensity value at the posi-

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tion \((i, j)\) of the color image. Furthermore, for the nodes that are visited by the ants, their corresponding pheromone values will be updated; otherwise, they remain unchanged. That is,

\[
f_{i,j}^{(k,n)} = \begin{cases} 
  f_{i,j}^{(k,n)} + 1, & \text{if the node } (i, j) \text{ is visited by the } k\text{-th artificial ant;} \\
  f_{i,j}^{(k,n)}, & \text{otherwise.}
\end{cases}
\]

(3)

To summarize, the proposed approach guides the spatial movement of artificial ants on the coupled graph based on local statistics \((i.e., (2))\) of the color image, and records the frequency \((i.e., \text{pheromone matrix } (3))\) of each pixel is visited by each artificial ant. Finally, the unknown depth value is copied from the that of the artificial ant visiting the corresponding pixel position most frequently.

3 Experimental results

Experiments are conducted to compare the proposed approach with conventional approaches \([1, 2, 4-7, 15, 16, 18]\). Two images Tsukuba and Teddy, which are downloaded from Middlebury database, are used as the ground truth in our simulations. The ground truth depth map is first convoluted with a point spread function, which is a Gaussian low-pass filter with a window size of \(4 \times 4\) and the standard deviation of 1, followed by a down-sampling operation with a decimation factor of two in both horizontal and vertical directions, respectively. Lastly, each processed image is added with a zero-mean white Gaussian noise to yield a noisy low-resolution image with a SNR 20dB. The above-mentioned steps are independently carried out to generate one low-resolution depth map based on each original high-resolution depth map.

In the first experiment, each depth map up-scaling algorithm is independently exploited to utilize one depth image, plus a higher-resolution color images to produce a \(2 \times 2\) enlarged high-resolution depth map and compare it with the ground-truth depth map to calculate the mean square error (MSE) performance. The parameters of the proposed approach is set as \(\alpha = 1, \beta = 1, N = 100\). The MSE performance comparison is shown in Table 1. Furthermore, the absolute difference images between the reconstructed depth map and the ground truth are compared in Figures 2, 3. As seen from above Table and Figures, the proposed approach outperforms the conventional approaches to produce smallest MSE values and most accurate depth maps.

<table>
<thead>
<tr>
<th>Table 1. The MSE performance comparison.</th>
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<tr>
<td>Method</td>
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<tr>
<td>Bi-cubic interpolation</td>
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<td>Proposed approach</td>
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4 Conclusions

A graph-based depth map up-scaling approach using the ACO technique has been proposed in this paper. The proposed approach propagates the depth information from the input low-resolution depth map to its up-sampled counterpart based on local statistics of the color image. The proposed approach can produce depth maps at better quality than conventional approaches, as verified in our experiments.

References

Figure 2. Absolute difference images between the reconstructed depth map and the ground truth (Tsukuba). The darker pixels indicate larger absolute differences. Furthermore, the intensity values are scaled up two times for demonstration. (a). color image; (b). ground truth depth map; (c)-(k). bi-cubic interpolation and Refs. [2,4–7,15,16,18]; (l). proposed approach.

Figure 3. Absolute difference images between the reconstructed depth map and the ground truth (Teddy). The darker pixels indicate larger absolute differences. Furthermore, the intensity values are scaled up two times for demonstration. (a). color image; (b). ground truth depth map; (c)-(k). bi-cubic interpolation and Refs. [2,4–7,15,16,18]; (l). proposed approach.


