Real-Time, Full 3-D Reconstruction of Moving Foreground Objects From Multiple Consumer Depth Cameras

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Abstract—The problem of robust, realistic and especially fast 3-D reconstruction of objects, although extensively studied, is still a challenging research task. Most of the state-of-the-art approaches that target real-time applications, such as immersive reality, address mainly the problem of synthesizing intermediate views for given view-points, rather than generating a single complete 3-D surface. In this paper, we present a multiple-Kinect capturing system and a novel methodology for the creation of accurate, realistic, full 3-D reconstructions of moving foreground objects, e.g., humans, to be exploited in real-time applications. The proposed method generates multiple textured meshes from multiple RGB-Depth streams, applies a coarse-to-fine registration algorithm and finally merges the separate meshes into a single 3-D surface. Although the Kinect sensor has attracted the attention of many researchers and home enthusiasts and has already appeared in many applications over the Internet, none of the already presented works can produce full 3-D models of moving objects from multiple Kinect streams in real-time. We present the capturing setup, the methodology for its calibration and the details of the proposed algorithm for real-time fusion of multiple meshes. The presented experimental results verify the effectiveness of the approach with respect to the 3-D reconstruction quality, as well as the achieved frame rates.

Index Terms—3-D reconstruction, CUDA, Kinect sensor, mesh zippering, real-time, tele-immersive applications.

I. INTRODUCTION

ACCURATE, robust and fast 3-D reconstruction of objects in real-life scenes is a challenging task, studied by the computer-vision, multimedia and computer-graphics scientific communities. It is an important element in numerous applications, ranging from cultural heritage (e.g., reconstruction of museological objects) to movie industry and augmented or immersive reality applications. The target application specifies the requirements with respect to reconstruction accuracy and execution time. The work described in this paper targets real-time applications, such as Tele-Immersion (TI). Multi-party TI is an emerging technology that can support realistic inter-personal communications, allowing remote users to share an activity (e.g., teaching of physical activities). This is achieved by generating realistic 3-D reconstructions of users and placing them inside a common virtual space [1], [2], where users can interact with each other. However, the accurate construction of 3-D data at the frame rates required for TI applications, is still a challenging task.

In this paper, we present a TI-oriented system that can produce realistic, full 3-D reconstructions of foreground moving objects (e.g., humans), in real-time. Most of the relevant real-time approaches used in Tele-Presence applications (e.g., [2], [3]), fuse partial 3-D data only at the rendering stage, in order to produce realistic view-point-dependent views. Such approach has the advantage of enabling the use of viewing-direction weights at the rendering stage to improve the visual quality of the displayed results. However, in this multi-party TI framework architecture, the fusion has to be performed for each viewer (rendering site). More importantly, a TI system cannot benefit from the capabilities offered by recent and future rendering systems, where the captured 3-D can be rendered in a full 3-D, holography-like mode, and hence view-point-dependent rendering becomes meaningless. On the other hand, the proposed method combines explicitly partial 3-D meshes at the reconstruction stage (i.e., before data transmission and rendering), in order to produce a single realistic full-geometry 3-D mesh model, independent of the view-point. This explicit fusion generally presents challenging issues with respect to the computational effort, since it deals with actual fusion in 3-D. Most full 3-D reconstruction methods that produce a single 3-D surface work off-line. On the contrary, the proposed algorithm runs in real-time, handling many of the 3-D geometric operations on the depth-image plane. Thus, it presents reduced computational effort and enables a GPU-based implementation for most of its algorithmic parts.

Reconstruction in this work is achieved by the fusion of multiple 2.5D (RGB-Depth) data, captured by multiple inexpensive depth sensors, and specifically Kinect devices. The Microsoft’s Kinect sensor, released in November 2010, has attracted the attention of many researchers, as well as home enthusiasts and many Kinect-based applications have already begun to appear over the Internet (e.g., the open-source ROS Kinect project1), including 3-D reconstruction applications. However, only a few relevant works have been published so far [3]–[6]. To the authors’ knowledge, the presented system is among the first systems that uses multiple Kinect cameras for real-time 3-D reconstruction.

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1http://www.ros.org/wiki/kinect
The rest of the paper is organized as follows. In Section I-A, we shortly present previous works in 3-D reconstruction and highlight either their limitations in a TI framework, or their differences with the proposed approach. In Section II, we give an overview of the proposed system, including a description of the capturing setup as well as an abstract description of the reconstruction approach. In Section III, we present all the necessary details of the proposed real-time reconstruction algorithm. Implementation details with respect to the calibration of the capturing system, as well as the algorithm’s acceleration using CUDA,\(^2\) are given in Section IV. In Section V, we present experimental results with respect to the execution time as well as the visual quality, before concluding in Section VI.

### A. Related Work

Previous work can be classified based on the nature of the outcome: either i) a single 3-D mesh, independent of the rendering stage, or ii) a synthesized 2-D view (or a pair of stereo views) for a specific view-point.

Regarding full 3-D reconstruction methods that can produce a single complete 3-D mesh, reconstruction is achieved either by the combination of dense range data, generated by active direct-ranging sensors, or by multi-view RGB images, captured by passive cameras. In the first subcategory, Hoppe et al.\(^7\) presented a volumetric method for constructing an implicit surface representation from unstructured 3-D points, while the final surface is generated by an isosurface extraction method. Soucy and Laurendeau\(^8\) described a method that uses canonic subsets of the Venn diagram to represent overlapping 3-D data regions and then perform re-parameterization and merging at those regions. Turk and Levoy\(^9\) integrated range data using a “mesh zipper” approach. Overlapping regions of the meshes are eroded and then merged using local 2-D triangulation. Curless and Levoy\(^10\) introduced a volumetric, cumulative weighted signed distance function. The final surface is generated by isosurface extraction. Most of these methods present relatively high accuracy. However, they require significant computation time, which is prohibited for real-time applications, and therefore they are applied off-line to combine range data generated at different time instances. A more recent approach in this subcategory, the Poisson reconstruction\(^11\) method, works with oriented point sets (i.e., vertices plus their oriented normals) and shows to be highly resilient to data noise. However, the required computational effort is high and therefore such a method is prohibited given our application’s specifications.

