A Navigation Paradigm Driven Classification for Video-Based Rendering Techniques

Rafael K. dos Anjos^{a,b,*}, João Pereira^{b,c}, José Gaspar^{c,d}

^aFaculdade de Ciências Sociais e Humanas da Universidade Nova de Lisboa ^bINESC-ID Lisboa ^cInstituto Superior Técnico, Universidade de Lisboa ^dInstitute for Systems and Robotics (ISR-Lisboa)

Abstract

The use of videos as an input for a rendering process (video-based rendering, VBR) has recently been started to be looked upon with greater interest, and has added many other challenges and also solutions to classical image-based rendering (IBR). Although the general goal of VBR is shared by different applications, approaches widely differ regarding methodology, setup, and data representation. Previous attempts on classifying VBR techniques used external aspects as classification parameters, providing little insight on the inner similarities between works, and not defining clear lines of research. We found that the chosen navigation paradigm for a VBR application is ultimately the deciding factor on several details of a VBR technique. Based on this statement, this article presents the state of art on video-based rendering and its relations and dependencies to the used data representation and image processing techniques. We present a novel taxonomy for VBR applications with the navigation paradigm being the topmost classification attribute, and methodological aspects further down in the hierarchy. Different view generation methodologies, capture baselines and data representations found in the body of work are described, and their relation to the chosen classification scheme is discussed.

24

48

49

Keywords: Video-Based Rendering, Data Representation, Application, Navigation Paradigm, Free Viewpoint Video 2000 MSC: 10.020, 10.080, 20.020, 20.050, 20.090, 110

1. Introduction

For a long time video has been used in our daily lives as the 25 2 media that more closely recreates an event as we live it in the 27 3 real world. The recent popularization of personal video cam-28 4 eras and video content distribution has been pushing the scien-29 5 tific community to expand the traditional video format beyond 30 6 its classical restrictions such as reproduction speed, which gave 31 7 birth to slow motion videos, and most recently the viewpoint 32 8 restriction. The process that uses video as input in order to cre-9 ate novel rendered content is generally defined as video-based 10 rendering. This field shares goals and challenges with image-35 11 based rendering, while having the extra time dimension that is 36 12 non-existent in its counterpart. By analyzing the visual con-13 tent of these images, one tries to extract enough data to add 200 14 processed information to the existing content or to create novel 30 15 views that extrapolate the original experience. 16

Video-based rendering is a topic that combines computer 41
 graphics and computer vision; competences from both areas of 42
 knowledge are needed. A great effort is made by each com-43
 munity to build the bridge between the two areas. Video-based 44
 rendering is without a doubt a challenging field of work. 45

²² Different paradigms of user interaction have been proposed $\frac{1}{46}$ ²³ for VBR applications, each one allowing users to navigate through the content in a different manner. Thus, creating widely varying lines of work and methodologies to be followed. Each group of applications face different problems, and apply different methodologies and steps on each level of the typical VBR pipeline. Previous classification schemes presented in the past focus either on external aspects to the techniques (e.g. type of input/output, level of automation). These, however, do not present clearly identifiable classes of techniques and methodologies in which one can easily group and classify newly developed work. Moreover, previous state-of-art reviews of VBR works have used a definition that was tied to specific methodologies and data representations, which as research in this field progresses, ceases to be accurate.

This article reviews and classifies VBR works in different groups with the most high level classification parameter being the navigation paradigm, while giving insight on the chosen methodologies, data representation, and techniques in the VBR pipeline. This document will start by defining video-based rendering, the taxonomy to be used in this article, and the VBR pipeline. Followed by a state of the art report on video-based rendering applications and data representation, comparing the most popular trends and grouping similar techniques in general categories. Finally, conclusions and insight will be given on what is the current trend of research, where research should be focused for the near future, and what is there to expect from future work.

Email address: rkuffner@fcsh.unl.pt (Rafael K. dos Anjos) *URL:* https://rafaelkuffner.github.io (Rafael K. dos Anjos)

Preprint submitted to Computers & Graphics

^{*}I am the corresponding author

⁵⁰ 1.1. Video-based rendering definition

Video-based rendering is a term that has been applied to a 51 wide range of techniques, sometimes in a more broad way than 52 it usually is, and other times focused on only a specific type of 53 application. So it is important to establish the definition that 54 will be used on this survey. The term was firstly used on the 55 article by Schödl et al. [1] referring to image-based render-56 ing techniques extrapolated to the temporal domain, using two-57 dimensional images of a scene to generate a three-dimensional 58 model and render novel views of the scene. 59

The book from Magnor [2] defines video-based rendering as 60 the process of fusing image-based rendering with motion cap-61 ture in order to generate a novel view. Borgo et al. [3] on their 62 more broad survey classifies at a top level the techniques under 63 the definition of video-based graphics (a more generalist defi-64 nition for VBR), focused on creating new content (other videos 65 or 3D reconstructions) based on video input, and video visual-66 ization that would encompass the attempts of allowing the user 67 to see video from new/synthetic points of view not previously 68 recorded. 69

The survey from Stoykova et. al [4] focused only on 3D time-varying reconstruction, more in line with the classical definition of Magnor [2], and would be only a subset of the previous classification, as also Szeliski [5] who stays with the classical definition.

The common ground among all different definitions made at 75 different points in time is the shared goal of creating novel view-76 points of a certain scene, not necessarily sharing a methodology 77 as suggested by Magnor, or a specific type of input, as sug-78 gested by Borgo et al. We also consider scenarios where depth 79 information or three-dimensional models are used combined 80 with videos, since the goal of view synthesis is still shared. 81 Considering this, we define VBR as the process generating 82 novel views of a recorded event on video. 83

84 1.2. Navigation paradigm driven classification

The chosen definition accommodates a large group of works₁₀₆ 85 which have considerable differences among them. Not only₁₀₇ 86 different devices are used for input, but also processing tech-108 87 88 niques, and type of data representation will differ considerably $_{109}$ from one work to another. Due to this fact, defining clear groups₁₁₀ 89 of applications considering every applied technique is not vi-111 90 able. Few attempts of classifying VBR techniques as a whole₁₁₂ 91 have been made, with surveys commonly focusing on classify-113 92 ing each type of application or lower level techniques. 93 114

Authors have classified techniques according to taxonomies₁₁₅ based on external aspects of the application such as level of au-₁₁₆ tomation, type of output and input information [3], or had to₁₁₇ focus on a more specific domain of applications where classifi-₁₁₈ cation is simpler [4].

We found that the chosen navigation paradigm for a VBR₁₂₀ application is ultimately the deciding factor on three key aspects₁₂₁ of a VBR technique: **View generation methodology, capture setup, and data representation.** The amount of freedom that is given to the user, and the type of navigation through the novel views (which we refer to as the navigation paradigm), guides



(c) Navigation through viewpoints

(d) Free virtual camera

Figure 1: Different user interaction paradigms for VBR, which are the basis for our classification.



Figure 2: Diagram showing the used classification scheme for this survey. User interaction paradigm defines what capture setup is needed, which relates closely to view generation methodologies and data representations.

the decisions made regarding how to capture and generate the content. Four navigation paradigms were found in the reviewed literature. 1)Head-face parallax, where the user can navigate a plane parallel to the visualization plane. (Figure 1a), 2)Navigation through time, where the novel views are generated in a fixed timeline that the user can control (Figure 1b), 3)Navigation through viewpoints, where one is allowed to navigate between predefined viewpoints (Figure 1c), and 4)Free Virtual camera, where there are no positional restrictions to navigation (Figure 1d). These will be analyzed in depth in section 6.

Figure 2 shows the choices for each one of these aspects according to the user interaction paradigm of the application. By classifying the techniques according to the five possible combinations of choices that can be made, we have clear different classes of works that one can easily identify and apply to different real world problems. Each one of the described aspects and grouping of applications will be described in Section 2.

122 2. Video-based rendering applications

As stated in Section 1.1, the main objective of VBR appli-¹⁷⁶ cations is the generation of novel views. We selected sixty-one¹⁷⁷ articles from over the last 15 years which share this objective,¹⁷⁸ yet use different approaches. We sought to answer a group of¹⁷⁹ questions for each one of them:¹⁸⁰

- 128 1. What capture device was used?
- ¹²⁹ 2. Which lower level techniques were applied?
- ¹³⁰ 3. Which higher level techniques were applied?
- 4. What view generation methodology was used?
- 5. What was the data representation used for that applica-186 tion?
 - 6. What was the capture setup used?
- ¹³⁵ 7. What is the navigation paradigm applied to it?

Questions 1-3 give us insight on individual decisions each¹⁹¹ one of the works make, but did not reveal clear groups of appli-¹⁹² cations, or informed us about high level methodologies. This is¹⁹³ due to the fact that these decisions are relatively low level, and¹⁹⁴ techniques are applied with different purposes and in different¹⁹⁵ combinations, not necessarily defining an approach or applica-¹⁹⁶ tion.

