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ORIGINAL RESEARCH

altiro3d: scene representation from single image and novel view synthesis

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Abstract We introduce altiro3D, a free extended C++ library developed to represent reality starting from a given original RGB image or flat video. It allows to generate a light-field (or Native) image or video and get a realistic 3D experience. To synthesize *N*-number of virtual images and add them sequentially into a Quilt collage, we apply MiDaS models for the monocular depth estimation, simple OpenCV and Telea inpainting techniques to map all pixels, and implement a "Fast" algorithm to handle 3D projection camera and scene transformations along *N*-viewpoints. We use the degree of depth to move proportionally the pixels, assuming the original image to be at the center of all the viewpoints. altiro3D can also be used with DIBR algorithm to compute intermediate snapshots from a equivalent "Real (slower)" camera with *N*-geometric viewpoints, which requires to calibrate a priori several intrinsic and extrinsic camera parameters. We adopt a pixel- and device-based Lookup Table to optimize computing time. The multiple viewpoints and video generated from a single image or frame can be displayed in a free-view LCD display.

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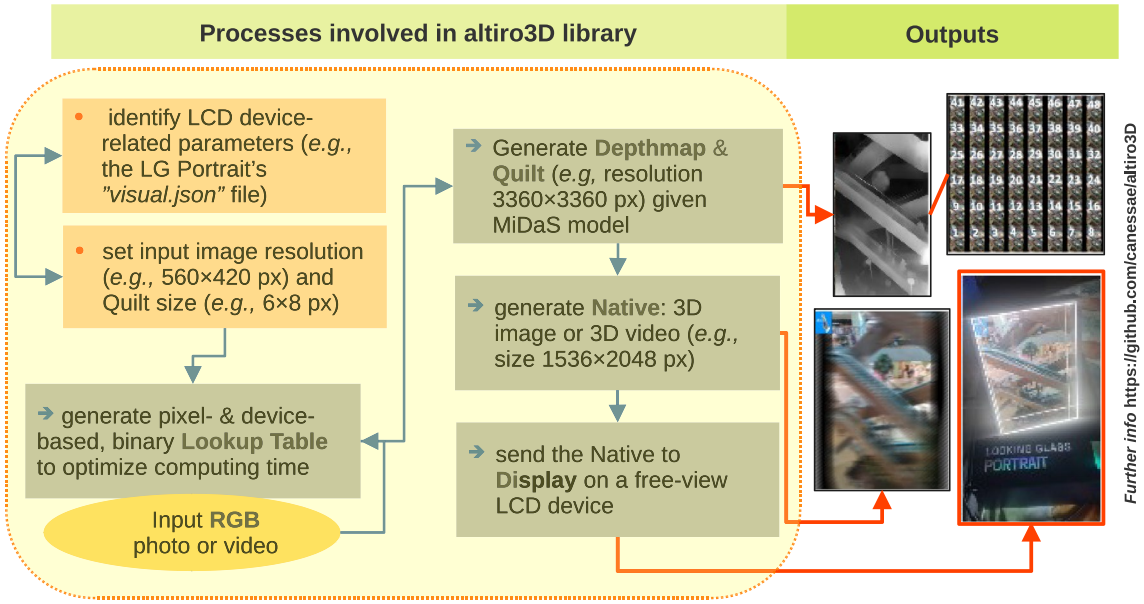
Graphical abstract **Flow diagram of altiro3D**



Keywords 3D computer vision · Light-field · Multiview · Deep convolutional neural networks

1 Introduction

There has been a growing interest in 3D scene representation and multiview synthesis using a RGB-D (color and depth) input image or a pair of stereoscopic images and their relative depth map (see e.g., [1], Morpholo [2, 3]). These efforts may lead to impressive realistic results but still incur high computational complexity, making them ill-suited to run live streaming applications. Alternative methods that have the key advantage of rendering the 3D computer reconstruction faster, are those novel methods starting from just a single, query RGB image given as the input, see e.g., [4–8]. This new possibility arises with the recent advancements in modeling the 3D visual world through the generation of depth maps from monocular images. These can be produced by convolutional neural network (CNN) models such as the so-called MiDaS (2.1 and 3.1) algorithms trained over large-scale RGB datasets (6 and 12, respectively) [7]. Tremendous progress has been done with this alternative framework in recent years [9, 10].