With respect to multi-view methods from multiple passive RGB cameras, one can find several accurate 3-D reconstruction methods\(^12\)–\(^22\) in the literature. Unfortunately, these are not applicable in real-time TI applications, since they are based on the iterative maximization of the surface integral of a certain cost function that incorporates photo-consistency and additional regularization/smoothness constraints on the reconstructed surface. Therefore, regardless of the mathematical tools employed for optimization (e.g., graph cuts\(^14\)–\(^16\), \(^19\), \(^20\) or level sets\(^13\), \(^18\), \(^23\)) the required reconstruction time may range from several minutes to hours. Other, non optimization-based methods are simpler and faster but they lack reconstruction accuracy and most of them do not meet the real-time requirements. Silhouette-based approaches\(^24\)–\(^28\) extract the foreground object’s silhouette in each image and construct its “visual-hull”. They are quite fast and robust; yet they are not able to reconstruct details and especially concavities, while requiring robust extraction of the object’s silhouette, which is not always feasible. The most promising near real-time silhouette-based work seems to be the Exact Polyhedral Visual Hulls (EPVHs) of Franco et al.\(^24\), \(^28\), which achieves a reconstruction rate of approximately 1 frame/second. Voxel-coloring or space-carving techniques\(^29\)–\(^33\) recover the objects’ “photo-hull”, by sequentially eroding photo-inconsistent voxels in a plane sweeping framework. These techniques, although potentially more accurate, are generally slower and less robust, since they are based on making hard and irreversible decisions on voxels’ removal. In a relatively recent space carving-based approach, Hasenfratz et al.\(^34\) described an interactive virtual reality system that features real-time 3-D reconstruction of the human body. However, the approach has limited ability to acquire clothing and facial features details, due to the inherent limitation of the space carving approach.

In the second category, many methods can be found that run in real-time\(^2\), \(^35\)–\(^39\) and are applicable in a TI scenario. In one of the early works that utilize RGB cameras\(^35\), a very large number of cameras (51 cameras) mounted on a 5-meter diameter geodesic dome was used to produce dense depth-maps. However, these were combined in real-time only to synthesize intermediate views for user-given view-points, rather than producing complete (full) 3-D models. Complete models were produced with the use of an adapted version of the Curless and Levoy volumetric algorithm\(^10\), neglecting the real-time requirements. In a recent work\(^37\), a viewpoint-based approach for quick fusion of multiple depth maps was presented. Depth maps are computed in real-time from a set of images captured by moving cameras, using plane-sweeping stereo. The depth maps are fused within a visibility-based framework and the methodology is applied for view-point rendering of outdoor large-scale scenes. The method was also tested on the Multi-View Stereo Evaluation dataset,\(^3\) presenting high accuracy, yet requiring an execution time of few seconds. Finally, in a state-of-the-art work\(^2\), \(^38\), \(^39\), a high quality system for 3-D TI applications is described. The authors give all the necessary details of the system, including a method for the creation of highly accurate textured meshes from a stereo pair. Exploiting multiple stereo pairs, they generate multiple meshes in real-time, which are intelligently combined to synthesize high-quality intermediate views for given view-points.

The proposed 3-D reconstruction method uses multiple Kinect RGB-Depth sensors to produce, in real-time, a single 3-D mesh model. Only a few Kinect-based works have been published so far\(^3\)–\(^6\). To the authors’ knowledge, the presented system is among the first works that uses multiple Kinect
cameras targeting a TI application. In [4], personalized avatars are created from a single RGB image and the corresponding depth map, captured by a Kinect sensor. In [5], the authors present an efficient system for scanning and off-line generating human body models using three Kinects and a rotating table. In [6], the problem of dynamic 3-D indoor scenes reconstruction is addressed through the fast fusion of multiple depth scans, captured by a single hand-held Kinect sensor. Finally, in [3], an efficient system with six Kinects is presented. It deals with two important elements of a Tele-Presence system, 3-D capturing and reconstruction and view-point-dependent rendering, demonstrating a good performance in terms of visual quality. However, compared to our approach, it combines the separate 3-D meshes from each Kinect only at the rendering stage to produce intermediate stereo views, rather than producing a single 3-D mesh model.

II. OVERVIEW OF THE SYSTEM

For reader’s convenience, the notation used in this paper is given in Table I, where the most important symbols of this paper along with their meaning and values are explained.

<table>
<thead>
<tr>
<th>CONSTANT / SYMBOL</th>
<th>VALUE / RANGE / MATRIX SIZE</th>
<th>MEANING / COMMENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M$</td>
<td>4</td>
<td>Number of devices, point clouds and separate meshes</td>
</tr>
<tr>
<td>$N_x \times N_y$</td>
<td>640 \times 480</td>
<td>Depth and RGB image size</td>
</tr>
<tr>
<td>$x = (x,y)^T$</td>
<td>$x \in [0, N_x - 1] \times [0, N_y - 1]$</td>
<td>2D point (pixel)</td>
</tr>
<tr>
<td>$X = (X,Y,Z)^T$</td>
<td>$X \in$ Working volume</td>
<td>3D point</td>
</tr>
<tr>
<td>$P_m$</td>
<td>$m = 1, \ldots, M$</td>
<td>$m$-th point cloud (set of points)</td>
</tr>
<tr>
<td>$A_m$</td>
<td>$m = 1, \ldots, M$</td>
<td>$m$-th mesh, i.e. point cloud (set of vertices) plus triangles</td>
</tr>
<tr>
<td>$T^m_i(x,y)$</td>
<td>$m = 1, \ldots, M$, $i = 1, 2$</td>
<td>A triangle of the $m$-th mesh, indexed by $i$ and $(x,y)$ (see text for details). When referring to a mesh $A$, this appears as $T^A(x,y)$ in the text.</td>
</tr>
<tr>
<td>$C^m_i(x,y)$</td>
<td>As above</td>
<td>The center of triangle $T^m_i(x,y)$. As above, it may appear as $C^A_i(x,y)$.</td>
</tr>
<tr>
<td>$p^{AB}(x,y)$</td>
<td>$i = 1, 2$</td>
<td>A 2D point: The projection of $C^A_i(x,y)$ to the depth-map plane $B$.</td>
</tr>
<tr>
<td>$T_d$</td>
<td>2cm</td>
<td>Threshold for depth discontinuities in SDC triangulation (subsection III-B).</td>
</tr>
<tr>
<td>$T_e$</td>
<td>2cm</td>
<td>Threshold at scale $2^s$, used in the FRBR algorithm (subsection III-C).</td>
</tr>
<tr>
<td>$T_e$</td>
<td>2cm</td>
<td>Maximum accepted edge length for the re-triangulation step (subsection III-D).</td>
</tr>
</tbody>
</table>

B. Capturing and Processing Setup

The capturing system is composed of $M = 4$ Kinect sensors, connected on a single host PC. The positions and orientations of the Kinect devices are shown in Fig. 1(a). The devices are horizontally positioned at the vertices of an imaginable square, with a diagonal of length approximately 3 meters, at a height of approximately 1.1 meters and pointing to the center of the working volume. Considering that the depth cameras’ FOV is approximately 45° and a mean human height of 1.7 meters, the described setup introduces an “active” region of approximately $1.4 \times 1.4$ square meters, as shown in Fig. 1(b), where the whole human body above the knees can be captured. A part of the capturing setup (two out of the four devices) is depicted in Fig. 1(c). The whole reconstruction approach runs in real-time on the single host PC used in this work, featuring an Intel i7 processor and 4 GB RAM, along with a CUDA-enabled graphics card NVidia GTX 560 Ti. The PrimeSense Kinect driver and the OpenNI API were used for communicating with the devices. Interference issues may arise due to the simultaneous operation of multiple Kinects’ IR projectors. However, experiments have showed that interference is not as strong as expected and does not introduce significant quality degradation, as confirmed also by other studies [3] (see also in the ROS wiki). Moreover, according to our experiments, interference manifests itself mainly as a few missing values, especially near the boundaries of the objects. Due to the partial overlap of the depth maps from multiple sensors, this missing-values effect fades out by the applied fusion method. Finally, various solutions to the interference problem have recently been proposed, exploiting time division multiple access (TDMA) scenarios (or even Wavelength DMA), for example using fast rotating disks [40].

