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Linear Optimization Approach for Depth Range Adaption of Stereoscopic Videos

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Abstract

Depth-Image Based Rendering (DIBR) techniques enable the creation of virtual views from color and corresponding depth images. In stereoscopic 3D film making, the ability of DIBR to render views at arbitrary viewing positions allows adaption of a 3D scene's depth budget to address physical depth limitations of the display and to optimize for visual viewing comfort. This rendering of stereoscopic videos requires the determination of optimal depth range adaptions, which typically depends on the scene content, the display system and the viewers' experience. We show that this configuration problem can be modelled by a linear optimization problem that aims at maximizing the overall quality of experience (QoE) based on depth range adaption. Rules from literature are refined by data analysis and feature extraction based on datasets from film industry and a human visual attention model. We discuss our approach in terms of practical feasibility, generalizability w.r.t different content, subjective image quality, visual discomfort and depth quantity, and demonstrate its performance in a user study on publicly available and self-recorded datasets.

Introduction

The production of high quality stereoscopic videos becomes more challenging than conventional 2D film shooting, since multi-camera aspects such as inter-camera positioning must be addressed. A major challenge is optimizing for the best 3D depth impression which amounts to the problem of visual discomfort [11, 13, 20, 21, 24, 28, 29, 31–33, 35]. In order to handle visual discomfort, various approaches for automating the depth mapping process based on image processing have been proposed in literature [2, 4, 15, 22, 23, 27, 34]. These approaches are distinguished by the underlying mapping class of transformations, e.g. linear [2, 4, 23] or non-linear [15, 22, 27, 34], the way how visual discomfort is modelled, and how such models are used in the workflow. However, from the point of view of a stereographer an approach is preferable that is capable of taking best practice design patterns and stereographers' preferences into account.

We address the problem of finding an optimal trade-off between maximizing the depth quantity perceived by the user while guaranteeing visual comfort. Our major objective is to model this optimization problem within a sound mathematical framework that is capable of integrating quantitative datasets of configurations from the professional film industry, on the one hand, and qualitative best practice design patterns from stereographers, on the other hand. A further objective is to derive a computationally efficient workflow with low tuning efforts from this approach.

A DIBR framework for stereoscopic videos that performs disparity computation and DIBR is implemented. Generally, a DIBR pipeline that builds upon stereoscopic input videos comprises several steps. After appropriate calibration and rectification, the two input videos are subject to stereo analysis in order to compute a disparity (or depth) map, which forms the basis for the subsequent rendering process. Over the last decade, local stereo matching algorithms that rely on adaptive support weight techniques (e.g., [9,36]) have received considerable attention in stereo research due to their ability to deliver high-quality depth maps at reasonable computing effort. The incorporation of edge preserving filtering into the matching process (e.g., [5]) supports the localization and preservation of depth discontinuities in the matching result, which is an important requirement for the production of high-quality novel views from simulated camera viewpoints. Suitable post-processing techniques can further refine the quality of the computed depth maps in view of the subsequent rendering step (e.g., [19]). Furthermore, temporal filtering of the depth video may be applied to suppress disturbing flickering effects caused by stereo matching artefacts. After projection of the input video content into the selected new geometry, image inpainting techniques need to be applied in order to fill in missing information due to disocclusions in the synthesized view (e.g., [17]). For our experimental evaluation we use the Stereoscopic Suite [6] of emotion3D which includes implementations of all necessary processing steps.