The purpose of this work is to introduce altiro3D[1], a new 2D-to-3D image and video conversion library for free-view LCD designed to efficiently compress all the image processing time to approach realistic 3D rendering. This is a free, extended C++ library developed to reconstruct reality starting from a still RGB image or flat video to generate a light-field (or Native) image or video and get a realistic 3D experience. In order to synthesize N-number of virtual images and add them sequentially into a $N \times M$ Quilt collage, we apply MiDaS coding for the monocular depth estimation [7], the OpenCV mapping [11] and Telea [12] inpainting techniques to map all pixels, and implement a "Fast" algorithm to mimic 3D projection and scene transformations along the synthesized N-viewpoints. altiro3D uses the degree of depth to move proportionally the pixels, assuming the original image to be at the center of all the viewpoints. altiro3D can also be used with the Depth Image Based Rendering (DIBR) algorithm to compute in-between snapshots from a equivalent "Real (slower)" camera with N-geometric viewpoints, which requires to calibrate a priori several intrinsic and extrinsic camera parameters [13]. We adopt a pixel- and device-based Lookup Table (LUT) taking into account display calibration data for specific 3D monitors. As discussed in [2, 3], the implementation of LUT allows reduction in the computing time of about 50%. The multiple viewpoints and video generated from single-shot data can be displayed in any free-view LCD display [14], such as the slanted lenticular Looking Glass (LG) Portrait [15]. The latter is a low-cost lenticular 3D device which allows to reduce loss of resolution in the horizontal direction by slanting the structure of the lenticular lens.

[1] *'altiro'*: Real Academia Española: adv. coloq. Chile. *'inmediately'* (to the point, fast).

altiro3D is implemented with the goal of minimizing the image processing time to approach real time applications in 3D streaming without the need for the viewer to wear any special 3D glasses. On the whole, altiro3D command lines allows to effectively

- Create Native (i.e., 3D image) from photo using MiDaS small.
- Create Native from photo using MiDaS large.
- Create Native from a given original RGB image and depth image.
- Create Native from a given Quilt (N×M).
- Create Native from sorted *N*-views (i.e., sequential set of plain images) stored in a given directory.
- Convert Quilt views to 2D video (.mp4).
- Convert given 2D video to Native 3D video (.mp4).

Our work leverages the advancement on 3D vision using a single image or frame and presents a framework designed for the Linux O.S. environment. Moreover, our work does not require the use of heavy computing runtime, thus can support a wide range of application scenarios in education and science, among others. The visual quality of our synthesized views provides a rather realistic immersive experience.

2 Related work: depth map from single image

As discussed in [16], monocular deep estimation networks are classified into these categories: supervised, unsupervised and self-supervised learning. The first to apply supervised learning for monocular image depth estimation were Eigen et al. [4]. Their method uses for training, the input image and the corresponding depth map to directly output the depth prediction. Semi-supervised methods can obtain the corresponding depth map by training with less data sets [17]. Unsupervised and self-supervised learning methods enables the network to perform deep predictions from unlabeled images. Some approaches pass the whole image into the network and perform convolution operation to only capture local information. This limits passing information to other sequence representations and leads to low prediction accuracy. Despite these limitations, deep learning-based monocular depth estimation that uses, e.g., CNN is a growing area of research. These are methods limited to those scenarios present in the process of training on the datasets [18, 19].

Recent review articles on the state-of-the-art development and representative algorithms for deep learning-based monocular depth estimation, which perform more accurately under the many restricted conditions, can be found in [5, 6]. They review some mainstream monocular depth estimation methods based on deep learning with examples according to different datasets training. In particular, included are a variety of supervised learning methods to address the monocular depth estimation, in terms of (i) CNN-based method: to capture depth features layer by layer through their convolution kernels and recover depth maps by deconvolution to meet the spatial features of the scene; (ii) recurrent neural network (RNN): designed to learn spatial-temporal features from video sequences; (iii) generative adversarial network (GAN): introduced to generate and discriminate between depth maps. The confrontation between a generator and discriminator function facilitates the training of the framework. These surveys also introduce publicly available datasets and evaluation metrics that have made significant contributions to monocular depth estimation.