C. Overview of the System and the Reconstruction Approach

A rough description of the overall 3-D reconstruction approach is given in the schematic diagram of Fig. 2. The offline
the calibration approach includes: a) RGB cameras’ intrinsic calibration, based on checkerboard captures and the employment of Zhang’s method [41], and b) Global (all-to-all) external calibration, a combination of the works in [42], [43]. It is based on multiple captures of a hand-made calibration object and pairwise (stereo) calibration, refined globally with Bundle Adjustment [44]. An outline of our calibration method is given in Section IV-A.

In the online, real-time algorithmic part, optionally one may initially apply edge-preserving smoothing filtering of the captured depth maps (e.g., using a bilateral filter [45]), to reduce noise. Then, a set of point clouds $\mathcal{P}_m, m = 1, \ldots, M$, generated from each Kinect’s data. Based on the fact that these actually lie on a closed surface, pairwise registration can lead to inaccuracies, due to pair-wise errors’ accumulation. Therefore, the problem has to be handled by a global (all-to-all) registration approach. The method selected for this work is based on the idea of using Global Procrustes Analysis (GPA) [46]–[48] within an Iterative Closest Points (ICP) algorithm, which runs on a parallel thread, due to executional time limitations. The run-time registration algorithm, running in a parallel thread, updates the registration matrices in intervals of a few frames. One may opine that this could cause reconstruction artifacts for fast-moving objects; however this was not observed in our experiments (see Section V).

The registered meshes $\mathcal{A}_m, m = 1, \ldots, M$ could be the final output for some types of applications. However, the reconstruction results at this point present significant visual artifacts, due to the overlap between the generated meshes and the redundancy of the generated triangles. Furthermore, our final objective is the generation of a single connected mesh. Therefore, the overall method continues in the next module with the decimation/removal of the redundant overlapping mesh regions, handling the meshes in a pairwise manner. Finally, the “clipping” module performs the “stitching” of the multiple meshes and produces the method’s final output.

### III. The Real-Time 3-D Reconstruction Algorithm

#### A. Global Iterative Closest Point Registration

Optionally, in an effort to avoid re-calibrating the camera network before each experiment, which is needed for accurate calibration data, one could use a run-time registration approach instead. The objective is to align the $M$ point-clouds $\mathcal{P}_m, m = 1, \ldots, M$, generated from each Kinect’s data. Based on the fact that these actually lie on a closed surface, pair-wise registration can lead to inaccuracies, due to pair-wise errors’ accumulation. Therefore, the problem has to be handled by a global (all-to-all) registration approach. The method selected for this work is based on the idea of using Global Procrustes Analysis (GPA) [46]–[48] within an Iterative Closest Points (ICP) framework, in order to benefit from both procedures and offer a global registration solution. The idea is shortly described below. For further details the interested reader is referred to [46], [47].

Regarding the initial formulation of GPA theory, it is assumed that $M$ point-clouds contain the same set of points (let $N$ in number), which are however expressed in $M$ different 3-D coordinate systems. GPA [47], [48] provides a solution to the registration problem, by minimizing the mean Euclidean distance between the registered point-clouds, let $\mathcal{P}_m, m = 1, \ldots, M$. In our problem, not all $N$ points are present (visible) in each view (point-cloud). The point-clouds have generally a small overlap. Therefore, the initial GPA objective function is modified in order to take into account the “visibility” of each point in each view:

\[
e(T_1, T_2, \ldots, T_M) = M \cdot \sum_{m=1}^{M} \text{tr} \left( (P_m - C)^T B_m (P_m - C) \right).
\]
where $T_m, m = 1, \ldots, M$ express the registration matrices to be found, $P_m^{e}$ are the $N \times 3$ matrices containing the registered 3-D points, $C = (1/M) \sum_m P_m^{e}$ is the matrix containing the geometrical centroids of the transformed points and $B_m$ are a binary diagonal “visibility” matrices, of size $N \times N$, that indicate the “visibility” of the points in the $m$th point-cloud. By taking the advantage of GPA in an ICP framework, in order to globally register multiple point-clouds, one should consider that the point correspondences are not given and fixed. They have rather to be updated in an ICP iterative framework: Pairwise ICP is performed to find pairwise point correspondences and their centroids, while GPA is used to globally register the point-clouds based on the found point correspondences and centroids. In [46], in order to get a robust subset of compatible point matches, the approach takes into account only matches of points that are in a mutual closest neighbor relation.

1) Coarse-to-Fine Application of GPA-ICP: The ICP-based approach can be faster when used within a coarse-to-fine framework. Initially, the registration parameters are estimated from low-resolution point clouds, obtained by sub-sampling the original depth maps by a factor of $2^{s_0}$ along both $x$ and $y$ directions ($s_0 - 1$ in our implementation). The computed transformations are then used to refine the positions of the point clouds in the next hierarchy level $s = s_0 - 1$, before the GPA-ICP is re-applied. The approach continues up to full resolution ($s = 0$).

Although convergence is achieved in only few iterations, we preferred to use a maximum number of iterations equal to four at each hierarchy level, in order to get the ICP transformation matrices in a reasonably short time.

**B. Initial Triangulation, Generation of Separate Meshes**

This subsection concentrates on the creation of a single mesh, denoted as $I_z(x, y), x = 0, \ldots, N_x - 1, y = 0, \ldots, N_y - 1$, where $(N_x, N_y)$ denote the depth image size. A mesh is created by the application of what is referred as “Step Discontinuity Constrained (SDC) triangulation” [50]. The idea is that depth measurements that are adjacent in the 2-D depth image plane are assumed to be connected, unless their Euclidean 3-D distance is higher than a predefined threshold $T_d$. The minimum value of the threshold to be used should take into account the resolution $(\Delta X, \Delta Y)$. Its maximum value is constrained by the largest accepted triangle edge in the mesh. For the presented results, the used threshold value was fixed and set equal to $T_d = 2$ cm. Actually, since the resolution $(\Delta X, \Delta Y)$ is much smaller than the selected threshold $T_d$, the constraint can be applied to the depth distance of the adjacent measurements, rather to their Euclidean distance, so as to reduce the execution time.