Questions 4-6 are higher level decisions which clearly re-143 late to each other and allow us to classify different works into 144 categories. Methodologies for view generation (4) were iden-200 145 tified in our review, which have strong relations to other of the $_{201}$ 146 raised questions, and also allow different types of application 147 for each one of them. Data representation (5) will decide what 148 data is stored, and what can be generated in these novel views. 149 Finally, the capture setup (6) is directly related to the naviga-150 tion paradigm (7) of the application, since it decides the spatial²⁰⁴ 151 limits of the interaction. We considered these four aspects to be²⁰⁵ 152 the most relevant on defining a VBR application. Nevertheless²⁰⁶ 153 the navigation paradigm (7) was found to be the key deciding²⁰⁷ 154 factor on what approach is used, as discussed in section 6. 155

We will start by describing the different capture devices²⁰⁹ 156 used in the reviewed VBR works, since this decision trans-210 157 versely influences methodology, setup and representation. The²¹¹ 158 following sections (4 5 and 6) will describe the answers to the²¹² 159 last four questions listed before, giving insight on each one of²¹³ 160 the reviewed works, explaining its relevancy in a VBR applica-²¹⁴ 161 215 tion and the navigation paradigm in hand (Section 6). 162 216

163 3. Data capture

cations.

174

The data capture step in a VBR process will define what²¹⁹ 164 type of input information we have available for all the follow-²²⁰ 165 ing steps. The presence of either depth information, a 3D co-²²¹ 166 ordinate system or skeletal information, will directly affect the²²² 167 used data representation, and also influence the chosen view²²³ 168 generation methodology. Also, different types of devices are²²⁴ 169 225 better suited for specific types of setup baselines and naviga-170 226 tion paradigms. This aspect will be discussed in Section 6 171 Besides conventional color cameras, color-depth, laser scan-²²⁷ 172 ners, and mixed inputs have been used on VBR and IBR appli-173

175 3.1. Color cameras

181

182

183

184

185

188

189

190

Main efforts in image and video-based applications are focused on capturing images with conventional color cameras [6] [7] [8] [9] [10], not only due to the lower cost of the devices, but the popularity of the developed methodologies (code publicly available) and the amount of data already available that could be used for applications such as shown in the work of Ballan et al. [11]. Although being a bigger challenge than using more complex and informative data, it is of great interest to be able to use raw images for a VBR process, specially from mainstream media outlets.

Regarding the type of cameras suited for the VBR, there are some core requirements that should be met for the data to be useful. Data acquisition using all the cameras must be possible to trigger from an external switch so the several different sources can be synchronized, and the camera should be able to record in progressive scan mode, not interlaced half-images [2] which should be common in modern cameras. Camera resolution and recording speed are up to the application objectives, not being a general and essential parameter as the previous two. Other useful features are the ability to record raw pixel data, in order not to deal with images preprocessed by the camera internal hardware, flexible to high f-stop numbers, high dynamic range, good color properties, and other features. The book from Magnor [2] gives useful insight on some of the issues that should be considered for both image and video-based rendering.

3.2. Color depth cameras

Another input device that has been recently popularized on VBR applications is the color depth camera. It enables depth estimation to be performed reliably with a single device. Asus Xtion Pro, ZED, Intel RealSense, and most popularly The Microsoft Kinect Sensor have been used due to their real time nature and low-cost. Depth sensors were already an option on the past [12] but recently they were made more accessible and complete with other built-in functions, such as body tracking, which can be used as secondary information in some VBR scenarios. Differently from traditional laser scanners, these devices try to operate in real time, making them suited for VBR, unlike traditional scanners [13] [14] [15] which deliver high quality results, but have long capture times.

Different depth estimation techniques have been used in the commercialized devices. Infrared disparity matching [16] was used in the first Kinect sensor, where a pattern is projected to the scene and recognized by a infrared camera so the distance between recognizable features can be estimated. This was substituted by time-of-flight laser scanning in the newest sensor which has considerably higher precision. Both approaches are not set back by textureless regions as image-based stereo methods [17], but might suffer from interference from sunlight in outdoor scenarios. The ZED sensor uses stereo matching between two color cameras, which combined with spatial localization of the sensor, is able to reconstruct the environment at a higher distance, but lower precision. This approach suffers from lighting variations and low-fidelity reconstruction at

217

218

. 1400-045

textureless regions. Lightfield cameras, or plenoptic cameras 230 have also been recently made commercially accessible, and ap-231 plied to VBR in different contexts. These devices are essentially 232 composed by an array of micro-lenses and sensors, and allow 233 one to obtain precise information about the captured scene in-234 cluding depth [18]. A strong comparison can be made between 235 them, and a grid disposition of cameras [19, 20], and they have 236 both been used in similar VBR scenarios. 237

238 3.3. Hybrid input

Duan et al. [21] showed that is possible to perform fusion 239 between depth maps from stereo cameras and Kinect sensors 240 in real time, having an overall better result than using a single 241 device. The work from Goesele et al. [22] is an example of 281 242 another type mixed input that combines the raw images with an²⁸² 243 estimated bounding box for the object to be scanned. Also Bal-283 244 lan et. al [11] take other information as input such as available284 245 3D models for a prior reconstruction of the scenery and better285 246 positioning of the cameras, since the input videos are not cali-286 247 brated by default. The 3D model input does not always guaran-287 248 tee a better result, but having an initial geometry estimate does288 249 improve with the efficiency of the technique, as shown by the289 250 image-based rendering review from Shum and Kang [23]. 290 251

4. Novel view generation method

Having captured an event from one or more viewpoints, un-294 253 recorded visualizations can be generated through different pro-295 254 cesses. The chosen methodology will depend on the available²⁹⁶ 255 data (3D information, images, depth values, etc) and the desired²⁹⁷ 256 navigation paradigm (navigate freely vs. recorded viewpoints).²⁹⁸ 257 Older definitions of VBR mentioned on Section 1.1 defined²⁹⁹ 258 VBR through the used methodology. Schödl et. al [1] and Mag-300 259 nor [2] defined it as processes that necessarily required recon-³⁰¹ 260 struction. The fact that the field evolved in different directions³⁰² 261 and newer processes and applications were created, we decided³⁰³ 262 to use a definition based on goal only, and use the methodology³⁰⁴ 263 305 as one of the classification parameters of a certain work. 264

265 4.1. 3D Reconstruction and rendering

308 The classical definition of VBR was grounded on 3D recon-266 309 struction and rendering procedures to generate views [1] since 267 this resembled the traditional process to generate novel views in 268 Computer Graphics (CG). Rendering 3D models into 2D photo-269 realistic images accordingly to the position and orientation of a 270 virtual camera is a straightforward task that has been well doc-271 umented and investigated by the CG community. When 3D in-272 formation about the scene is available, any desired viewpoint 273 can be rendered through this process. The outline of this pro-274 cess can be seen in Figure 3 275

In the VBR context, the 3D reconstruction step poses a chal-³¹⁸ lenge because the initial input of the process does not com-³²⁰ monly provide three-dimensional information. The inclusion³²¹ of the recent depth sensors in the capture process could fix the³²² problem but as mentioned in Section 3, using such sensors is³²³



Figure 3: Outline of the 3D Reconstruction and rendering view generation method. Captured data is used to create different types of representations (3D Reconstruction), which are then used differently to create a 3D visualization (rendering).

not always viable, so we must still consider 3D reconstruction without direct 3D information from the input video streams.

As we are going to see next, despite of different approaches to provide 3D information for performing the 3D reconstruction, the novel view creation is accomplished by executing afterwards the classical rendering process with the available 3D models or structures that were estimated from the input.

When the focus of the application are human performers (e.g. sports and dance applications), very simplistic 3D information such as an estimated skeleton can be sufficient for novel view generation. Players are segmented from the background, and their skeletons are recognized from the poses captured in video. On the works of Gall et al. [24] and Li et al. [25], a mesh is estimated using a visual hull for the performer so it can be applied to the tracked skeleton. Stoll et al. [26] and Wu et al. [27] move this task to a pre-processing step where depth sensors are used to create an animated model of the performer. The drawback is that changes in the outfit or hair of the performer will not be supported.

Germann et al.[28] has a similar but unique approach, where the same process for estimating the skeleton is used, but instead of applying a 3D mesh to it, segmented billboards of each body part of the performer are applied to the tracked skeleton, this approach is not a pure 3D reconstruction case since the applied textures are view interpolated. We chose to describe it here due to the similarities to the previous approaches.

Volino et al. [29] and Imber et al. [30] use a initial capture of the performer to construct a texture map, which will be applied to the estimated visual hulls in each frame. A skeleton is not estimated on these works, instead a sequence of visual hulls is calculated.

Finally, the most straightforward approach to 3D reconstruction relies on directly estimating depth information from camera inputs, or depth sensors, creating complex three-dimensional structures that will be used for rendering. Zeng et al. [31] and Kuster et al. [32] use directly the input from the Microsoft Kinect for that task. Google Tango [33] and the work from Liu et al. [34] use multiview stereo to estimate depth information, and on the latter, a visual hull is used to define the limits of the human performer that is being captured, refining the MVS process.