The DIBR framework enables adaption of the depth range and to optimize visual comfort. After computing disparity maps from the stereo input videos and selecting the desired viewpoint for depth-image based rendering, we model the depth range adaption as linear optimization problem which maximizes the QoE such that a) the depth perception of object of interest should be near the screen-plane, b) the overall depth range should lie in a so-called comfort zone and c) depth jumps of objects of interest should be limited. The objective function takes the minimization of visual discomfort and maximization of depth quantity into account, while keeping the subjective image quality unchanged. The optimization can be restricted by constraints which can be interpreted in terms of comfort zone limits. By this, best practices and rules from literature for such comfort zone limits can be taken into account in the proposed disparity mapping approach in a natural way. As outlined in Section IV, experimental studies based on

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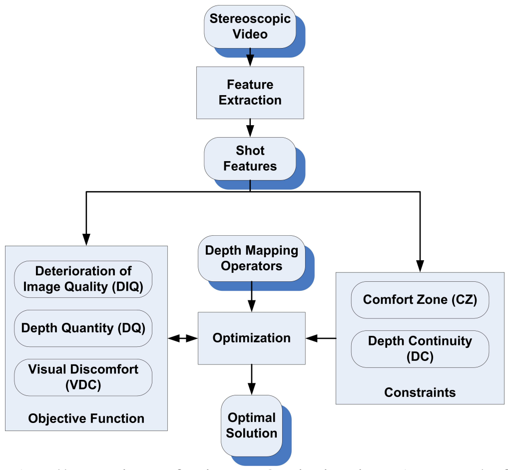

Figure 1: Illustration of Linear Optimization Approach for the Depth Mapping Problem by taking into account a measure for depth quality (DQ), a measure for visual discomfort (VDC), a measure for deterioration of image quality (DIQ), a model for a depth comfort zone (CZ) and a model for depth continuity (DC) on shot cuts. The optimization approach is designed in a way that it maximizes DQ, while it minimizes VDC and DIQ, takes CZ into account in terms of restricting the domain of admissible depth ranges and it guarantees DC on shot cuts in terms of restricting the depth transition of objects of attention on shot cuts.

subjective assessment results considering visual discomfort, depth quantity and subjective image quality, underpin this approach.

The rest of the paper is organized as follows. Section *Related Work* briefly summarizes related works. Section *Linear Optimization Approach* gives an overview of our approach and Section *Experiments* presents some experimental results, user evaluations and a new S3D visual discomfort database under development. Section *Conclusion* briefly concludes the work presented in this article. Finally, Appendix *Subjective Assessment* gives details concerning our subjective assessment and in Appendix *New Database* we propose our new S3D visual discomfort database.

Related Work

Due to [3], a model of quality of experience (QoE) can be conceptually split into three aspects: depth quantity, visual discomfort and image quality:

- The depth quality (DQ) refers to the perceived amount of depth someone experiences when watching stereoscopic content [3].
- Visual discomfort (VDC) refers to the subjective sensation of discomfort someone experiences when watching stereoscopic images or video content [14, 29, 38].
- The deterioration of image quality (DIQ) refers to a perceived loss of quality of an image or video w.r.t. characteristics like resolution, color, artefacts or noise.

The challenge of finding an optimal depth mapping is therefore to find an acceptable tradeoff between the conflicting objectives of maximizing DQ and minimizing VDC and DIQ [3].

For example, visual discomfort is smaller for smaller depth ranges, due to a decrease of the accommodation-vergence conflict, where the depth quantity is positively correlated to the size of the depth range [22]. To handle this conflict of objectives, depth mapping algorithms have been proposed [2, 4, 15, 22, 23, 27, 34] which try to optimally adapt the disparity range to the viewing environment. These approaches distinguish by the underlying articulation of preference of the three objectives (a), (b) and (c), the underlying mapping operators, i.e. linear [2, 4, 23] or non-linear [15, 22, 27, 34], and the way how visual discomfort is modeled.