The applied triangulation algorithm is as simple as follows: For each pixel $Z = I_z(x, y)$ of the depth map,

- Consider its adjacent pixels at the right, bottom and right-bottom, $Z_r = I_z(x + 1, y)$, $Z_b = I_z(x, y + 1)$ and $Z_{rb} = I_z(x + 1, y + 1)$, respectively.
- If all depth distances $|Z - Z_r|$, $|Z - Z_b|$ and $|Z_r - Z_b|$ are smaller than $T_d$, then generate a triangle by connecting the corresponding 3-D points. Let this triangle be denoted as $T_1(x, y)$.
- Similarly, if all depth distances $|Z_{rb} - Z_r|$, $|Z_{rb} - Z_b|$ and $|Z_r - Z_b|$ are smaller than $T_d$, then generate a second triangle, denoted as $T_2(x, y)$.
An illustrative example is given in Fig. 3. Notice that any constraints to the minimum and maximum accepted depth distance from the capturing sensor can be easily embodied in the algorithm. For example, reasonable depth threshold values for the Kinect sensors are $T_{\text{min},A} = 0.5$ m and $T_{\text{max},A} = 4$ m.

C. Removal of Overlapping Mesh Regions

The meshes created from the depth data of two adjacent sensors normally contain a large portion of overlapping regions. Therefore, many triangles in each mesh are redundant in the sense that the other mesh contains an unbroken surface at the same position. An example is shown in Fig. 4(a), where it can be noticed that apart from the triangles’ redundancy, significant visual artifacts are introduced at the overlapping regions.

The first step towards the fusion of two adjacent meshes is to remove redundant triangles from each mesh. Applying a methodology similar to [9], we iteratively decimate triangles from the boundaries of the two meshes, until no overlapping triangles are present. Removing overlapping mesh regions constitutes the bottle-neck part of the whole reconstruction algorithm, due to its iterative nature. Therefore, the main criterion in the implementation of this algorithmic part is the reduction of the computational effort required in each iteration, without sacrificing the desired reconstruction accuracy.

Let the triangles in meshes $A$ and $B$ be denoted as $T_i^A(x, y)$ and $T_i^B(x, y)$, $i = \{1, 2\}$, respectively, generated by Step Discontinuity Constrained (SDC) triangulation. The methodology for removing the redundant triangles can be summarized as follows:

1) **Triangles’ centers calculation:** Calculate the triangle centers in both meshes $A$ and $B$. Let these be denoted as $C_i^A(x, y)$ and $C_i^B(x, y)$, $i = \{1, 2\}$, respectively. This step can be accomplished during the creation of the separate meshes and requires minor execution time, especially considering the CUDA implementation described in Section IV.

2) **Projection from $A$ to $B$ and vice-versa:** Project the center of each triangle in mesh $A$ to the depth camera $B$. The 2-D projection points are

$$p_i^{AB}(x, y) = \Pi \{m_B, C_i^A(x, y)\}$$

where $\Pi \{m_B, C_i^A(x, y)\}$ represents the 3-D to 2-D projection, considering the camera matrix $m_B = \{K_B, R_B, t_B\}$.

An illustrative explanation is given in Fig. 5(a). Similarly, project the centers of the triangles in $B$ to the depth camera $A$, obtaining the 2-D points $p_i^{BA}(x, y)$. 
3) Iterations for redundant triangles removal: Repeat:
   • Apply the Fast Redundant Boundary Removal (FRBR) algorithm to remove the boundary triangles of mesh $\mathcal{A}$, which are redundant with respect to $\mathcal{B}$,
   • Apply the FRBR algorithm to remove the boundary triangles of mesh $\mathcal{B}$, which are redundant with respect to $\mathcal{A}$,
   until both meshes $\mathcal{A}$ and $\mathcal{B}$ remain unchanged.

1) Fast Redundant Boundary Removal (FRBR) Algorithm:
   The algorithm decimates in a fast manner the boundary triangles of a mesh $\mathcal{A}$ that are redundant with respect to a mesh $\mathcal{B}$. It is described in detail in Appendix A. In order to infer about the redundancy of a boundary triangle, the algorithm uses a redundancy-check distance threshold $T_r$. Taking into account the accuracy of the Kinect sensor and possible accuracy’s degradation due to interference, a reasonable value for this threshold is $T_r = 1 \text{ cm}$. Although heuristically selected, this value was kept constant throughout all the presented experiments, revealing the rightness of this choice. With more expensive and accurate range sensors, the value of $T_r$ could be selected to be smaller.

2) A Coarse to Fine Strategy: Due to its iterative nature, the methodology just described presents an execution time of a few hundreds msecs, when applied directly at full resolution of the depth maps. Although not very high, this computational time is quite high for real-time applications. To render the approach faster, a coarse-to-fine strategy was implemented.

The methodology is initially applied at a coarse scale $2^{\alpha_0}$ ($\alpha_0 = 2$ for our experiments), with the triangulation data obtained from the depth maps down-sampled by $1:2^{\alpha_0}$, along both $x$ and $y$. All redundant triangles at the coarse scale $2^{\alpha_0}$ are removed. The triangles’ decimation is “propagated” to the next finer scale $2^{\alpha_{r-1}}$, before re-applying the algorithm. This algorithmic scheme continues up to the finest resolution. The idea is depicted in Fig. 6. Let the number of redundant triangles at the finest resolution be $N_r$. The number of boundary triangles in each algorithm’s iteration, as well as the required number of iterations to remove all redundant triangles, are of the order of $O(N)$. At a coarse resolution $1:2^{\alpha}$, both of these numbers are of the order of $O(N/2^{\alpha})$, resulting in a much lower computational effort. After the propagation of the decimation results to the finer scale, only a few fine triangles remain to be removed, much fewer than $N_r$. Based on these facts, the use of the described coarse-to-fine approach to reduce the computational effort seems reasonable.

With a distance threshold value $T_r$ that is constant along scales, the described coarse-to-fine strategy may lead to final results that are slightly different from those obtained by considering directly the finest scale. The reason is that the decimation at a coarse resolution and the “propagation” to the next finer scale may lead to the removal of fine-scale triangles that should have been preserved. Experiments showed that this has practically no effect to the visual quality of the 3-D reconstruction results, since the size of the triangles is practically very small compared to the used threshold value $T_r$. However, in order the methodology to be as precise as possible, a variable threshold value was used. The threshold is decreased at each coarser scale as $T_r^{[s+1]} = k \cdot T_r^{[s]}$, with $T_r^{[0]} = 1 \text{ cm}$ and $k \in (0,1)$. With a value of $k$ close to zero, the decimation approach would had no effect at coarse scales, leaving all triangles untouched. A reasonable value for $k$, selected in our experiments, is $k = 0.9$.