The most recent work using this methodology was from Pagés et al. [35], which uses different sources of information

291

292

293

306



Figure 4: Outline of the View interpolation method. Optical flow between ad-375 jacent viewpoints is estimated, and interpolation is performed to create an intermediate point of view.

to create a full high quality 3D reconstruction of a recorded³⁷⁹ scene. Multiview stereo is used to estimate rough 3D coor-³⁸⁰ dinates of each pixel, which is combined with silhouette and³⁸¹ skeletal detection to refine the performers mesh. The advantage³⁸² over similar work [24, 25] is that there is no pre-processing step³⁸³ to estimate a mesh, as it is performed in real time. This allows³⁸⁴ deformable tissues and hair to be correctly reconstructed. ³⁸⁵

331 4.2. View interpolation

When the required novel views are close to a previously³⁸⁸ 332 recorded video stream, 3D reconstruction step may not be nec-389 333 essary to perform the rendering operation. Chen and Williams³⁹⁰ 334 [36] described this process on their pioneer work. This ap-391 335 proach introduced in 1993 allowed very complex scenes to be³⁹² 336 rendered through this process, since it is not reliant on the com-393 337 plexity of the objects to be rendered. Szeliski presents this³⁹⁴ 338 methodology in his survey [5] and also in his own research as³⁹⁵ 339 396 one of the basic building blocks for VBR applications. 340

The scene is captured with an array of aligned cameras, and³⁹⁷ 341 the relative position between pixels from different viewpoints³⁹⁸ 342 is estimated through the optical flow from one point to another.³⁹⁹ 343 These vectors are stored in a "morph map", a disparity matrix,⁴⁰⁰ 344 which will be used to interpolate the values between each one of 401 345 the viewpoints and generate the new images on the unrecorded⁴⁰² 346 viewpoints, as seen on Figure 4. If the changes are parallel403 347 to the viewing plane, the interpolated result is perfect. Also,⁴⁰⁴ 348 as mentioned before, the closest the images are to the original⁴⁰⁵ 349 viewpoints, the better the estimated results. 350

One relevant reference is the work from Kanade [37] about⁴⁰⁷ 351 the coverage of the Super Bowl XXXV, where the broadcast- $^{\rm 408}$ 352 ing team, instead of individual users, was able to cycle seam-353 lessly through the several cameras in the stadium to give more $^{\scriptscriptstyle 409}$ 354 insightful replays. View interpolation and a rough reconstruc-410 355 tion which is possible due to the playing field being known, are⁴¹¹ 356 used to create transition frames between cameras. A similar⁴¹² 357 recent product by Vizrt [38] has been extending the function-413 358 ality to allow not only transition between cameras but also to414 359 generate other points of view. This and similar approaches that415 360 combine traditional view interpolation with specialized infor-416 361 mation have been referred to as "view interpolation*" in Figure⁴¹⁷ 362 418 2 363

Goorts et al. [6] uses a similar methodology, but uses multiviewstereo to estimate depths for each point, and render better interpolated images. Similarly, Taguchi et al.[20], Wang et al. [39], and specially Tanimoto et al. [40] have used MVS, but in order to represent the scene in the Ray-space using the plenoptic function. This representation allows an easier generation of views given the accurate estimation of this space. Ng et al. [41] uses the same methodology but with a more object focused approach, improving the results in object boundary regions. Tanimoto et al. [40] introduced specialized devices to quickly create such representation for small scale object Similarly, recent work from Domanski et al. [42] uses this approach the chosen view generation technique when neighboring cameras are placed in an arc, not in a line (where DIBR is used). For synthetic views that are not the originally captured, an audio interpolation technique is also discussed.

One particular interpolation use case is video stitching, where closely captured sequences are used to generate a wider video. Image-stitching is a classical problem of computer vision and has been widely discussed by the community [43]. When adding a temporal dimension camera stabilization, new challenges have to be considered in the performed interpolation. Efficiency [44], color correction [45], wider baselines [46], ghosting artifacts [47], video stabilization [48] among others. These have been the main focus points in recent research, with each different algorithm and proposed technique being more suited to different type of content. Regarding our VBR definition, they can be considered borderline VBR, as most of the times no completely novel views are being created, but through distortion and interpolation of part of the data, views with wider fovs are generated.

One interesting view interpolation work that must be mentioned is the one from Ballan et al. [11] which applies this methodology for a different purpose: to navigate between casual uncalibrated captures of the same performance. A rough three-dimensional reconstruction of the background is performed using SfM to estimate each camera position. Then view interpolation is used to create transition frames between one viewpoint to the other. The performer is represented as a billboard naturally changes during transitions, and the background information is interpolated between viewpoints. This work extends the work from Kanade [37] and [38] to a more casual scenario, where the capture is performed in an uncontrolled scenario. Similarly, Lipski et al.[49] presented a similar approach where the user could navigate in time and space on interpolated views of neighboring videos.

4.2.1. Temporal interpolation

Interpolation within a single input video has been used in different VBR works as a methodology for generating novel content. The two main techniques in this category found in the revised papers are the hyperlapse, and video summarization. These methods have been referred to as "View Interpolation*" in Figure 2.

The hyperlapse appeared as an adaptation of the time-lapse videos to scenarios where the camera is moving. Time-lapse videos will typically record one frame every x seconds and

378

386

combine everything in a single video. If the camera is moving during the video capture process, it will generate unstable
videos that are unsuitable for watching. Hyperlapses will try to
temporally stabilize such videos.

The groundbreaking work of Kopf et al. [50] uses SfM 423 to create a rough reconstruction from the environment based 424 on different frames. A stable path is calculated through the 425 3D estimate of the environment, and new frames are rendered 426 through that path at the new camera positions. Using interpola-427 tion between different frames, texture information is projected 428 to the extrapolated proxy geometry, creating novel views of un-429 recorded data, based on existing frames. 430

The work from Joshi et al [51] uses purely image informa-473 431 tion to create a hyperlapse. By dropping frames that destabilize474 432 the camera flow, a smooth video is created. In this particu-475 433 lar work, new information is not created by any interpolation⁴⁷⁶ 434 method, putting it in the border line between VBR and video477 435 editing. A similar approach by Halperin et al .[52] also selects478 436 the best frames, but creates novel information by using such479 437 dropped frames to increase the field of view of the recorded480 438 video, creating unrecorded information for visualization. A481 439 similar case is the work of Lai et al. [53] which does hyper-482 440 lapses for 360 degrees videos, creating a smooth path for the⁴⁸³ 441 camera by focusing on certain points of interest throughout the484 442 video. While no unrecorded information is created, all the re-485 443 sulting frames are created through an automatic process, and the486 444 camera path is created through interpolation between different487 445 positions of subsequent 360 degrees frames. 446

Video summarization is another area where temporal inter-489 447 polation is applied and also has borderline VBR work. Differ-490 448 ent methods have been applied where frames are also selected491 449 in order to only keep only the most relevant information. De-492 450 Menthon et al. [54] does it through curve simplification, while⁴⁹³ 451 the work of Ma et al. [55] uses a user attention model to detect⁴⁹⁴ 452 which instants in the video are relevant and should be visualized495 453 as a whole, and which can be summarized. While a new video496 454 is created, no unrecorded information and visual information is497 455 produced. 456

On the other hand, the "Video Summagator" from Nguyen499 457 et al. [56] can create complete novel views while summarizing⁵⁰⁰ 458 the video. It uses the complete video information to create a⁵⁰¹ 459 3D representation of the video as a whole. The authors demon-502 460 strate scenarios where a panning camera could be used to stitch503 461 a wider background through temporal interpolation, so fore-504 462 ground elements could be visualized over a complete overview505 463 of the camera's trajectory. 464

One notable video stitching example that can be placed slightly 465 off the curve, and more in the line of other VBR applications⁵⁰⁸ 466 is the work from Agarwala et al. [57], where a single mov-509 467 ing video is used to create a panoramic texture. Both time and⁵¹⁰ 468 content are manipulated to transform a sweeping motion of a⁵¹¹ 469 camera into a wider video, manipulating the content in each512 470 different time frame to match the past, and create a seamless⁵¹³ 471 514 animation. 472 515



Figure 5: Depth Image Based Rendering. A set of 2.5D depth images is warped to create a 3D render that can be visualized from a set of positions.

4.3. Depth image-based rendering

Depth image-based rendering as a view generation methodology has been acquiring popularity in the recent years since depth data is easier to be captured or estimated with modern cameras or specified sensors. In their quality assessment work on FVV [58] Sandić-Stanković et al. consider DIBR to be the main view generation methodology applied in the field. Novel views are rendered through warping the Color Depth data into three-dimensional information, which then can be viewed through chosen viewpoints. This process, shortly named "3D warping", was introduced by McMillan [59] in his 1997 work, and is summarized in Figure 5. The work from Zitnick et. al [60] can be considered one of the recent precursors of this line of research. In this work depth is estimated through MVS and used for DIBR. The resulting dancers data set has been used as a standard benchmark in the majority of work described below.

The novel view generation methodology is the same but each group of works has focused on different aspects of the process.

Yoon et. al [61] and Muller et. al [62] have presented specific data representation for this field (5), focusing on compression of data. This line has been followed by several authors [63] [64] [65] [66] al [67] and will be discussed in Section 5.

Due to the fact that the estimated depth values might not create a complete scene due to occlusions, or depth discontinuities might exist due to differences in estimation from one viewpoint to the other, other works have focused on in-painting and hole filling. Zhu and Li's approach [68] performed hole filling through background segmentation where missing information can be recovered from other views or frames, only interpolating between neighboring pixels when necessary. Rahaman and Paul more recent work introduces Gaussian mixture models so when the 3D warped views are created and holes are filled with information from a different perspective, boundaries are less perceivable due to low correspondence between the views. Daribo and Saito [63] and Yang et. al [69] techniques have worked towards this goal using different data representations, and fitting the hole filling task in the process of representing the data.