Pan et al. [23] try to minimize visual discomfort by simply scaling the depth range in the Percival's Zone of Comfort [25] that is similar to a commonly used limit called *depth of field* (DOF). Chamaret et al. [2] handle visual discomfort by adaptively scaling and shifting an object of interest onto the screen plane. The object of interest is computed by a saliency map and the disparity map. In addition, they use the binocular fusion limit as lower disparity limit. Choi et al. [4] scale and shift the images into a predefined comfort zone for large cinema screens, proposed by [16], if a measured visual discomfort value exceeds a heuristic value. The visual discomfort model is trained using subjective assessment data of 10 videos and 10 subjects. Lang et al. [15] proposed different non-linear disparity mapping operators which can be used to improve the overall QoE. Yan et al. [34] propose a linear depth mapping algorithm which enables maintaining the image quality. This is done by minimizing distortions based on preserving relationships of neighboring features and preventing line and plane bending. They evaluate their algorithm considering visual discomfort, depth quantity and image quality aspects and made some of their results publicly available. Recently, Sohn et al. [27] used non-linear disparity mapping operators and a model of visual discomfort to iteratively compress problematic regions of S3D images in order to minimize visual discomfort, similarly did Oh et al. [22] for S3D videos. Unfortunately the iterative computations and compressions per frame make their algorithms less computationally efficient than linear approaches (see, e.g., [22]).

Linear Optimization Approach

Our approach based on linear optimization is outlined in Fig. 1. First of all, we take up the notion of overall quality of experience (QoE) as tradeoff between DQ, VDC and DIQ and model it by a weighted sum

$$\mu_{\text{QoE}} = \omega_{\text{DQ}}\mu_{\text{DQ}} - \omega_{\text{VDC}}\mu_{\text{VDC}} - \omega_{\text{DIQ}}\mu_{\text{DIQ}} \tag{1}$$

of measures μ_{DQ}, μ_{VDC} and μ_{DIQ} for the corresponding aspects DQ, VDC and DIQ, respectively. In our first simplified approach we assume that these weights are independent from characteristics of individual frames and parameter settings for the depth mapping. This simplification seems to be justified at least for similar scenes and contents. For the purpose of this paper it is introduced as a heuristic which needs further analysis in future research.

While assuming the weights to be insensitive w.r.t. to content characteristics and depth mapping operators, we consider the measures μ_{DQ}, μ_{VDC} and μ_{DIQ} to be sensitive w.r.t content characteristics of similar frames. A natural partition of such frames is given by the shots of video. Summarizing, this simplification means that the measures in (1) only depend on shot-based depth mappings, i.e., $\mu_A = \mu_A(\phi_{p_1,\ldots,p_n}(s))$, where A denotes one of the aspects DQ, VDC or DIQ and $\phi_{p_1,\ldots,p_n}$ denotes the depth mapping of the shot s with parameters $p_1,\ldots,p_n$.

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The mathematical optimization problem is as follows. Summarizing, we obtain the objective function

$$\max_{p_1,\ldots,p_n} \frac{1}{N}\sum_{i=1}^{N} \mu_{\mathrm{QoE}}(\phi_{p_1,\ldots,p_n}(s_i)). \tag{2}$$

Now, we refine the model (2) by taking knowledge in terms of best practices for comfort zone limits into account,

$$d_\delta(f), d_{1-\delta}(f) \in [d_m(s), d_M(s)], \tag{3}$$

where $d_m(s)$ and $d_M(s)$ give the lower and upper limit, i.e. the comfort zone boundaries, for the mean of the δ-percent quantile of disparity values of frame $f \in s$, denoted by $d_\delta(f)$. Note that, in contrast to standard approaches as outlined in Section *Related Work*, we allow more flexibility of the model by taking into account that the comfort zone for disparity values might depend on the characteristics of shot s. In order to bound visual discomfort that results from depth jumps at the border of shots, we track the most attractive object of interest by means of a visual attention model and postulate that the corresponding depth profiles of this objects in last frame of shot s_i and the first frame of the subsequent shot s_{i+1} are similar. This means that

$$|d_{ooi}(\phi(f_i^+)) - d_{ooi}(\phi(f_{i+1}^-))| \leq \lambda \tag{4}$$

for all shots s_i, where $d_{ooi}(\phi(f_i^+))$ denotes the disparity map value of the object of interest in the last frame f_i^+ of shot s_i after applying ϕ; $d_{ooi}(\phi(f_i^-))$ denotes the corresponding value on the other side at the shot border.