An example of the methodology’s results in decimating the redundant overlapping mesh regions is given in Fig. 4(b). The visual artifacts introduced at the overlapping regions are removed by decimating the redundant triangles. Another important benefit is that the number of triangles that will be stitched
during the clipping process, described in Section III-D, reduces significantly. Therefore, the clipping process is much faster.

D. Mesh Clipping by Retriangulation

A clipping process is required to smoothly join two decimated meshes at the region of their adjacent boundaries, closing any introduced small hole and producing a single mesh. An approach for that purpose is described in [9]. The approach requires the two meshes to slightly overlap so that the boundary edges of \( A \) and \( B \) intersect (if projected to a common 2-D plane), which is not always true for our decimated meshes. Moreover, in order to find precisely the points of intersection in the 3-D space, a relatively complicated procedure is introduced in [9], that uses a “thickening” wall along the boundary edges of one mesh, which has to be perpendicular to the boundary triangles. This would increase the computational cost, which is vital for our real-time application. Due to these reasons, we preferred to use a simple, yet robust re-triangulation approach, described below.

1) Detection of the Adjacent Triangles: The objective is to find the near-boundary triangles \( T_i^A(x, y) \) in mesh \( A \) that are adjacent to mesh \( B \) and vice versa. Therefore, a distance threshold value \( T_a \) has to be introduced. Any triangle \( T_i^A(x, y) \) with a distance less than \( T_a \) from \( T_i \) from \( B \) is dropped from the original mesh and added to a list of triangles \( L\{A, B\} \), to be retriangulated. Similarly, the triangles \( T_i^B(x, y) \) in \( B \) are checked with respect to their distance from all triangles in \( A \) and added to the list \( L\{A, B\} \), to be retriangulated. To describe a triangulation of the initial points and precisely the points of intersection in the 3-D space, a relatively complicated procedure is introduced in [9], through homography obtained from a checkerboard.

In order to accelerate the minimum distance calculation, the approach described in the FRBR algorithm (see Appendix) and illustrated in Fig. 5, is used. Notice that the projections \( p_i^{AB}(x, y) \) (projections of the triangles’ centers \( C_i^A(x, y) \) onto the depth camera \( B \)) and \( p_i^{BA}(x, y) \) have already been calculated during the decimation process.

2) Retriangulation: Given that the adjacent boundary triangles were selected from the two meshes and added to the list \( L\{A, B\} \), retriangulation of the triangles’ vertices is realized. Let \( \mathbf{P}_{\mathbf{A}, \mathbf{B}} \) be a \( N \times 3 \) matrix containing the vertices of the triangles in \( L\{A, B\} \). All duplicates have been removed from \( \mathbf{P}_{\mathbf{A}, \mathbf{B}} \). Ideallly, a triangulation in the 3-D space should be performed, dealing directly with points in the 3-D space. However, such a step would require significant computational time, prohibited for a real-time system. Therefore, we preferred to use a terrain triangulation method, being much faster, by projecting the points onto a plane.

3) PCA and Projection to the Optimum Plane: In order the 2-D triangulation to be robust and provide quality results, one should use the points’ projections onto the optimum plane. As optimum, one should consider the plane that is defined by two orthogonal axes, along which the 3-D data present the maximum variances. This means that Principal Component Analysis (PCA) of the 3-D points \( \mathbf{P} = \mathbf{P}_{\mathbf{A}, \mathbf{B}} \) has to be performed, so as to find their two principal axes (components). The appropriate transform matrix \( \mathbf{W} \) is obtained via mean subtraction and Singular Value Decomposition (SVD). The data are transformed by \( \mathbf{W} \) and its two first components constitute the 2-D projection onto the optimum plane. The corresponding 2-D points are Delaunay-triangulated [51]. It should be noted that the smaller the variance of the 3-D data along the third axis is, compared to the variances along the two other axes, the more robust the triangulation step is expected to be. For the example in Fig. 4, the standard deviations of the original and the transformed data were \([7.8, 13.1, 9.3]\) cm and \([13.5, 11.0, 4.1]\) cm along \( X, Y \) and \( Z \) respectively.

4) 2-D Delaunay Triangulation [51]: We used the 2-D Delaunay triangulation implementation of the CGAL (Computational Geometry ALgorithms) ver. 3.8 library,\(^7\) which showed to be fast and reliable. The edges of the created 2-D triangles describe a triangulation of the initial points \( \mathbf{P} \) in the 3-D space. However, some of the corresponding 3-D triangles may contain long edges and should be discarded. We used a threshold value for the maximum accepted edge length, set equal to \( T_e - T_a - 2 \) cm.

An example for the clipping process is shown in Fig. 4(c). It can be verified that small holes are covered and the meshes are smoothly “stitched” together.

IV. IMPLEMENTATION DETAILS

A. Multiple-Kinect Network Calibration

1) Single Kinect Calibration: The internal calibration of a single Kinect involves the estimation of i) the RGB’s camera intrinsic parameters, ii) the depth camera’s intrinsic parameters and iii) the relative pose between them. The OpenNI API uses the factory calibration, stored onboard. For our application these data could be considered as sufficiently accurate. Since, however, the external calibration of the Kinects network is based on RGB data, in order to increase accuracy, we estimated the internal RGB cameras’ parameters using Zhang’s method [41], through homography obtained from a checkerboard. For robustness, as well as to avoid complex non-linearities in the application of the Bundle Adjustment method (see next paragraph), we ignored radial and tangential distortion of the lens, since these are small for the Kinect cameras and the “active” region of the capturing setup is small compared to the cameras’ FOV. According to our experiments, we found that the obtained calibration parameters are improved over the standard OpenNI parameters. Specifically, we captured three different sets of checkerboard images, with 400 images in each set. One set was used at a time as the “training” set for optimization and the remaining two were used for evaluation of the Mean Reprojection Error (MRE). In each case, the obtained MRE was lower than 1 pixel. Comparing the MRE with the one calculated with the standard OpenNI parameters, the improvement ranged from 4% to 27%.

2) External Calibration: We employed a global (all-to-all) external calibration method, which constitutes a combination of the works in [42], [43] and uses inputs from the Kinects’ RGB cameras. The method requires establishing point correspondences across all camera images. For that purpose, we used a calibration object with two LEDs of different colors (a red and a green one), positioned at a fixed distance \( d = 445 \) mm (see

\(^7\)http://www.cgal.org/
Fig. 7. Calibration results for camera #1. (a) Reprojection error before bundle adjustment. The mean error is quite high. (b) Reprojection error after bundle adjustment. The mean error reduces below 1 pixel.