With the recent advances in rendering capabilities of mobile devices, several works have been published in adapting DIBR to mobile platforms. The work from Shi et al. [70] from 2009 talks about rendering data in a remote location, and just request the result, since processing power on the device could be not enough for interactive view synthesis. Miao et al. [71] has

516

a different approach to minimize interaction delay, since the transmission might be slower than the generating the view locally. Their approach performs local rendering that is halted in case the result comes through the network. Most recently, Malia and Debono [72] divide frames into smaller tiles so they can be processed in different threads, since more recent devices have better processors.

Huszák [73] focused on less bandwidth use. His work describes a specialized network structure for FVV where each node can who both render and cache rendered views, so view synthesis results can be re-used by other clients, since they are stored in the network nodes. Li et al.[74] proposed a standard for LTE networks, which reduces the bandwidth in 30%, optimizing the routing of the transmitted data.

532 5. Data representation

After going through the lower steps of the VBR pipeline, 533 information about the captured scene is encoded in a suitable 534 format for the chosen rendering process. We found three groups 535 of representation in the surveyed works. Geometry based rep-536 resentations, where the scene was modeled as a group of three-537 dimensional objects along the time. Mixed representations, where 538 part of the scene is modeled through images, and part through 539 geometry. And image based representations, where the scene 540 is stored in bi-dimensional matrices with color and optionally 541 depth. 542

Although it might usually be considered just an implementation detail, the data representation on a VBR process is tightly₅₇₁ related to the chosen methodology for novel view generation,₅₇₂ and also to the desired type of application. Different representations enable the development of alternative methodologies for₅₇₄ view generation. As seen on Section 4, reconstruction was performed in different ways, all creating different types of data.

550 5.1. Geometry-based representation

577

The most straightforward way to represent a scene is through geometric primitives. It has been the go-to approach in most rendering scenarios. On VBR, they result from a 3D reconstruction process, and employed in traditional rendering to generate novel views.

Animated meshes were used in several works [24] [26] [25]₅₈₃ 556 [27] where the target of the visualization is one or more human₅₈₄ 557 performers which can be segmented properly in order to esti-558 mate the skeletons. Scenarios with large groups, occlusions, 559 and close interactions pose challenging issues. When a static 560 mesh has been captured in a previous step for that single per-561 former [26], this representation is very efficient. The recent 562 work from Pagés et al. [35] performs 3D mesh reconstruction 563 using different sources of information (MVS, pose information, 564 565 visual hull), creating complex geometric information. 592

When a skeleton can not be reliably tracked, surfaces [34]₅₉₃ [32], point clouds [33] and octrees [31] can be used. These are₅₉₄ classically used for static reconstructions, but can be applied in₅₉₅ dynamic scenarios. Although more flexible and being complete₅₉₆ representations (contain full and precise information about the



Figure 6: Two different image-based representations based on depth.

objects in the scene), they are less efficient for VBR. Applying temporal compression requires specialized algorithms [75], while image-based representations can apply video compression, which is always evolving. Geometry-based representations are usually applied in real-time applications where storage and compression is not an issue.

5.2. Image-based representation

Image-based representations are independent of scene complexity, being well suited for these scenarios. On the other hand, they are typically discrete, and do not allow certain rendering effects that require precise geometric information. Specifically for VBR, they have the advantage of enabling ordinary video compression techniques to be applied to them, which is not possible with geometry-based representations.

On several view interpolation scenarios [37] [5] [20], ordinary video streams for each recorded viewpoint are the only information about the scene in hand. Although effective, further work has shown that depth information is important not only for view-interpolation and DIBR when pursuing accurate results. Color plus depth video streams have been used for this matter [60] [69], where depth information is estimated through MVS or captured with specialized sensors.

Two other image-based representations have been presented as alternatives to RGBD streams. Multiview plus depth (MVD) by Merkle et. al [62], and the Layered depth video (LDV) by Yoon et. al[61].

Multiview plus depth coding is performed by encoding each 597 separate RGBD viewpoint as a different stream, and compres-598 sion is applied separately to each stream as illustrated on figure 599 6b. The Layered depth image format introduced by Shade et. al 600 [76] (the basis for LDV) is one of the most efficient on render-601 ing 3-D objects with complex geometries. It represents a scene 602 as viewed from a chosen point of view, but storing not only 603 color values for each pixel but also depth information and other 604 features that can be used for the rendering process. One of their 605 key characteristics is the fact that they store more than one point 606 for each pixel. Figure 6a shows an example of an LDI formed 607 from a three-dimensional object. Rays are emanated from a cer-608 tain viewpoint and intersections with an object are stored with 609 depth and color information. When the same ray goes through 610 more than one point of the object, the subsequent intersections 611 are added to the back layers. Typically the front layers are more 612 populated, with only residual information on the last layers. 613

Layered depth videos [61] extend this representation to a 614 video format, and their authors argue that is a more efficient 615 than the multiview plus depth approach on this type of setups. 616 Both use this image-based representation to apply video com-617 pression algorithms to the stream, with the difference of the 618 former (MVD) keeping every stream separate, and using them 619 to generate a new viewpoint on the viewer side, and the latter 620 (LDV) warping the scene to a single point of view, eliminat-621 ing some redundancy, but possibly losing some information due 622 to thresholding. One recently introduced alternative was the 623 Multiview layered depth image (MVLDI) [77], which applies 624 a similar process than the LDI one, but uses a global thresh-625 olding approach, not image-based. Also, each layer is encoded651 626 according to a different viewpoint. By doing this, the advan-652 627 tages of the LDI can be extended to wider baseline scenarios653 628 and more flexible navigation paradigms. 654 629

Finally, Plenoptic videos [40] [39] have been successfully655 630 employed on view-interpolation. They capture color and depth656 631 information from different viewpoints and represent it as the857 632 Plenoptic function (7D) [78], or the Lumigraph [79], its 4D₆₅₈ 633 simplification. With θ and ϕ being the azimuth and elevation₆₅₉ 634 angle of the rays, and λ the wavelength, it is calculated at a po-660 635 sition (v_x, V_y, V_z) in space, and on the VBR scenario, the func-661 636 tion is 7D due to the time component. So we have the following662 637 form to the function, which can be considered a complete scene663 638 description: 639 664

$$p = P(\theta, \phi, \lambda, V_x, V_y, V_z, t) \tag{1}_{666}$$

640

Although it is a complete scene description, on a real sce-641 nario we cannot capture the scene from every possible view-642 point. In practice, data is captured with a narrow grid with 670 643 several cameras, or cameras based on arrays of micro-lenses 644 (plenoptic or light field cameras). This representation is used by $_{_{672}}$ 645 sampling this function at the eye positions (v_x, V_y, V_z) represent-646 ing the capture viewpoints, and interpolating the values given 647 by each one of them to generate intermediate views. Such rep-648 resentation is promising for 3D television, but is still far from 649 being accessible for research. 650 677



(c) Visual hull + Texture-maps

Figure 7: Mixed representations with part represented by a geometric reconstruction, and part by sequences of images.

5.3. Mixed representation

Although MVD and LDI contain geometric information in the form of depth values, we still consider them as image-based representations due to the fact that they are stored as images, and warping needs to be performed during rendering to obtain the three-dimensional values. Examples in this category are partly represented by sequences of images, and partly by geometry.

As mentioned in section 4.1 Germann et. al [28] uses articulated billboards (Figure 7a). Skeleton information (geometry) is stored alongside images which are interpolated and applied to each skeleton. Also the approaches from Volino et al. [29] and Imber et al.[30], which use a simplified mesh through a visual hull (geometry) combined with sequences of textures (images) that are mapped into it (Figure 7c). Ballan et. al [11] has a similar approach but keeping the background geometry static since it is only used to track positions of each viewpoint in order to generate the transitions (Figure 7b).

Finally Ng et. al [41] use the Plenoptic function representation, but segmented to individual objects in the scene, which can be considered a mixed representation, due to the fact that individual objects in the scene are separated from each other, making the representation more tied to the content of the scene than other image-based representations.