The approach outlined so far consists of posing the objective function (2) while restricting the search for an optimal depth configuration $(p_1,\ldots,p_n)$ by a comfort zone (3) and a bound for discontinuity at shot borders (4).

In this paper, we propose to model the measures μ_{DQ}, μ_{VDC} and μ_{DIQ} by linear functions. In addition, we use linear depth mapping operators in order to linearise the optimization problem. An optimal solution can then be computed efficiently by the well-known Simplex algorithm [18].

Let us characterize the class of linear depth mappings $\phi_{c,t}$ of shot s with shift t and constant scale c by the property $D(\phi_{c,t}(s)) = c \cdot D(s) + t$ for the disparity map D of s. Furthermore, as a linear measure of the depth quantity μ_{DQ}, we propose to use the mean size of the depth range of all frames in a shot. As measure for the deterioration of the image quality μ_{DIQ}, we use the scaling amount of the used depth mapping parameter. As linear measure of visual discomfort μ_{VDC}, we use the mean depth deviation of the object of interest from the screen, which is motivated by the accommodation-vergence conflict [29]. Though some linear measures for visual discomfort have been proposed [38], these measures depend on subjective assessment results, which are not always available for shots having special characteristics, e.g. high-motion.

The object of interest is computed by means of a 2D human visual attention model [10] combined with a motion map [7], the disparity map and a center bias (see Fig. 3).

Finally, we implemented a motion-based comfort zone. It consists of a lower $d_m(s)$ and upper $d_M(s)$ depth limit of shot s, and is calculated by means of optical flow motion vectors [7] and the computation of a machine learning function that is based on various shots from well-known S3D movies.

For example output of an optimization task, consider Fig. 2. It shows the original depth transition (dashed) and optimal depth transition (solid) of the minimum depth (lower), maximum depth (upper) and the mean depth of the object of interest (middle) in all frames of two shots. For example extraction of the objects of interests depth of frame 5 see Fig. 3. The vertical line specifies a shot cut, the dotted and dashed horizontal lines show the minimum depth of the motion-based comfort zone and the screen respectively. The high-motion shot from frame 0 to frame 59 has a smaller comfort zone that the second shot. Thus, the optimization algorithm computes a smaller scaling parameter than for the second shot. The depth difference of the objects of interest on the shot cut were limited by $\lambda = 0.5\%$ of image width, see equation 4.

The original video causes a high amount of visual discomfort since it is in conflict with the well-known depth of field rule [29]. The algorithms output is optimized using our motion-based comfort zone, that includes rules as the depth of field. Thus, the optimized video causes a lower amount of visual discomfort including a more comfortable depth continuity of the objects of interest on the shot cuts.

Figure 4: Subjective assessment result. Vertical axis: mean opinion scores for visual comfort, image quality and depth quantity, top bars: Yan et al's results, bottom bars: our results.

Experiments

Yan et al. proposed a linear depth mapping algorithm for stereoscopic videos and placed some results for reference at [34]. Some of their results (Ex1, Ex10, Ex11) are computed from a free and well-known S3D video clip Oldtimers [30]. For the other videos we could not find any freely available source data.

In order to compare our algorithm to their results, we optimized the Oldtimer video clip by our algorithm and compare the results pair-wise to Yan et al.'s results. Since, they provide their results only in red-cyan anaglyph format, we converted our results with these color settings. Example frames of output can be seen in figure 5. One can observe that our algorithm produces results with the most attracting image parts (front of train, person in the middle) closer to the screen. Due to a smaller depth range, our algorithm produces results which are closer in the background and therefore farer away from the binocular vision limit. This results