The employed approach can be shortly summarized in the following steps:

- **Establishment of point correspondences**: A large number of RGB images is simultaneously captured from all Kinect devices, while waving the calibration object inside the whole working volume, as shown in Fig. 1(c). Then, considering separately the red and the green color channels, we detect the 2-D positions of the red and green points LED points, respectively. Since it is not always possible to make the working volume completely dark, we used the approach of [42], which showed to be stable and robust. The method was applied with a subpixel accuracy of 1/4.

- **Pairwise calibration**: Given detected point correspondences in a pair of cameras, pairwise stereo calibration is performed based on the epipolar geometry constraints [52], as expressed by the Fundamental and Essential matrices. In our specific application, we calculated the Fundamental matrix using the 8-point algorithm with RANSAC-based outliers’ rejection, exploiting the OpenCV ver. 2.2 library. Due to the nature of the epipolar geometry constraints, the relative translation vector between two cameras can be calculated up to a scale factor $\lambda$. This factor is estimated from the actual distance of the red and green LED markers and the 3-D estimates obtained via stereo triangulation.

- **Global optimization**: The pairwise calibration-based approach cannot be very accurate. Indeed, due to pairwise errors’ accumulation, the mean reprojection error can be as high as 4 pixels as shown in Fig. 7(a). Therefore, the calibration data are globally refined using Bundle Adjustment [44], a methodology known from the Structure-from-Motion literature. Specifically, estimations of the 3-D LED points are initially produced by averaging the pairwise stereo-triangulation estimates. Then, the 3-D point estimates (structure term), as well as the extrinsic camera parameters (motion term) are globally refined using the Sparse Bundle Adjustment implementation [44]. The re-projection error after global optimization is presented in Fig. 7(b) for one of the cameras. The mean re-projection error for all cameras was 0.84 pixels. Finally, given the globally optimized 3-D point structure, the scale factors $\lambda$ are refined.

B. Algorithmic Implementation Details, CUDA and Multi-Threading Issues

1) **Encoding of Triangle Sets**: With a general encoding scheme, a set of triangles is represented by a list of triplets of vertex indices. However, according to the initially applied SDC triangulation in our approach, two triangles may be generated for each pixel $(x, y)$ on the depth map. Therefore, throughout the previous sections the generated triangles were denoted as $T_i(x, y), x = 1, \ldots, N_x, y = 1, \ldots, N_y, t = \{1, 2\}$. Consequently, the set of generated triangles from each depth map may be represented by a $2 \times N_x \times N_y$ matrix of isA (boolean) elements, with each element indicating whether the corresponding triangle exists. This representation offers some benefits from the implementation point of view, such as: a) Checking whether the triangle $T_i(x, y)$ is boundary reduces to checking the existence of its three neighbor triangles $T_2(x, y), T_3(x - 1, y)$ and $T_5(x, y - 1)$; b) The calculation of the projection of a triangle to another depth camera is simple and consequently, the adjacency of the triangles in two meshes can be efficiently inferred; c) A convenient realization of the coarse-to-fine strategy, as described, is straightforward; d) The removal of a triangle is performed by changing the corresponding matrix element to “false”, avoiding the use of long variable-length lists; e) The calculations can be easily mapped into parallel execution threads using CUDA. Therefore, we preferred to keep this encoding scheme, until the final step of the method (re-triangulation).

2) **CUDA-Based Implementation Issues**: Given that modern GPUs have evolved into highly parallel, multi-threaded, multicore processors of high computational power and memory

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8http://opencv.willowgarage.com/wiki/
bandwidths, applications can use their parallel calculation model to speed up computations. Therefore, in order to speed up the algorithm’s execution and realize higher frame rates, we implemented some of its parts exploiting the CUDA’s (Compute Unified Device Architecture) parallel computing architecture. CUDA enables parallel computations on modern GPUs without the need of mapping them to graphics APIs. The employed GPU (Nvidia GTX 560Ti) features 8 multiprocessors, 384 CUDA cores, with processors’ clock rate equal to 1645 MHz.

The idea is that independent pixel-wise (for each (x,y)) calculations can be mapped into many parallel blocks of independent processing threads. This is realized by the definition of CUDA “kernels” that, when launched, are executed in parallel by different CUDA threads. All threads of a block reside on the same processor core. Various parts of the presented reconstruction methodology can exploit this scalable parallel computing model, in order to speed up the whole algorithm, as can be verified from the experimental results presented in Section V. More specifically, a) The projections of all 2-D pixels (x, y) of a single depth-image to the 3-D space is performed by the launch of the corresponding kernel in N_x blocks of N_y threads; b) A kernel for the generation of all triangles (filling the corresponding boolean matrix) is also called in N_x × 2 (two dimensional) blocks of N_y threads; c) The projections of all triangles’s centers in a mesh A to the depth map B are computed in N_x × 2 blocks of N_y threads; d) Finally, the detection and removal of redundant boundary triangles is achieved with the corresponding kernel’s launch in N_x × 2 blocks of N_y threads.

3) Multi-Threading Issues: As already explained, the final step of the method involves re-triangulation of points in pairs of neighbor meshes. Based on the capturing setup, the re-triangulation step has to be executed for four mesh pairs. In order to take advantage of the host computer’s multi-threading capabilities, this step is executed in four parallel CPU threads, resulting into a high gain in computation time, as can be verified in the experimental section.

4) Bilateral Filtering: We applied bilateral filtering [45] to the captured depth maps for the experiments of Section V-B (in contrast to Section V-A). We used the CUDA-based implementation included in the NVIDIA’s GPU Computing SDK v.4.0. Throughout the experiments, we fixed the filter’s parameters as follows: The radius and the standard deviation (σ) of the spatial Gaussian kernel were set equal to 6 pixels and 4 pixels, respectively. The standard deviation of the intensity (i.e., depth value) Gaussian kernel was set equal to 50 mm.

V. EXPERIMENTAL RESULTS

A. Experimental Results—Reconstruction Quality

In this subsection, we present experimental results with respect to the visual quality of the obtained reconstructions. Some preliminary results were already presented in Fig. 4, which prove the significance of the proposed algorithm’s steps. The results presented below were obtained with the capturing setup described in Section II and correspond to three different capturing sessions. These capturing sessions were realized under different, non-uniform illumination conditions. No color calibration was employed to extenuate the visual effects due non-uniform illumination. Additionally, we fixed the methodology’s parameters throughout all presented experiments, equal to \( T_d = 2 \) cm, \( T_r = 1 \) cm, \( T_b = 2 \cdot T_r = 2 \) cm and \( T_n = T_p = 2 \) cm. This reveals the appropriateness of these choices.