All of these representations aim to combine advantages from both worlds. Having three-dimensional representation allow one to generate novel viewpoints further away from the original recording points, and using image-based representations,

678

665

data compression is considerably easier to be applied, and therase
representation complexity is scene independent. It is impor-ras
tant to notice though, that in all of the reviewed works, strongrad
assumptions about the storing content needed to be made. Typ-ras
ically these were used to represent human performers in con-rase
trolled conditions, such as a studio capture setup, or a sportsrar
event where the layout and the captured elements are known. 738

6. Baseline of the data acquisition setup, and navigation paradigm

Multi input setups are the typical scenario for VBR. Only⁷⁴³ 688 a small portion of the surveyed works have used a single in-744 689 put camera, and could be classified as VBR. Devices can be745 690 placed in a narrow, wide, or semi wide-baseline setup as seen746 691 on Figure 8. In a narrow set up, the cameras are placed closer to⁷⁴⁷ 692 each other with little disparity between adjacent views, usually⁷⁴⁸ 693 with each device parallel to each other. A wide setup typically⁷⁴⁹ 694 aims to capture a scene or object from all different perspectives,⁷⁵⁰ 695 having the cameras placed further away from each other, where751 696 disparity between views is now desired, not avoided. The semi-752 697 wide scenario would be a step in between where disparity is⁷⁵³ 698 avoided but different viewpoints are desired. 699

On multi-streams approaches there is also the need of ex-755 700 trinsic calibration for the cameras, i.e. know the relative po-756 701 sitions between them. In controlled environments this can be757 702 done by using markers detected by the camera [80] [9], but on⁷⁵⁸ 703 dynamic environments the most common approach is to track759 704 features using structure from motion [11, 81, 82], providing a⁷⁶⁰ 705 reliable position calibration for the camera. When depth cam-761 706 eras are used, specific systems that take advantage of higher⁷⁶² 707 level information have been proposed, as in the work of Sousa 708

et al. [83] where skeleton information is used to quickly cal-⁷⁶³
ibrate a group of Kinect sensors, and point cloud information⁷⁶⁴
is used to fine-tune the resulting calibration. A parallel prob-⁷⁶⁵
lem to this is the stream synchronization problem, which can be⁷⁶⁶
solved by an external centralized trigger on controlled scenar-⁷⁶⁷
ios [9] [6]. Audio stream aligned can be used on uncontrolled⁷⁶⁸
scenarios [21] [11].

Although the general goal of VBR is the same across appli-770 716 cations, each one of them have different specific goals depend-771 717 ing on the desired navigation paradigm, as seen on Figure 1.772 718 On all reviewed works, we found that navigation paradigm is773 719 tightly connected to the capture setup. According to the objec-774 720 tive of the application, the setup will be adapted, and all other775 721 factors mentioned previously are then a consequence of this de-776 722 cision. Due to this fact, this section groups each work by the777 723 camera setup, and explain the typical application for each setup,778 724 and how it relates to the previously raised questions. 779 725

6.1. Narrow baseline applications: Head-face parallax

One navigation paradigm associated to a free viewpoint vide⁷⁸³
 consists of a moving user in front of a screen while having the⁷⁸³
 perception of depth through parallax. By adjusting the view-⁷⁸⁴
 point to the position of the user's eyes, this effect is possible.⁷⁸⁵
 Since the user performs movements in a parallel plane to the

captured scene, novel views only need to be generated in this domain. For this purpose, a narrow capture setup parallel to the captured scenario will suffice for the desired results. Figure 9 summarizes this application group.

When a narrow capture setup is used, cameras and/or depth sensors are arranged in a line [60] or in a grid [20, 19], according to the freedom of choice of views provided by the application. Here we also consider lightfield capture and plenoptic cameras. A close comparison can be made between them and a grid narrow-baseline disposition, as mentioned in Section 3, and they have been successfully used to generate novel views in a head-face parallax scenario [84]. This setup is ideal for a performance type of recording, where the audience is supposed to be facing a stage from a certain direction.

Methodologies such as view interpolation (VI) and DIBR have good performance in this scenario due to the small disparity between adjacent viewpoints. Applications that perform video stitching also fall in this category, where the user either visualizes the whole stitched video, or has a head-face parallax experience. 3D reconstruction will create incomplete results, since only one side of the object is being captured. VI has been used when depth estimation is not reliable enough for rendering, but used sometimes as an aid to the interpolation process.It was also applied when lightfield reconstruction is performed, as mentioned in Section 4.2. DIBR have been used in all other works reviewed in this survey.

All strategies for this setup have used image-based representations because they are meant to work on any kind of data with no expected restrictions, and as mentioned previously, imagebased representations are independent of the complexity of the scene.

6.2. Semi-wide baseline applications: Navigation through viewpoints

A small subset of works reviewed in this survey aims a similar experience to wider setups, where the user can navigate in a full circle around a scene, but the content of the visualization is more complex than having a single performer. Similarly to wide setups with mixed representations, strong assumptions can be made about the content, but the type of result desired is closer to narrow baseline applications. Either navigating through camera viewpoints, or generating intermediate viewpoints but not widely far from the defined grid of visualization. For this sense, a "less narrow", or "semi-wide" setup is used (Figure 10).

Instead of performing 3D reconstruction with view interpolation in some components such as the work from Volino et. al with articulated billboards [29], the preferred approach is view interpolation supported by three-dimensional information about the scene (marked with a * in Figure 2). On sports scenarios [37] [11] [38], this information has been used to generate transition frames between viewpoints. Given the fact that the reconstruction is rough, the user never gets to properly visualize intermediate frames. The remaining works in this category [41] [6] create intermediate viewpoints, but use background geometry information to support this view generation process.

780

781



(a) Narrow setup with color cameras for stereo (b) Wide baseline of a low-cost setup for a 360 matching degrees capture of a subject.

Figure 8: Different capturing setups for VBR with different input devices.

809

810

819

820





Figure 10: Navigation through viewpoints applications

6.3. Single camera capture applications: Navigation through
 time





In the works where only a single viewpoint is captured,₈₂₁ novel views can only be generated by temporal interpolation,822 789 extrapolating the data captured by that single viewpoint [50, 56]₈₂₃ 790 In this case, the user experience is similar to watching a nor-791 mal video, albeit seeing novel rendered images or modified₈₂₅ 792 perspectives. Some of the works in this category are difficult₈₂₆ 793 to compare to other VBR works, due to the fact that a true₈₂₇ 794 novel view is sometimes not created, but merely chosen from 795 a group of available views. Also due to the fact that the naviga-796 tion paradigm does not change much from a traditional video.828 797 However, since novel content is created and such works are tra-798 ditionally considered to be VBR works, we include them in our 799 classification as their own category (Figure 11). 800

The data representation applied in these works is typically image-based, with certain works [50, 53] using it to estimate a proxy geometry, making their data representation mixed. Mixed representation will typically support more complex systems which is able to generate more novel content.

6.4. Wide baseline applications: Free virtual camera



Figure 12: Free-camera navigation applications

When the created application aims to generate novel views all around the subject of visualization, and not only on a parallel plane in front of it, a wide setup must be used (Figure 12). Interaction with the video is usually done indirectly, moving a virtual camera freely around the point of interest.

This type of setup has been used on scenarios where the focus of the video are human performers in a controlled environment [24] [26] [25] [85].

A wide-baseline setup can be comparable to a single depth sensor moving widely around a scene for static reconstruction purposes [34] [33], since the camera will end up assuming positions equivalent to a wide-baseline setup.

Because the viewpoint disparity is too high for view interpolation and DIBR, 3D reconstruction was the methodology applied in all of the surveyed works. Regarding data representation, when stronger assumptions about the content of the scenes could be made such as in sports scenarios, or controlled environments, mixed representations could be used [28] [29] [30]. All the remaining papers in this category used different geometry-based representations. Figure 9 shows the different choices that can be made in this application group.

7. Conclusion and future trends



Figure 13: Classes of applications (setup, representation, view generation methodology) placed on a straight line according to the similarities between their approaches regarding to geometry used in their data representation.

(c) Semi-Wide baseline setup for Sports

As explained in Section 1.2 and seen on Figure 2 the different works can be separated in a hierarchy according to the aspects reviewed above. Each navigation paradigm is closely tied to a camera setup, and to one or two methodologies or data representations. These two aspects are chosen according to the type of data to be captured.

Summarizing the reviewed aspects, DIBR and View inter-835 polation have been used in uncontrolled scenarios, where image BOS 836 based representations can be applied. When strong assumptions893 837 can be made about the scene in hand, mixed representations⁸⁹⁴ 838 have been used for view interpolation or 3D reconstruction. 839 Geometry based representations have been applied on generic₈₉₇ 840 scenarios with low requirements regarding quantity of data, or898 841 when the subject of the free viewpoint video was a human per-899 842 former in a controlled environment. Finally, view interpolation³⁰⁰₉₀₁ 843 in the form of timely interpolation has been used primarily for₉₀₂ 844 845 single camera setups.

The presented classification for VBR groups different ap-⁹⁰⁴₉₀₅ proaches not only into clearly identifiable classes that share₉₀₆ methodologies and problems, but also gives meaningful insight₃₀₇ on how they operate on the traditional VBR pipeline. Figure⁹⁰⁸ 13 organizes the reviewed classes in a straight line according to⁹⁰⁹₉₁₀ similarity between each approach.