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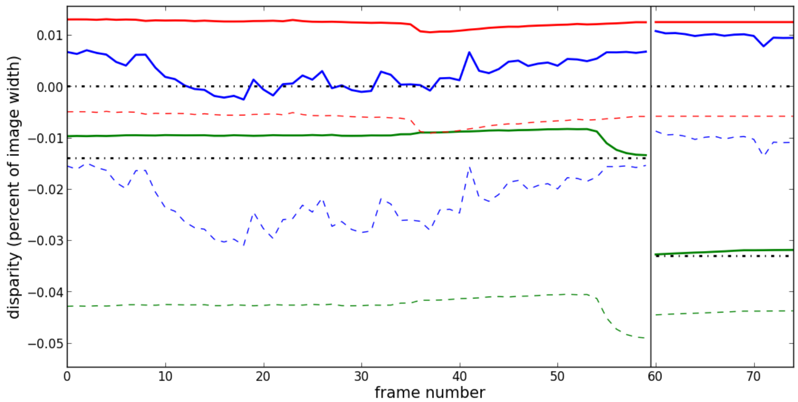

Figure 2: Linear depth mapping result of a short two-shot S3D video. Black dashed lines: screen (0.00) and minimum of comfort zone (-1.4 first shot, -3.3 second shot), thin dashed lines: minimum depth of frame (lower line), mean depth of object of interest (middle line), see e.g. figure 3), and maximum depth of frame (top line), solid lines: data of mapped video (order equal to dashed lines), vertical line: shot-cut.

Figure 3: Saliency map computation of proposed S3D human visual attention model for multi-shot stereoscopic video analysed by figure 2. From left to right: left view of stereoscopic image, motion saliency map, disparity map, spectral residual saliency map and combined map based on maximum pooling and linear combination with center-bias.

in less sensitivity for perceiving visual discomfort when looking at the background. It is also interesting to observe that there are some errors at the floor at the bottom right image produced by our algorithm, coming from inappropriate disparity production.

The mean opinion scores of the users in our subjective assessment (see Appendix), visualized in Fig. 4, do not show any decrease in image quality when compared with Yan et al.'s results. The mean scores of all six videos and user ratings show a statistically significant improvement with significance level 0.99 in visual comfort ($t = 3.606, p = 0.0004$), image quality ($t = 4.6, p = 2 \cdot 10^{-5}$) and depth quantity ($t = 3.786, p = 0.0002$). The improvement of the depth quantity could have the reason for the adjustment of the S3D scenes closer to the viewer. Statement 1 summarizes these results. We made all subjective assessment data and the rendered videos publicly available in a small database, see Appendix .

Statement 1 (Performance)**.** *The mean level of visual comfort, image quality and depth quantity observed by the subjects in our assessment is significantly higher for our results than for the Oldtimer examples of Yan et al. [34] (one-tailed paired T-test, significance level* 0.99*).*

Conclusion

From the point of view of a stereographer a disparity mapping approach is preferable that is capable of taking best practice design patterns and stereographers' preferences into account [26]. Thus, we address the overall objective by a linear optimization

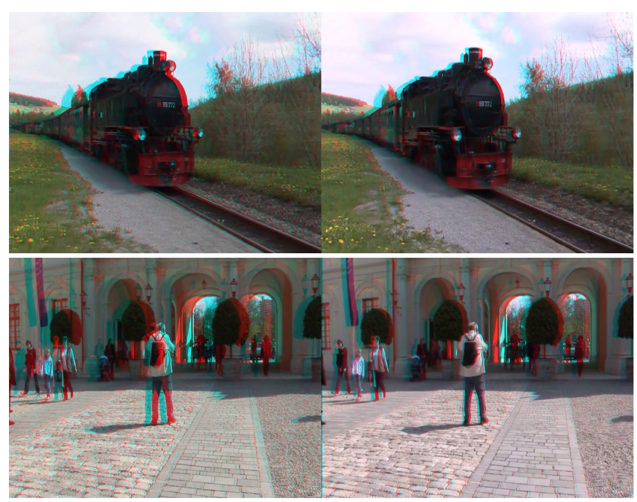

Figure 5: Comparison of Yan et al.'s result (left) with our result (right). Results of our disparity mapped videos show the attracting image parts closer to the screen (front of train, person in the middle). In addition it can be observed that our algorithm produces slightly nearer results for far image parts (smaller shift between views).