Very recently, a biologically inspired deep learning network for monocular depth estimation has been reported in [16]. This is based on a relationship between the self-attention mechanism in biological visual systems and the monocular depth estimation network. The input to the network are normalized 3D (RGB) pixel values and information interaction is established between an encoder, decoder and self-attention fusion unit. The function of the encoder is similar to the retina, processing visual information through integration, and transmitting the information to a next-level module. The information transfer between each module in this bio-network mapping enables the deep learning network to output a depth map with rich object information and detailed information.

In our work we follow some of the ideas in [5, 6] and apply a CNN-based method. Specifically we utilize MiDaS models [7] to process an input image and produce multiple views of a scene. By estimating a reasonable accurate depth map in this way, we render synthesized views with a DIBR process [13]. Output pixels in the *N*-views are shifted copies of the input image's pixels. Unlike prior work, the depth map generated within our altiro3D algorithm is not compared against any real depth map and it serves the purpose to represent horizontal parallax upon geometric constraints between image sequences. As another difference, computing calculations are speed up by implementing a pixel- and device-based LUT as in [2, 3].

3 Implementation

The simplest hardware needed to implement altiro3D is a standard PC Computer (Intel Core i5, 64bit and at least 4 G RAM), running a recent release of Linux O.S. (22.04LT or newer) and any slanted lenticular display such as the LG Portrait [15]. This is an external HDMI video monitor which provides a novel glasses-free way to preview 3D objects and scenes within an exteded FoV.

Fig. 1 Upper left: Original RGB input photo. Upper right: Depth map obtained using MiDaS [7]. Lower left: (6×8) Quilt tile containing sequential views of a scene, starting from the bottom-left tile as the input image. Lower right: A section of the Quilt

The overall system has been developed in C++ and deeply exploits libraries Qt v.5 [20] and OpenCV v.4 [21]. The system consists in a main library, libaltiro3D, where all developed algorithms have been implemented together with a set of program tools exploiting the library routines. All important aspects of the library have been properly documented with Doxygen [22] in order to provide other users a good reference to use the library.

The present altiro3D library is an evolution of our previous Morpholo library [2, 3]. These two have been designed taking into account the naming convention used in the literature related to the field of 3D rendering and in particular, to the conventions used by the display produced by the LG. So Quilt, Native, Multiviews and other similar terms are used to identify graphical objects and processing steps inside the new altiro3D library. In addition to the algorithm to produce *N*-views feeding the holographic display, the Morpholo library implemented both routines to get info about the calibration of the target display and functions to produce the LUT in order to speed up the mapping from Quilt to Native.

With respect to the previous Morpholo library, the altiro3D library has been integrated with sources taking into account the CNN neural network inference and two new models to generate, from a single image, intermediate views. These views are used to create the Quilt and, hence, to produce the Native image. Both these steps have been

Fig. 2 A task for image inpainting: example of holes in some overall virtual digital images

optimized to speed up the processing and to approach future real-time implementations. The CNN processing exploits the capabilities provided by OpenCV to get the inference from the deep neural network (DNN) and is able to use the CUDA core, if present, or the usual CPU, as a fallback solution. Some parts of the source code (such as the creation of the views) have been optimized by using the parallel architecture provided by OpenCV. The problem image can be divided in some parts and each part can be processed by a CPU core, improving the speed.

To achieve the goal of a scene representation from single image and novel view synthesis, altiro3D (*i*) takes into account display calibration data for each specific 3D monitor (including lenticular pitches, slope, screen height and width and number of lens per inch); (*ii*) implements a one-time configuration LUT as a simple array indexing operations that save runtime computation of Eq. (1) below; (*iii*) uses the MiDaS 2.1 DNN for a robust monocular depth map estimation. Although the MiDaS 2.1 small model (included in altiro3D code) cannot provide complete depth information on distant regions. We mainly extrapolate information from nearby pixels only. Intermediate views generated using altiro3D are then added into a Quilt collage sequentially from a given $N \times M$ number of computed intermediate snapshots as shown in the example of Fig. 1.