With our navigation paradigm driven taxonomy, four dif-912 852 ferent classes which have their own line of research were iden-913 853 tified. Despite of the fact that they share similar techniques, $\frac{914}{915}$ 854 each one aims to solve different application requirements. We₉₁₆ 855 have noticed that geometrical information, including depth val-917 856 ues, plays an increasingly important role in the three classes.918 857 This is justified by the hardware advances, namely, more pow-858 erful graphic cards and low-cost depth sensors availability. Ap-921 859 proaches such as view-interpolation were initially a solution to922 860 complex scenes in VBR since full geometry could not be pro-923 861 cessed in real time to generate views. We believe 3D recon-862 struction will increase even more their relevance in this field as₉₂₆ 863 a methodology. 864

DIBR has been a good example of an approach that inte-928 865 grates well the geometric component because it is able to apply $\frac{1}{930}$ 866 image-based representations which can be easily compressed in931 867 the temporal domain for transmission. With the continuously⁹³² 868 increasing requirements regarding viewing resolution, these as-869 pects will become more significant. Successful data representa-870 tions for future VBR applications have to include compression936 871 mechanisms, as has been seen in the growing body of work937 872 938 which adapts DIBR to mobile phones and networks. 873 939

874 Acknowledgments

This work was supported by the European Research Coun-⁹⁴³ cil under the project (Ref. 336200). This work was also sup-⁹⁴⁴ ported by national funds through FCT - Fundação para a Ciência₈₄₆ e Tecnologia, with reference UID/CEC/50021/2013. 947

879 **References**

 [1] Schödl, A., Szeliski, R., Salesin, D.H., Essa, I.. Video tex- ¹⁰⁵/₉₅₂
 tures. In: Proceedings of the 27th Annual Conference on Com-¹⁰⁵/₉₅₂
 puter Graphics and Interactive Techniques. SIGGRAPH '00; New York, NY, USA: ACM Press/Addison-Wesley Publishing Co. ISBN 1-58113-208-5; 2000, p. 489-498. doi:10.1145/344779.345012. URL http://dx.doi.org/10.1145/344779.345012.

- [2] Magnor, M.. Video-based rendering. Ak Peters Series; A K Peters; 2005. ISBN 9781568812441. URL http://books.google.com.br/books?id=RbWz0CocpbMC.
- [3] Borgo, R., Chen, M., 1Daubney, B., Grundy, E., Heidemann, G., Höferlin, B., et al. State of the art report on videobased graphics and video visualization. Computer Graphics Forum 2012;31(8):2450-2477. doi:10.1111/j.1467-8659.2012.03158.x. URL http://dx.doi.org/10.1111/j.1467-8659.2012.03158.x.
- [4] Stoykova, E., Alatan, A., Benzie, P., Grammalidis, N., Malassiotis, S., Ostermann, J., et al. 3-d time-varying scene capture technologies, a survey. Circuits and Systems for Video Technology, IEEE Transactions on 2007;17(11):1568–1586. doi:10.1109/TCSVT.2007.909975.
- [5] Szeliski, R.. Video-based rendering. In: 2nd European Conference on Visual Media Production. The Institution of Electrical Engineers, Savoy Place, London, UK; 2005, p. 1–8.
- [6] Goorts, P., Ancuti, C., Dumont, M., Rogmans, S., Bekaert, P., Real-time video-based view interpolation of soccer events using depthselective plane sweeping. In: Proceedings of the Eight International Conference on Computer Vision Theory and Applications. ISBN 978-989-8565-48-8; 2013,.
- [7] Hauswiesner, S., Straka, M., Reitmayr, G.. Coherent image-based rendering of real-world objects. In: Symposium on Interactive 3D Graphics and Games. I3D '11; New York, NY, USA: ACM. ISBN 978-1-4503-0565-5; 2011, p. 183–190. doi:10.1145/1944745.1944776. URL http://doi.acm.org/10.1145/1944745.1944776.
- [8] Furukawa, Y., Ponce, J.. Accurate, dense, and robust multiview stereopsis. Pattern Analysis and Machine Intelligence, IEEE Transactions on 2010;32(8):1362-1376. doi:10.1109/TPAMI.2009.161.
- [9] Carranza, J., Theobalt, C., Magnor, M.A., Seidel, H.P., Free-viewpoint video of human actors. ACM Trans Graph 2003;22(3):569-577. doi:10.1145/882262.882309. URL http://doi.acm.org/10.1145/882262.882309.
- [10] Vogiatzis, G., Hernández, C.. Video-based, real-time multi-view stereo. Image and Vision Computing 2011;29(7):434 – 441. doi: 10.1016/j.imavis.2011.01.006.
- [11] Ballan, L., Brostow, G.J., Puwein, J., Pollefeys, M.. Unstructured video-based rendering: interactive exploration of ACM Trans Graph 2010;29:87:1casually captured videos. doi:http://doi.acm.org/10.1145/1778765.1778824. 87:11. URL http://doi.acm.org/10.1145/1778765.1778824
- [12] Curless, B., Levoy, M.. A volumetric method for building complex models from range images. In: Proceedings of the 23rd annual conference on Computer graphics and interactive techniques. SIGGRAPH '96; New York, NY, USA: ACM. ISBN 0-89791-746-4; 1996, p. 303–312. doi:10.1145/237170.237269. URL http://doi.acm.org/10.1145/237170.237269.
- [13] Koutsoudis, A., Vidmar, B., Ioannakis, G., Arnaoutoglou, F., Pavlidis, G., Chamzas, C.. Multi-image 3d reconstruction data evaluation. Journal of Cultural Heritage 2014;15(1):73 – 79. doi: http://dx.doi.org/10.1016/j.culher.2012.12.003.
- [14] Huang, H., Brenner, C., Sester, M.. A generative statistical approach to automatic 3d building roof reconstruction from laser scanning data. {ISPRS} Journal of Photogrammetry and Remote Sensing 2013;79(0):29 - 43. doi:http://dx.doi.org/10.1016/j.isprsjprs.2013.02.004.
- [15] Besl, P. Active, optical range imaging sensors. Machine Vision and Applications 1988;1(2):127-152. doi:10.1007/BF01212277. URL http://dx.doi.org/10.1007/BF01212277.
- [16] Arieli, Y., Freedman, B., Machline, M., Shpunt, A.. Depth mapping using projected patterns. 2012. US Patent 8,150,142.
- [17] Lee, S., Ho, Y.. Real-time stereo view generation using kinect depth camera. APSIPA ASC 2011;:1–4.
- [18] Bishop, T.E., Favaro, P. Plenoptic depth estimation from multiple aliased views. In: 2009 IEEE 12th International Conference on Computer Vision Workshops, ICCV Workshops. 2009, p. 1622–1629. doi: 10.1109/ICCVW.2009.5457420.
- [19] Zhang, C., Chen, T. A self-reconfigurable camera array. In: ACM SIGGRAPH 2004 Sketches. ACM; 2004, p. 151.
- [20] Taguchi, Y., Takahashi, K., Naemura, T.. Real-time all-in-focus video-

940

941

942

949

950

- based rendering using a network camera array. In: 2008 3DTV Conferto25 954 ence: The True Vision - Capture, Transmission and Display of 3D Video1026 955 2008, p. 241-244. doi:10.1109/3DTV.2008.4547853. 956
- [21] Duan, Y., Pei, M., Wang, Y.. Probabilistic depth map fusion of 028 957 kinect and stereo in real-time. In: Robotics and Biomimetics (RO4029 958 BIO), 2012 IEEE International Conference on. 2012, p. 2317-2322. doit030 959 10.1109/ROBIO.2012.6491315. 960