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problem optimizing a weighted sum of three models for (a),(b) and (c). In particular, we address (a) by adapting the well-known Depth of Field limit based on motion features. (b) is modelled by analysing the depth difference of the most salient regions and the screen plane, similarly to [2]. The saliency regions are detected by means of a computationally efficient human visual attention model with depth information. (c) is modelled based on scaling amounts of the DIBR method, with similar image quality results as the one of [34] (see Section *Experiments*). Constraints for depth differences of saliency regions on shot-cuts are added to solve the overall linear optimization problem computationally efficient by using the well-known Simplex algorithm [18].

In the future, we plan to analyse also long-term effects of depth-range adaptions on visual discomfort.

Appendices

Subjective Assessment

17 subjects, from twenty five to fifty years old, participated in our psychological assessment. After testing them for stereo-blindness, color blindness and low vision according to [12], we had to break the experiment for three users because of low vision. The videos were shown on a 55-inch stereoscopic display with the eyes of the viewers horizontal centred and 3.1 times the images height [29] away from the display.

Since, the subjective assessment aims at providing evidence regarding subjective image quality, depth quantity and visual discomfort, we designed four questions, similarly to [34], as follows:

- Q1 What is the level of image quality of the video (Bad-Poor-Fair-Good-Excellent)?
- Q2 What is the level of the depth quantity of the video (Bad-Poor-Fair-Good-Excellent)?
- Q3 What is the level of visual comfort associated with the video (Extremely uncomfortable-Uncomfortable-Mildly uncomfortable-Comfortable-Very Comfortable)?

During the assessment, all the subjects were allowed to stop and rerun the videos as often as desired and small breaks where added between every video in order to relax their visual system. The stopping of the video is required to answer especially the image quality question Q1.

New Database

We have developed a stereoscopic three-dimensional video database with scenes of different content and characteristics used also for the experiments reported in this article. For all the videos, we provide subjective assessment data considering visual comfort, depth quantity and image quality. The resulting scores can be used to evaluate performance of quality metrics, visual discomfort prediction models and disparity mapping algorithms.

A first version of the database has been made publicly available along with this paper. Currently this database contains subjective assessment results for the following data:

- Ten low-resolution (640x480), non-expert, high-motion, outdoor videos, captured by means of a Bumblebee 2 camera from Point Grey and re-rendered using two different depth comfort zones;
- Eight high-resolution (1920x1080), expert, low-motion, indoor videos with four original videos from [8] and four re-rendered videos using our disparity mapping algorithm for quality optimization;
- Anaglyph videos showing results of [34] side by side with our optimized results.

For details regarding the data and subjective assessment setup we refer to [1].

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Author Biography

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Bernhard A. Moser received his master degree in mathematics from the Paris Lodron University of Salzburg in 1991 and his Ph.D from the Johannes Kepler University Linz in 1996. He was with the University of Salzburg as a research assistant at the Department of Computer Science for 2 years with focus on fundamental research in the field of fuzzy similarity measures. Later, he joined the staff of the Fuzzy Logic Laboratory Linz-Hagenberg (FLLL) for 4 years where he participated in developing data and signal analysis systems. After this, he entered the non-profit Austrian research organization SCCH, where he is Scientific Head of the Knowledge-Based Vision Systems group.

Chouikhi Ayadi is a junior computer science engineer who received his master from the University of Technology of Belfort-Montbéliard (UTBM) in France with a thesis on image segmentation. He worked as ERASMUS student at the Mathematical Image Analysis (MIA) Group at Saarland University and was junior researcher at the Knowledge-Based Vision Systems Group (KVS) at the SCCH in Austria.

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