The processes involved and repeated within altiro3D (for the creation of any Native image/frames output as shown in Fig. 1), include

- identify LCD device-related parameters (e.g., the LG Portrait's "visual.json" file)
- set input image resolution (e.g., $560 \times 420px$) and Quilt size (e.g., $6 \times 8px$)

→ generate LUT binary file (e.g., "portrait-6x8.map")

→ generate Quilt (e.g, resolution $3360 \times 3360px$) given MiDaS model

→ generate Native: 3D image or 3D video (e.g., size $1536 \times 2048px$)

→ send the Native to display on a free-view LCD device.

3.1 Calibration data from LG portrait

The device used to test the developed library is the LG Portrait holographic display. In order to proper map the pixels from Quilt image to the Native one, it is necessary to acquire the calibration of the display. As mentioned, the calibration data changes from device to device, so the calibration file is vital to produce the Native image.

The LG Portrait display provides the calibration data available from a simulated storage device accessible from the USB port. The user can connect the PC to the display to read the internal storage and to get the required file "visual.json". The internal storage is provided by a Raspberry PI embedded in the Portait display.

3.2 LUT map from calibration file, quilt and inpainting

The LG Portrait per-device calibration file is necessary to create the LUT to properly create the Native image. The altiro3D suite provides the tool altiro3Dnative to exploit the data inside the calibration file and to create the LUT. The parameters required to generate the mapping are: the resolution of each image inside the Quilt and the number of rows and columns of the Quilt. From these arguments the program produces an output file, usually with extension .map, containing the map matrix, which is crucial for the other altiro3D generation steps and for all the other provided command tools.

The LUT is created only once at the beginning of the needed device-dependent mapping. Three matrices are allocated for the color channels RGB. Each matrix provides the X coordinate of the Quilt from which one takes the corresponding value and the Y coordinate. The multiplication by 2, allows to avoid unnecessary waste of resources and consume the least possible amount of RAM memory. All positions of the pixels are considered and one then calculates the mapping value for each pixel in the Quilt image. This value is stored in the 3 different allocated matrices and each element of the matrices is made of type uint16_t. The matrices are then saved in binary format and these are reload (without recalculating) when applying the mapping to all the $N \times M$ images. This LUT procedure allows to speed up significantly the needed mapping procedure—the rendering operation of the final native image which is essentially achieved by accessing the elements of the 3 matrices to map the Quilt pixels. The resolution of the LG display system corresponds to the 1536×2048 pixels. Each of the LG Portrait devices combine light-field and volumetric technologies, and have specific display calibration values for a correct rendering. This class of lenticular, autostereoscopic display require multiple views of a scene to provide motion parallax and get a realistic 3D experience by perceiving different stereoscopic pairs.

A Quilt allows for an efficient way to store $N \times M$ images, or frames from a video, forming a collage ordered as shown in Fig. 1 Quilts serve to save disk space and fast retrieving images to be displayed. The $N \times M$ images forming the Quilt, are converted into a light-field image via the following expression for the relation between the pixels of a slanted lenticular 3D LCD and the multiple perspective views [23]

$$N_{i,j} = N_{tot}(i - i_{off} - 3_j tan(\alpha))mod(P_x)/P \quad , \tag{1}$$

where i and j denote the panel coordinates for each sub-pixel. Each sub-pixel on the 3D LCD is mapped to a certain view number and color value (i.e., in the light-field domain). N denotes the view number of a certain viewpoint, α the slanted angle between the lenticular lens and the free-view LCD panel and P_x the lenticular pitch.

The CPU time for the computer rendering of a Quilt, and especially the holographic multiview outputs, varies considerably between different interpolation algorithms used to obtain a virtual translation motion between consecutive virtual images and the inpainting techniques adopted. These include an interpolation for the approximate neighborhood pixel intensities, warping, optimization, and the inpainting of occlusions (i.e., empty spots, out-of-plane movements as shown e.g. in Fig. 2) to get an acceptable illusion of depth and parallax in the horizontal direction.

Inferring depth from a single input image and synthesizing novel views is a significant challenge because of the huge need for objects information and rich geometric details (landscape, buildings, sky, etc) [4, 24]. In addition to depth ambiguities, pixels in the generated N-views may connect invisible geometries across regions occluded in the original view causing missing data that must be handled with inpainting algorithms [25]. Image inpainting aims to fulfill those missing regions as in the image of Fig. 2 (in white) with plausible content and highly depends on the accuracy of the associated depth map.