- Goesele, M., Curless, B., Seitz, S., Multi-view stereo revis+032 [22] 961 ited. In: Computer Vision and Pattern Recognition, 2006 IEEE033 962 Computer Society Conference on; vol. 2. 2006, p. 2402-2409. doi1034 963 10.1109/CVPR 2006.199 964 1035
- [23] Shum, H., Kang, S.B.. Review of image-based rendering techniques. Into36 965 VCIP. 2000, p. 2–13. 966 1037
- Gall, J., Stoll, C., de Aguiar, E., Theobalt, C., Rosenhahn, B., Seidel1038 967 [24] H.P.. Motion capture using joint skeleton tracking and surface estimation1039 968 In: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE040 969 Conference on. 2009, p. 1746-1753. doi:10.1109/CVPR.2009.5206755.1041 970
- [25] Li, G., Wu, C., Stoll, C., Liu, Y., Varanasi, K., Dai, Q., et al1042 971 Capturing relightable human performances under general uncontrolledo43 972 973 illumination. Computer Graphics Forum 2013;32(2pt3):275-284. doi1044 10.1111/cgf.12047. URL http://dx.doi.org/10.1111/cgf.120471045 974
- 975 [26] Stoll, C., Gall, J., de Aguiar, E., Thrun, S., Theobalt, C.. Video+046 based reconstruction of animatable human characters. ACM Trans047 976 Graph 2010;29(6):139:1-139:10. doi:10.1145/1882261.1866161. URL1048 977 http://doi.acm.org/10.1145/1882261.1866161. 978 1049
- 979 [27] Wu, C., Stoll, C., Valgaerts, L., Theobalt, C.. On-set perforto50 mance capture of multiple actors with a stereo camera. ACM Transost 980 Graph 2013;32(6):161:1-161:11. doi:10.1145/2508363.2508418. URL1052 981 http://doi.acm.org/10.1145/2508363.2508418. 982 1053
- R., Ziegler,054 [28] Germann, Keiser. 983 M., Hornung, A., Würmlin, S., Gross, Articulated billboards055 984 R., M.. video-based rendering. Computer Graphics Forum056 for 985 2010;29(2):585–594. doi:10.1111/j.1467-8659.2009.01628.x. 986 URI1057 http://dx.doi.org/10.1111/j.1467-8659.2009.01628.x. 987 1058
- [29] Volino, M., Hilton, A.. Layered view-dependent texture maps. Into59 988 Proceedings of the 10th European Conference on Visual Media Pro+060 989 990 duction. CVMP '13; New York, NY, USA: ACM. ISBN 978-1-45034061 2589-9; 2013, p. 16:1-16:8. doi:10.1145/2534008.2534022. URL1062 991 http://doi.acm.org/10.1145/2534008.2534022. 992
- [30] Imber, J., Volino, M., Guillemaut, J.Y., Fenney, S. Hilton1064 993 A.. Free-viewpoint video rendering for mobile devices. In: Pro+065 994 ceedings of the 6th International Conference on Computer Vision /066 995 Computer Graphics Collaboration Techniques and Applications. MI+067 996 RAGE '13; New York, NY, USA: ACM. ISBN 978-1-45034068 997 2023-8; 2013, p. 11:1-11:8. doi:10.1145/2466715.2466726. URL1069 998 http://doi.acm.org/10.1145/2466715.2466726. 999 1070
- [31] Zeng, M., Zhao, F., Zheng, J., Liu, X.. Octree-based fusion forora 1000 realtime 3d reconstruction. Graphical Models 2013;75(3):126 - 1361072 1001 doi:http://dx.doi.org/10.1016/j.gmod.2012.09.002. Computational Visualo73 1002 Media Conference 2012. 1003
- [32] Kuster. C., Bazin, J.C., Öztireli, C., Deng, T., Martin1075 1004 T., Popa, 1005 T., et al. Spatio-temporal geometry fusion for mul+076 tiple hybrid cameras using moving least squares surfaces. Com+077 1006 puter Graphics Forum 2014;33(2):1-10. doi:10.1111/cgf.12285. URL1078 1007 http://dx.doi.org/10.1111/cgf.12285. 1008
- [33] Google, . Project tango. https://www.google.com/atap/projecttango/projecttago 1009 2014. 1010 1081
- Liu, Y., Dai, Q., Xu, W.. A point-cloud-based multiview stereo al4082 1011 [34] gorithm for free-viewpoint video. Visualization and Computer Graphics1083 1012 IEEE Transactions on 2010;16(3):407-418. doi:10.1109/TVCG.2009.881084 1013
- [35] Pagés, R., Amplianitis, K., Monaghan, D., Ondřej, J., Smolić, A., Aftoss 1014 fordable content creation for free-viewpoint video and vr/ar applications1086 1015 Journal of Visual Communication and Image Representation 2018;53:192087 1016 - 201. doi:https://doi.org/10.1016/j.jvcir.2018.03.012. 1088 1017
- Chen, S.E., Williams, L.. View interpolation for image synthesis. In1089 1018 [36] 1019 Proceedings of the 20th Annual Conference on Computer Graphics and090 Interactive Techniques. SIGGRAPH '93; New York, NY, USA: ACM1091 1020 ISBN 0-89791-601-8; 1993, p. 279-288. doi:10.1145/166117.1661531092 1021 URL http://doi.acm.org/10.1145/166117.166153. 1022 1093
- [37] Т.. Carnegie mellon goes to the super bowl1094 Kanade. 1023 http://www.ri.cmu.edu/events/sb35/tksuperbowl.html.; 2001. 1024 1095

- [38] Libero, V.. Viz libero: Sports broadcasting redefined. http://www.vizrt.com/products; 2014.
- Wang, C., Chan, S.C., Ho, C.H., Liu, A.L., Shum, H.Y.. A real-time [39] image-based rendering and compression system with kinect depth camera. In: 2014 19th International Conference on Digital Signal Processing. 2014, p. 626-630. doi:10.1109/ICDSP.2014.6900740.
- [40] Tanimoto, M.. Ftv: Free-viewpoint television. Signal Pro-Image Communication 2012;27(6):555 -570 cessing: doi: http://dx.doi.org/10.1016/j.image.2012.02.016. URL v.
- [41] Ng, K., Chan, S., Wu, Q., Shum, H.. Object-based coding for plenoptic videos IEEE Transactions on Circuits and Systems for Video Technology 2010;:2-s2.0-77951122418doi:10.1109/TCSVT.2010.2041820. URL http://hdl.handle.net/10722/128744.
- [42] Domański, M., Bartkowiak, M., Dziembowski, A., Grajek, T., Grzelka, A., Łuczak, A., et al. New results in free-viewpoint television systems for horizontal virtual navigation. In: 2016 IEEE International Conference on Multimedia and Expo (ICME). 2016, p. 1-6. doi: 10.1109/ICME.2016.7552993.
- Adel, E., Elmogy, M., Elbakry, H.. Image stitching based on feature [43] extraction techniques: a survey. International Journal of Computer Applications (0975-8887) Volume 2014;.
- Hu, J., Zhang, D.Q., Yu, H., Chen, C.W.. Discontinuous seam [44] cutting for enhanced video stitching. In: 2015 IEEE International Conference on Multimedia and Expo (ICME). 2015, p. 1-6. doi: 10.1109/ICME.2015.7177506.
- Xu, W., Mulligan, J.. Performance evaluation of color correction ap-[45] proaches for automatic multi-view image and video stitching. In: 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. 2010, p. 263-270. doi:10.1109/CVPR.2010.5540202.
- [46] Li, J., Xu, W., Zhang, J., Zhang, M., Wang, Z., Li, X.. Efficient video stitching based on fast structure deformation. IEEE Transactions on Cybernetics 2015;45(12):2707-2719. doi:10.1109/TCYB.2014.2381774.
- Jiang, W., Gu, J.. Video stitching with spatial-temporal content-[471 preserving warping. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). 2015, p. 42-48. doi: 10.1109/CVPRW.2015.7301374.
- T., Zhu, S., Zeng, B., Gabbouj, [48] Guo, H., Liu, S., He, Joint video stitching and stabilization from moving cameras. M., IEEE Transactions on Image Processing 2016;25(11):5491-5503. doi: 10.1109/TIP.2016.2607419.
- [49] Lipski, C., Linz, C., Berger, K., Sellent, A., Magnor, M.. Virtual video camera: Image-based viewpoint navigation through space and time. Computer Graphics Forum 2010;29(8):2555-2568. doi:10.1111/j.1467-8659.2010.01824.x.
- [50] Kopf, J., Cohen, M.F., Szeliski, R.. Firsthyper-lapse videos. ACM Trans Graph person 2014;33(4):78:1-78:10. doi:10.1145/2601097.2601195. URL http://doi.acm.org/10.1145/2601097.2601195.
- [51] Joshi, N., Kienzle, W., Toelle, M., Uyttendaele, M., Cohen, Real-time hyperlapse creation via optimal frame selection. M.F.. ACM Trans Graph 2015;34(4):63:1-63:9. doi:10.1145/2766954. URL http://doi.acm.org/10.1145/2766954.
- Y., Arora, C., Peleg, [52] Halperin. T., Poleg, S.. Egosampling: Wide view hyperlapse from egocentric videos. IEEE Transactions on Circuits and Systems for Video Technology 2017;:1-1doi: 10.1109/TCSVT.2017.2651051.
- [53] W., Huang, Y., Joshi, N., Buehler, C., Yang, Lai, M., S.B.. Semantic-driven generation of hyperlapse from 360 Kang, degree video. CoRR 2017;abs/1703.10798. 1703.10798: URL http://arxiv.org/abs/1703.10798.
- [54] DeMenthon, D., Kobla, V., Doermann, D.. Video summarization by curve simplification. In: Proceedings of the Sixth ACM International Conference on Multimedia. MUL-TIMEDIA '98; New York, NY, USA: ACM. ISBN 0-201-30990-4; 1998, p. 211–218. doi:10.1145/290747.290773. URL http://doi.acm.org/10.1145/290747.290773.
- Ma, Y.F., Lu, L., Zhang, H.J., Li, M.. A user attention model for video [55] summarization. In: Proceedings of the Tenth ACM International Conference on Multimedia. MULTIMEDIA '02; New York, NY, USA: ACM. ISBN 1-58113-620-X; 2002, p. 533-542. doi:10.1145/641007.641116. URL http://doi.acm.org/10.1145/641007.641116.