1) Session #1: Figs. 8–10 show the reconstruction results for a man standing on his knees and either remaining still or moving. Fig. 8 highlights the alignment improvement with the application of ICP-based registration. The separate (non zippered) meshes are presented in Fig. 8(a), without global GPA-ICP registration, showing that although calibration was quite accurate, still the alignment is not perfect. After ICP-based global registration of the four meshes, their alignment improves, as shown in Fig. 8(b). However, due to the partial overlap of the meshes and the noise mainly at the mesh boundaries, significant visual artifacts may be introduced. Most artifacts are removed with the application of the proposed algorithm. Fig. 9 presents the reconstruction results for a specific frame, from various viewpoints, before and after the application of the algorithm.

A set of reconstruction results for various frames, as viewed from the same view-point, are depicted in Fig. 10. Although the reconstructed human moves relatively fast, the visual quality of the results is realistic enough, for a real-time application.

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Fig. 9. Session #1: Reconstruction results for a single frame, from various viewpoints, (a) without and (b) with the application of the decimation plus re-triangulation method. With the application of the method, the visual artifacts on the face are partially removed, while the overlapping mesh regions on the t-shirt are smoothly “stitched”.

Fig. 10. Session #1: Reconstruction results for various frames, from the same viewpoint.

2) Session #2: Fig. 11 presents the reconstruction results from various viewpoints, considering a specific pose, (a) before and (b) after the application of the zippering algorithm, underlying the introduced improvement. Similar results are given in Fig. 12 for various poses of a slowly moving human. Finally, Fig. 13 depicts the real-time reconstruction results for a dancing human, in a sequence of frames. Despite the fact that the human moves quite fast, no significant visual quality degradation is introduced.

3) Session #3: The reconstruction of a human pose from various viewpoints is shown in Fig. 14, while results for a dancing sequence are presented in Fig. 15, showing the effectiveness of the proposed real-time reconstruction approach from multiple Kinect streams.

B. Comparative Results

In this section we provide comparative results against a state-of-the-art off-line method for surface reconstruction. As a “gold-standard” approach, we selected the Poisson surface reconstruction method [11], which handles the reconstruction problem from oriented point sets as a spatial Poisson problem. This method produces watertight models and shows to be highly resilient to data noise. The adaptive multi-scale algorithm of [11] presents time and space complexities that are proportional to the size of the reconstructed model. The method takes as input a point cloud and the directed points’ normals. Therefore, in our experiments, we pre-calculated the points’ normals using PCA (plane fitting) on the 24-points neighborhood of each point.
Fig. 11. Session #2: Reconstruction results for a single frame, from various view-points, (a) before and (b) after the application of the decimation plus clipping method. Due to non-uniform illumination conditions and noise near the mesh boundaries, significant visual artifacts are present before the method’s application. With its application, the overlapping mesh regions are decimated and smoothly clipped. This results into a significant visual quality improvement, as shown in (b).

Fig. 12. Session #2: Reconstruction results for various poses, (a) before and (b) after the application of the decimation plus clipping method. Due to non-uniform illumination conditions and noise near the mesh boundaries, significant visual artifacts are present in (a). With the method’s application, the visual quality improves significantly, as shown in (b).
Fig. 13. Session #2: Reconstruction results for many frames of a moving sequence and a fixed point of view. The frames correspond to time instances that differ approximately 300 ms.

Fig. 14. Session #3: Reconstruction results for a single frame and several points of view.
using the CGAL ver. 3.8 library. Then, the normals were oriented using the Minimum Spanning Tree-based algorithm [7], implemented in the same library. As for Poisson reconstruction, we used the source code implemented and freely offered by the authors of [11]. The algorithm was applied with the default parameter values, proposed by the authors and specified in the freely available code (e.g., maximum tree depth = 8). Then, texture was mapped to the reconstructed model as follows: The color of a point was calculated from the weighted average of the corresponding pixels in the “visible” RGB cameras’ images. Given the oriented point’s normal, we selected the weights proportional to the cosine of the capturing angle, i.e., proportional to the inner product of the point’s normal vector with the vector connecting the point with the camera’s center. Since Poisson reconstruction produces watertight models (it closes holes at surface regions that are invisible to any Kinects), some vertices of the reconstructed surface are invisible to any RGB cameras. In this case we assigned a gray color to the corresponding vertex (see last row of Figs. 16–18).

Comparative results with respect to the visual quality of the reconstructed models are presented in Figs. 16–18. We present the results of the proposed method (third row) in comparison with the separate, non-merged meshes (second row) and the Poisson reconstruction approach (bottom row). The original RGB views, captured by our Kinects, are also given in the upper row. As can be verified, the Poisson method produces watertight, smooth models, almost free of spurious reconstruction artifacts. The Poisson-based stitching of the meshes is almost perfect, since the fusion is performed implicitly by the method. Our method produces quite clear models, with only a few artifacts, which are much more visually pleasant than the non-merged separate-meshes in the second row. Although the proposed method does not produce so smooth models as the Poisson method does, the results are quite realistic, given its real-time execution. On the other hand, Poisson reconstruction requires execution time of the order of a few seconds and therefore is not applicable for on-the-fly reconstruction. Quantitative comparative results are given in the next paragraphs.

1) Subjective Evaluation: A subjective evaluation procedure was realized, as follows. We presented the reconstruction results for two frame sets to 17 raters, 13 men and 4 women. 8 of them are experts (MSc and/or PhD) in the general field of image processing/computer vision, while the rest 9 are not, but have a high-level education. The first set is comprised of totally 294 frames, while the second one of 130 frames. Representative frames of the two sets are those given in Figs. 16–18, respectively. Through a Graphical User Interface (GUI), the reconstruction results of the proposed method were presented (a single frame each time), in comparison to the four-separate-meshes and the Poisson reconstruction results, along with the original Kinect RGB views (exactly as in Figs. 16–18). We asked the raters to evaluate frame-by-frame the results of our method (assigning an integer score in the range [0, 10]) with respect to their visual quality (“How realistic did they find the results?”), taking into account the visual artifacts as well as the smoothness of the models. In order to have a reference, it was assumed that the four-separate-meshes and the Poisson reconstruction results are assigned scores equal to 2 and 8, respectively. Two evaluation rounds were realized. In the first one the frames were presented sequentially, while in the second one they were presented in a random order. In each round, we asked the raters to assess the results for at least 70 frames and 50 of the first and second

http://www.cs.jhu.edu/~misha/Code/PoissonRecon/
Fig. 16. Comparative results for a single frame of the 1st frame set—Upper row: The four RGB views captured by our Kinects; Second row: Four separate, unprocessed meshes; Third row: Proposed method; Fourth row: Poisson surface reconstruction [11]. The reconstruction results are presented for four different viewing angles, 180° (first column), 135°, 235° and 90°.

set, respectively. We instructed them to prefer assessing frames that make them feel more confident.