For inpainting in the generation of multiviews within altiro3D, a default ”Fast” algorithm is implemented using opencv::remap to map all the pixels even if the output may become distorted sometimes [11]. For the "Real" generation of multiviews, giving as input an original RGB image and keeping all calibration parameters fixed, altiro3D uses Telea –an standard image inpainting technique based on the fast marching method [12].

3.3 Neural network implementation

The altiro3D library exploits the well-known MiDaS DNN to produce a reasonable depth map from a single image. The trained network is very effective and can be easily evaluated by using the DNN module of the OpenCV library. This module can read the neural network coefficients and inference in an efficient way, the depth map starting from a generic single image. The format currently used by the altiro3D library is the onnx and the DNN module is configured to prefer CUDA speed-up. If the hardware is not present, the DNN automatically switches to the CPU. The depth map can be properly re-scaled to be used in the other stages of the library where

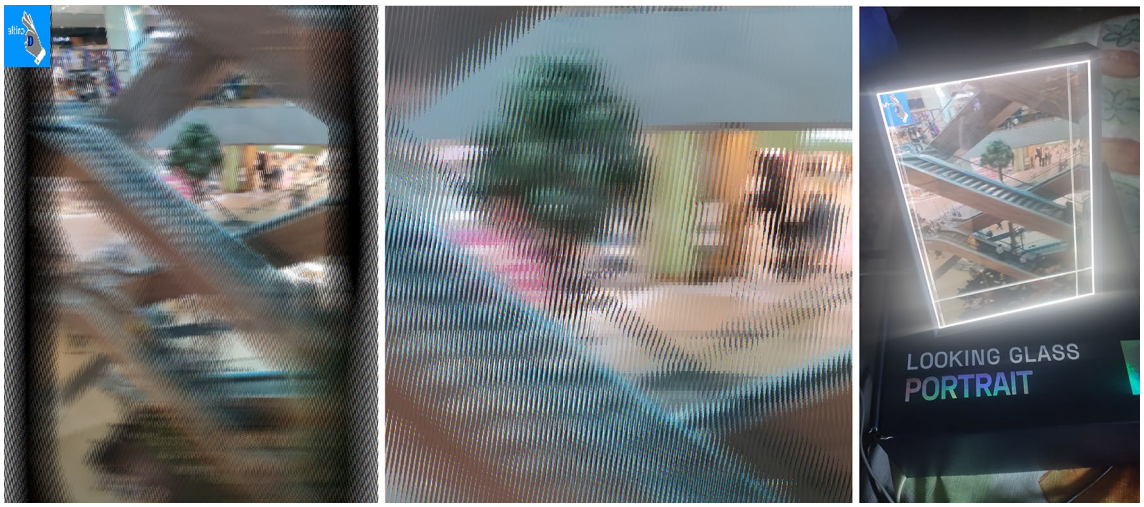


Fig. 3 Left: Multiview Native output by altiro3D library. Middle: a section of the multiview Native output. Right: 3D display on a headset-free LG Protrait [15]—see also YouTube video: https://www.youtube.com/shorts/hJDVb2TzBr0

views have to be fast generated to fill-in the Quilt image. From the Quilt image and the LUT, it is then possible to generate the output Native 3D image.

The C++ class devoted to the inference of the neural network inside the altiro3D library is Network2Quilt. This is an application of a generic class Depth2Quilt which implements the optimized reading of the network coefficients, the DNN module configuration and the creation of the depth map. Currently the class is able to exploit only the MiDaS 2.1 model-small.onnx and model-f6b98070.onnx. The source code will be updated in future releases of altiro3D to use other updated versions of MiDaS networks. From our test the small network is recommended if the speed is a crucial point.

By default, a “Fast" algorithm is adopted here to handle a 3D virtual projection camera and scene transformations along N-viewpoints. This method analyzes the (down-) degree of depth to move proportionally the pixels, assuming the original image to be at the center of all the novel views. This is achieved using the ’cv::remap’ command of OpenCV [11] by taking pixels from one place in the image and locating them in another position in a new image. This fast approach gives reasonable virtual interpretations of reality—at least, within a wide Field of View (FoV)—say, $40 - 100^o$. Generating arbitrary number of views can be sometimes cumbersome due to occlusion and opening regions leading to in-homogeneous motion fields.