- 1096 [56] Nguyen, C., Niu, Y., Liu, F.. Video summagator: An int167
 1097 terface for video summarization and navigation. In: Proceedings168
 1098 of the SIGCHI Conference on Human Factors in Computing Syst169
 1099 tems. CHI '12; New York, NY, USA: ACM. ISBN 978-1-45034170
 1015-4; 2012, p. 647–650. doi:10.1145/2207676.2207767. URL171
 1011 http://doi.acm.org/10.1145/2207676.2207767. 1172
- [57] Agarwala, A., Zheng, K.C., Pal, C., Agrawala, M., Cohen;173 1102 B., et al. Panoramic video textures. M., Curless, In: ACM174 1103 SIGGRAPH 2005 Papers. SIGGRAPH '05; New York, NY, USA1175 1104 ACM; 2005, p. 821-827. doi:10.1145/1186822.1073268. URI1176 1105 http://doi.acm.org/10.1145/1186822.1073268. 1106 1177
- Sandić-Stanković, D., Battisti, F., Kukolj, D., Callet, P.L., Carli₁₁₇₈
 M.. Free viewpoint video quality assessment based on morpholog₁₁₇₉
 ical multiscale metrics. In: 2016 Eighth International Conference₁₈₀
 on Quality of Multimedia Experience (QoMEX). 2016, p. 1–6. doi1181
 10.1109/QoMEX.2016.7498949.
- 1112[59]McMillan, L.. An image-based approach to three-dimensional computer1113graphics. Ph.D. thesis; Citeseer; 1997.1184
- III4
 [60]
 Zitnick, C.L., Kang, S.B., Uyttendaele, M., Winder, S., Szeliski₁₁₈₅

 III5
 R. High-quality video view interpolation using a layered representation₁₁₈₆

 III6
 In: ACM SIGGRAPH 2004 Papers. SIGGRAPH '04; New York, NY₁₁₈₇

 III7
 USA: ACM; 2004, p. 600–608. doi:10.1145/1186562.1015766. URL188

 http://doi.acm.org/10.1145/1186562.1015766.
 1189
- 1119
 [61] Yoon, S.U., Lee, E.K., Kim, S.Y., Ho, Y.S.. A framework for multi-view190

 1120
 video coding using layered depth images. In: Advances in Multimedia191

 1121
 Information Processing-PCM 2005. Springer; 2005, p. 431–442.
- 1122
 [62] Merkle, P., Smolic, A., Muller, K., Wiegand, T.. Multi-view video193

 1123
 plus depth representation and coding. In: Image Processing, 2007. ICIP194

 1124
 2007. IEEE International Conference on; vol. 1. 2007, p. I 201–I 2041195

 1125
 doi:10.1109/ICIP.2007.4378926.
- 1126[63] Daribo, I., Saito, H.. A novel inpainting-based layered depth video1971127for 3dtv. Broadcasting, IEEE Transactions on 2011;57(2):533–541. doi1198112810.1109/TBC.2011.2125110.
- 1129
 [64] Yoon, S.U., Lee, E.K., Kim, S.Y., Ho, Y.S.. A framework for repre+200

 1130
 sentation and processing of multi-view video using the concept of layered201

 1131
 depth image. The Journal of VLSI Signal Processing Systems for Signal;202

 1132
 Image, and Video Technology 2007;46(2-3):87–102.
 1203
- Kirshanthan, S., Lajanugen, L., Panagoda, P., Wijesinghe, L., De Silvat204
 D., Pasqual, A.. Layered depth image based hevc multi-view codec. Int205
 Bebis, G., Boyle, R., Parvin, B., Koracin, D., McMahan, R., Jerald, J.1206
 et al., editors. Advances in Visual Computing; vol. 8888 of *Lecture Notes207 in Computer Science*. Springer International Publishing. ISBN 978-34208
 319-14363-7; 2014, p. 376–385.
- [66] Kim, W.S., Ortega, A., Lai, P., Tian, D.. Depth map cod4210
 ing optimization using rendered view distortion for 3d video coding1211
 IEEE Transactions on Image Processing 2015;24(11):3534–3545. doi1212
 10.1109/TIP.2015.2447737. 1213
- 1143 [67] Merkle, P., Müller, K., Marpe, D., Wiegand, T.. Depth intra cod4214
 1144 ing for 3d video based on geometric primitives. IEEE Transactions on215
 1145 Circuits and Systems for Video Technology 2016;26(3):570–582. doi1216
 1146 10.1109/TCSVT.2015.2407791. 1217
- 1147[68] Zhu, C., Li, S.. Depth image based view synthesis: New insights and2181148perspectives on hole generation and filling. IEEE Transactions on Broad42191149casting 2016;62(1):82–93. doi:10.1109/TBC.2015.2475697.1220
- [69] Yang, X., Liu, J., Sun, J., Li, X., Liu, W., Gao, Y.. Dibr based view221
 synthesis for free-viewpoint television. In: 3DTV Conference: The True222
 Vision Capture, Transmission and Display of 3D Video (3DTV-CON)1223
 2011. 2011, p. 1–4. doi:10.1109/3DTV.2011.5877165.
- [70] Shi, S., Jeon, W.J., Nahrstedt, K., Campbell, R.H.. Real+225 1154 time remote rendering of 3d video for mobile devices. In: Pro+226 1155 ceedings of the 17th ACM International Conference on Multime+227 1156 dia. MM '09; New York, NY, USA: ACM. ISBN 978-1-60558+228 1157 608-3; 2009, p. 391-400. doi:10.1145/1631272.1631326. 1158 URI1229 http://doi.acm.org/10.1145/1631272.1631326. 1159
- [71] Miao, D., Zhu, W., Luo, C., Chen, C.W.. Resource allocation for cloud-based free viewpoint video rendering for mobile phones.
 In: Proceedings of the 19th ACM International Conference on Multimedia. MM '11; New York, NY, USA: ACM. ISBN 978-1-4503-0616-4; 2011, p. 1237–1240. doi:10.1145/2072298.2071983. URL http://doi.acm.org/10.1145/2072298.2071983.
- 1166 [72] Mallia, M., Debono, C.J.. Rendering of free-viewpoint

video on the cloud. In: IEEE EUROCON 2017 -17th International Conference on Smart Technologies. 2017, p. 9–14. doi: 10.1109/EUROCON.2017.8011069.

- Huszák, Á.. Advanced free viewpoint video streaming techniques. Multimedia Tools and Applications 2017;76(1):373-396. doi:10.1007/s11042-015-3048-9. URL https://doi.org/10.1007/s11042-015-3048-9.
- [74] Lee, J.T., Yang, D.N., Chen, Y.C., Liao, W. Efficient multi-view 3d video multicast with depth-image-based rendering in lte-advanced networks with carrier aggregation. IEEE Transactions on Mobile Computing 2018;17(1):85–98. doi:10.1109/TMC.2017.2707416.
- [75] Slomp, M., Kawasaki, H., Furukawa, R., Sagawa, R., Temporal octrees for compressing dynamic point cloud streams. In: 2014 2nd International Conference on 3D Vision; vol. 2. 2014, p. 49–56. doi: 10.1109/3DV.2014.79.
- [76] Shade, J., Gortler, S., He, L.w., Szeliski, R.. Layered depth images. In: Proceedings of the 25th Annual Conference on Computer Graphics and Interactive Techniques. SIGGRAPH '98; New York, NY, USA: ACM. ISBN 0-89791-999-8; 1998, p. 231–242. doi:10.1145/280814.280882. URL http://doi.acm.org/10.1145/280814.280882.
- [77] Anjos, R.d., Pereira, J.M., Gaspar, J.A., Fernandes, C.. Multiview layered depth image. Journal of WSCG 2017;25(2):115–122.
- [78] McMillan, L., Bishop, G.. Plenoptic modeling: An imagebased rendering system. In: Proceedings of the 22Nd Annual Conference on Computer Graphics and Interactive Techniques. SIG-GRAPH '95; New York, NY, USA: ACM. ISBN 0-89791-701-4; 1995, p. 39-46. doi:10.1145/218380.218398. URL http://doi.acm.org/10.1145/218380.218398.
- [79] Gortler, S.J., Grzeszczuk, R., Szeliski, R., Cohen, M.F.. The lumigraph. In: Proceedings of the 23rd Annual Conference on Computer Graphics and Interactive Techniques. SIG-GRAPH '96; New York, NY, USA: ACM. ISBN 0-89791-746-4; 1996, p. 43-54. doi:10.1145/237170.237200. URL http://doi.acm.org/10.1145/237170.237200.
- [80] Sturm, P., Maybank, S.. On plane-based camera calibration: A general algorithm, singularities, applications. In: Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on.; vol. 1. 1999, p. –437 Vol. 1. doi:10.1109/CVPR.1999.786974.
- [81] Izadi, S., Kim, D., Hilliges, O., Molyneaux, D., Newcombe, R., Kohli, P., et al. Kinectfusion: Real-time 3d reconstruction and interaction using a moving depth camera. In: Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology. UIST '11; New York, NY, USA: ACM. ISBN 978-1-4503-0716-1; 2011, p. 559–568. doi:10.1145/2047196.2047270. URL http://doi.acm.org/10.1145/2047196.2047270.
- [82] Newcombe, R.A., Fox, D., Seitz, S.M. Dynamicfusion: Reconstruction and tracking of non-rigid scenes in real-time. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2015,.
- [83] Sousa, M., Mendes, D., Anjos, R.K.D., Medeiros, D., Ferreira, A., Raposo, A., et al. Creepy tracker toolkit for context-aware interfaces. In: Proceedings of the Interactive Surfaces and Spaces. ISS '17; New York, NY, USA: ACM. ISBN 978-1-4503-4691-7; 2017, p. 191-200. doi:10.1145/3132272.3134113. URL http://doi.acm.org/10.1145/3132272.3134113.
- [84] Kalantari, N.K., Wang, T.C., Ramamoorthi, R.. Learning-based view synthesis for light field cameras. ACM Transactions on Graphics (Proceedings of SIGGRAPH Asia 2016) 2016;35(6).
- [85] Ribeiro, C., dos Anjos, R.K., Fernandes, C.. Capturing and documenting creative processes in contemporary dance. In: Proceedings of the 4th International Conference on Movement Computing. MOCO '17; New York, NY, USA: ACM. ISBN 978-1-4503-5209-3; 2017, p. 7:1–7:7. doi:10.1145/3077981.3078041. URL http://doi.acm.org/10.1145/3077981.3078041.