In Fig. 19, we present summarizing results of the above subjective evaluation procedure. For both frame sets, the most frequent score, as well as the median score, are equal to 7. In both cases, the distribution (histogram) of the scores is quite well concentrated around the peak value (Gaussian-like), deviating significantly from a uniform distribution. The mean scores are equal to 7.15 and 6.57, respectively, while the standard deviations equal to 1.6 and 1.66. As a conclusion, one can draw that the results of our method were assessed as much superior to the four-separate-meshes results. Our method also shows to be not significantly inferior to the Poisson reconstruction method, although much faster, as presented in the next paragraph.

2) Execution Time and Number of Model Faces: Considering humans and foregrounds objects of large sizes, quite high reconstruction rates (close to 10 fps) can be achieved using the proposed system with the presented reconstruction algorithm and the given implementation details. Such rates enable the use of the proposed method for on-the-fly reconstruction in
real-time applications, where other methods are not applicable. Comparable results with respect to the execution time and reconstruction rate are presented in Table II. The presented execution time results were calculated as the mean capturing plus reconstruction time per frame, for all 424 frames of the two sets used during evaluation (representative frames were given in Figs. 16–18). Notice that for the Poisson reconstruction method, we do not take into account the time required for calculating the directed vertices’ normals.

Table II presents also results with respect to the mean number of triangles per mesh. After the application of the proposed approach to the initial separate meshes, the number of triangles reduces significantly, while the visual quality also improves. The Poisson reconstruction method, applied with the specific octree depth ($\text{maximum tree depth} = 8$) produces generally lighter models. Increasing the maximum tree depth could probably further improve the visual quality of the results, but the reconstruction rate would further significantly reduce.

C. Detailed Experimental Results on Computational Effort

In this subsection we give details with respect to the execution time of the described method. The presented results were
obtained considering all 424 frames of the frames-sets used in the subjective evaluation procedure. Representative frames were given in Figs. 16–18.

1) CUDA and Multi-Threading: In order to justify the use of CUDA GPU-computing and Multi-Threading (MT), indicative results are presented in Table III. The CUDA-based implementation is compared with the corresponding Gold standard C implementation, while the MT-based implementation (re-triangulation part of the algorithm) with the corresponding Single-Thread one. The execution time, as well as the corresponding frame rate, are given considering the four different combinations of implementation. As can be verified, using both CUDA and MT, the algorithm’s execution speeds-up, so that a frame rate of 7.32 fps can be realized. All the results presented in the rest of the subsection refer to the CUDA plus MT implementation.

2) Break-Down With Respect to the Algorithm’s Part: The most time-consuming steps of the algorithm are the mesh redundancy removal and the clipping step. A break-down of the execution time with respect to the algorithm’s parts is presented in Table IV. Although these steps employ iterative methods, the corresponding execution times are quite low, enabling the realization of real-time applications.
Fig. 19. Subjective Evaluation Results: Distribution (histogram) of the scores assigned to reconstructions of the proposed method, given the instruction that the corresponding scores for the four-separate-meshes and the Poisson method are equal to 2 and 8, respectively (a) Frame-set #1 (b) Frame-set #2.

VI. CONCLUSIONS AND FUTURE WORK

We presented a novel, complete and easy to implement system for the realistic full 3-D reconstruction of moving humans, with the objective to be used in real-time applications, such as 3-D Tele-Immersion. All the necessary details of the multiple-Kinects capturing system, along with the applied methods for its accurate external calibration, were explained. We presented a novel algorithm, along with its necessary implementation details, for the real-time generation of full 3-D models. The approach is based on the generation of separate textured meshes from multiple RGB-Depth streams, optionally on their accurate ICP-based alignment and a fast zippering algorithm for the creation of a single full 3-D mesh. According to the experimental results, the 3-D reconstructions were shown to be quite accurate and realistic, even under the real-time constraints and the motion of the reconstructed humans. The achieved frame rate is slightly smaller than 10 frames per second, although the computations are performed by a single host PC.

In the future, we plan to study for the appropriate mesh-coding scheme that will enable real-time coding and transmission of the triangular mesh models, so that to be shared between different tele-immersion stations. The placement of the models inside a common virtual world, is an additional objective, along with the search for appropriate methodologies to enable the virtual interaction among users and with virtual objects, possibly exploiting among others the motion capture (MoCap) capabilities, offered by the Kinect technology.

APPENDIX

FAST REDUNDANT BOUNDARY REMOVAL (FRBR) ALGORITHM

The algorithm uses as input the triangles in a mesh $A$, $T_A(x, y)$, and decimates the boundary triangles that are redundant with respect to a mesh $B$, based on a redundancy-check distance threshold $T_r$. Auxiliary inputs are the calculated triangles’ centers in mesh $A$ and $B$, $C_A(x, y)$ and $C_B(x, y)$, as well as the 2-D projections $p_A^{1|y}(x, y)$ and $p_B^{1|y}(x, y)$ of the triangle centers in $A$ to the depth camera $B$. The algorithm’s steps are summarized as follows:

1) Find the boundary triangles in mesh $A$. As boundary triangles are defined those that do not share all of their three edges with other triangles in the mesh. Based on
the 2-D SDC triangulation scheme that was described in Section III-B, it is straightforward to check whether a triangle is boundary by checking whether all of the three neighbor triangles exist.

2) For each boundary triangle in \( A \), let \( T^A_k(x_0, y_0) \):

- Check whether any triangle in \( B \) has a distance smaller than the predefined threshold \( T_r \). The distance of two triangles is checked with respect to the Euclidean distance of the triangles’ centers. Given the very small size of the triangles in comparison to the introduced threshold value, this simplification practically will never lead to a false removal of a triangle.

- Notice that examining the distance of a given triangle \( T^A_k(x_0, y_0) \) from all the triangles in the other mesh \( B \) is very time consuming. In order to avoid this, we should take into consideration that the triangles in mesh \( B \) that are adjacent to \( T^A_k(x_0, y_0) \), project in the 2-D neighborhood of \( p^A_{xy}(x_0, y_0) \), let \( N(p^A_{xy}(x_0, y_0)) \), as shown in Fig. 5(b). Therefore, we calculate the distance of the given boundary triangle’s center \( C^A_k(x, y) \) from those \( C^B_i(x, y) \) for which \( (x, y) \in N(p^A_{xy}(x_0, y_0)) \). The used neighborhood size in our experiments is \( 16 \times 16 \) pixels².

- If \( T^A_k(x_0, y_0) \) has at least one triangle of \( B \) that is closer than \( T_r \), remove it.

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