In alternative to our “Fast" method for the generation of multiview images giving as input an original RGB image, altiro3D can also be used applying the DIBR algorithm [13] to synthesize N number of virtual images from a (almost equivalent) real camera with N geometric viewpoints between the original camera and the virtual camera. It requires to calibrate a priori several intrinsic and extrinsic camera for each RGB photo input.

3.4 Native image from N-views

The generation of multiview images starting from a single image (or video frame) through altiro3D can still offer a potential alternative method for fast 3D vision. Better results may be found using MiDaS 3.1 hybrid and large models, but these require extensive computations for the conversion and present limits for any real-time 3D streaming.

With such simple processes involved based on monocular (color or b/w) scene and novel view synthesis, the altiro3D library provides several different programs. While the accuracy of the present approach may not be yet competitive with other multiview stereo algorithms [1–3], our simpler line of research is particularly promising due to the availability of the diverse pre-trained models of MiDaS algorithm. Using MiDaS 2.1 (small or large) models, altiro3D creates from photo or videos frames a 3D Native image or a 3D video, respectively. The altiro3D library also allows to create Native from still N-views, i.e., sorted in sequential order and stored in a given directory, with output as in Fig. 3, and convert a given 2D video to Native 3D video (.mp4) as well.

Scaling $N \times M$ views—e.g., scaling from the (6×8) Quilt (of size $3360 \times 3360px$) to a Native image (of size $1536 \times 2048px$) with an output illustrated as in Fig. 3, leads to increase system complexity and requires lots of CPU resources. However, as we discussed in [2, 3], this problem can be reduced with the generation of a device-dependent LUT table.

The class concerning the views creation is Depth2Quilt implemented starting from the evaluated depth map and

Algorithm 1: Fast algorithm to create intermediate views

```
Require: depthMap, offset, cols, rows, origImage
Ensure: destImage
  function GetFastMapFromDepth(depthMap, offset, cols, rows)
    MapX ← 0
    MapY ← 0
    for c = 1 to cols do
      for r = 1 to rows do
        MapX[r,c]= r
        MapY[r,c]= c−depthMap[r,c]∗offset
      end for
    end for
    return MapX, MapY
  end function

  MapX,MapY ← GetFastMapFromDepth(depthMap, offset, cols, rows)
  destImage ← cv::remap(origImage, MapX, MapY)
```

from the input image view. As anticipated, the current class provides two rendering methods: “Fast" and “Real". The “Fast" method is an efficient method to fast create multiple views to feed the Quilt image. The "Fast" implementation leverages on the fast remap method provided by the OpenCV library [11]. This is a simplified method and does not use a real model based on intrinsic and extrinsic matrices of camera. There are simple approaches to estimate the focal length of a camera given the horizontal FoV and image width [26].

altiro3D simply creates a dense map to the new pose from the original image which is considered as the central image (mapped in the central position of the Quilt) and the depth as proportional to the distance. In a dual-camera depth reconstruction algorithm, the depth map is related to the difference position of the same object in the reference frames of two cameras, so called “disparity map". So the depth can be interpreted as produced by a disparity map and it can be used to remap pixels of the central image according to the depth/disparity map. The process used in our simpler “Fast" method maps pixels in the new pose accordingly and proportionally to the depth. Then the produced map is applied to the original by the OpenCV remap function which is implemented with a linear interpolation algorithm. Such interpolation algorithm avoids artifacts due to occlusion and dis-occlusion with a modest image deformation. The flow of the "Fast" algorithm is shown with pseudo-code in Algorithm 1.

Where the *depthMap* is the depthmap obtained by the MiDaS network, *offset* is a multiplicative constant controlling the output view position, *cols* and *rows* are the the width and the height of the input image, *origImage* is the image acquired by the camera. If “specular views” have to be produced, the function *GetFastMapFromDepth* has to be called twice: the first time with *offset* and the second time with *-offset*.

On the other hand, the “Real" method considered is a more sophisticated implementation of a real camera DIBR model [13]. It takes into account two matrices, intrinsic and extrinsic, to produce the new real pose. The intrinsic matrix is related to the acquisition parameters such as focal and center of camera frame, while the extrinsic matrix is related to the position and attitude of the camera frame relative to the real world frame, where the original object is located. By modifying the extrinsic camera it is possible to create a new view of the original image: the extrinsic matrix allows rotation or translation of the frame. This method takes into account the real model to get new views, but it produces more artifacts due to the occlusion and dis-occlusion effect. In order to reduce artifacts in the final view (c.f., Fig. 2), we apply an inpainting technique [12], along with a median spatial filter.

The “Real" method may be more effective, but the evaluation of view is computational intensive compared to the alternative “Fast" method, so it is not well suited for real-time implementations. To obtain geometric viewpoints between the original and virtual camera, the “Real" method also require calculation power for generating a final Native image with resolution $3360 \times 3360px$. RGB color channels for a 6×8 Quilt—such that, once the pixel to be mapped is fixed, the map value for each color channel implies separated calculations. In essence this procedure as such makes real-time video in 3D difficult to achieve.

The pseudo-code of the “Real" algorithm is summarized in Algorithm 2. In main loop the views are created according

Algorithm 2: Real algorithm to create intermediate views

```
Require: depthMap, offset, origImage
Ensure: dst1, dst2
  function GetRealMapFromDepth(origImage, depthMap, offset, K_o, R_o, K_v, R_v)
    R ← init rotation matrix
    T ← init translation vector
    T[0] ← offset
    R_v ← createExtrinsicMatrix(R, T)
    setMatrices(K_o, R_o, K_v, R_v)   ▷ To create transform from original matrices to the new virtual pose
    setInput(origImage, depthMap)     ▷ To set input image and depth
    evalTransform                     ▷ To create a new view
    return getProducedView
  end function

  for i = 1 to numberOfViews/2 do     ▷ Main loop
    offset ← position of view to be produced
    dst1 ← GetRealMapFromDepth(origImage, depthMap, offset, K_o, R_o, K_v, R_v)
    dst2 ← GetRealMapFromDepth(origImage, depthMap, -offset, K_o, R_o, K_v, R_v)
  end for
```

to the value of the *offset* parameter. Every loop produces two output images with a symmetric *offset* value. The function GetRealMapFromDepth sets all the needed structures to evaluate the transform from the single image to the required view. This function exploits a camera model composed by intrinsic and extrinsic matrix: the function generates the transformation from the original set of matrices (K_o, R_o) to the virtual pose (K_v, R_v).

4 Conclusion and future work

We introduced the altiro3D C++ library to synthesize *N*-number of virtual images and add them sequentially into a Quilt collage by applying MiDaS code for the monocular depth estimation. Novel view synthesis from a single image is carried out by using simple inpainting techniques to map all pixels, and implementing “Fast" and “Real" algorithms for the camera and scene transformations along *N*-viewpoints. A unique pixel- and device-based LUT to optimize computing time is implemented. In the absence of a LUT procedure, it would become computationally expensive and difficult to apply many techniques for real-time video in 3D.

This latter aspect of our algorithm could stimulate further investigations toward real-time 3D applications deployed from Desktop computers and/to mobile devices [27]. Streaming in real time a hologram feed is computationally demanding, because of the larger amount of information contained in the many light-fields to be streamed live, as compared to sending “realistic" frames (of monocular views) via 2D video streams. Finally, removing the dependency on stereoscopic images as input [2, 3], it makes our altiro3D algorithm more widely applicable to a larger amount of entire (historical) datasets. The generated images may be further improved by obtaining more “realistic" perspectives from recent machine learning or deep learning algorithms of MiDaS 3.1 to obtain meaningful information [7].

In future work, we want to extend the present scene static representation from a single image to a more dynamical, glasses free live 3D vision. The *N*-view synthesis of altiro3D in this case requires a fast conversion of each video frame into native light-field images, and respective Quilts, at a reasonable frame rate of at least 10*fps* in order to get a free-viewpoint real-time streaming on lenticular displays. These interesting directions have tremendous potential to be explored.

Data availability Further information, binaries, papers, presentations, manuals, or to report bugs, can be found athttps://github.com/canessae/altiro3D.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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