Development of an Automated Method for Removing Objects from 4D Scan Datasets

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Abstract

The analysis of human movements based on 4D scan data is playing an increasingly important role in various fields of application, such as digital clothing development, ergonomics and motion research. 4D body scanners provide time-resolved point cloud sequences that can be used to capture movement sequences and body deformations in detail. In realistic recording situations, however, test subjects often use aids such as stools, steps or boxes to perform certain movements. These objects are included in the raw data and cause considerable problems in the subsequent generation of homologous meshes. Especially in close contact or movement, humans and objects can merge in the point cloud, leading to faulty mesh surfaces and significantly impairing the accuracy of simulations and visual representations. The aim of this work was to develop three automated methods for removing such static and dynamic auxiliary objects from 4D scan data sets. The methods developed are based on clustering algorithms (DBSCAN), color weighting and registration methods (ICP). Depending on the application scenario, they enable the reliable separation of the human body from surrounding objects. The methods were evaluated using three practical motion scenarios: running on a treadmill (static object without body contact), stepping onto a step (static object with contact) and lifting a box (dynamic object with contact). The results show that each method has specific strengths in terms of object type and scene complexity. Overall, the use of these methods significantly improved the network quality in all cases. The tools developed represent an important step towards the automation of 4D scan processing and open up new possibilities for realistic simulations of human movements in practical scenarios.

Keywords: 4D-Body-Scanning, Point Cloud Processing, Data Cleaning, Object Removal, Clustering

1. Introduction

In various fields of research and application – such as the textile and automotive industries, orthopedics and ergonomics – human movements and body deformations during movement are analyzed. In digital clothing development and virtual pattern design in particular, such data provides valuable information about the fit and wearing behavior of clothing [1]. An advanced technology for capturing these movements is 4D scanning, which produces a time-resolved sequence of 3D point clouds. Systems such as the Move4D body scanner from the IBV (Instituto de Biomecánica de Valencia) [2] enable the detailed capture of human movements and body shapes over time [3].

In real-life scenarios, test subjects do not always move freely around the room. They sit on stools, climb steps or use handrails. These aids serve as orientation points and enable the test subjects to move naturally. However, these additional objects pose a considerable obstacle in downstream data processing. In order to generate a so-called homologous mesh from 4D point cloud data – i.e. a consistent, topologically identical representation of the body across all points in time – it must be ensured that only the human body is included in the scan [3].

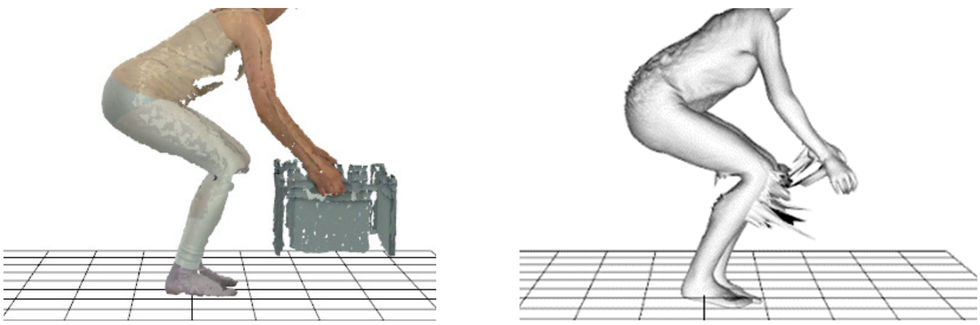


Fig. 1. 4D-scan raw data: woman picking up a box (l); 4D-scan processed to homologous mesh having defects because of not proper processing using raw data with additional objects there (r)

Otherwise, there is a risk of humans and objects merging into a single point cloud structure, resulting in incorrect or distorted mesh surfaces (see Fig. 1). These distorted mesh surfaces significantly impair the accuracy of simulations and measurement analyses as well as the visual representation.
To clean up 4D scan data from objects, there is currently only one manual method for removing such objects in the associated scanning software Move4D from IBV [2]. However, the lack of automation and the resulting need to manually process each individual frame makes this a very time-consuming task.
This work develops tools that are capable of automatically removing static and dynamic objects such as stools, boxes and other aids from 4D scan data sets. This prevents the static or dynamic aid object from merging with the dynamic, moving human body – which in turn enables error-free mesh generation. The developed tool works directly with point cloud data in .ply format and is based on various variants of clustering and matching methods that can be used depending on the requirements. A total of three methods were developed.
The add-on significantly improves the quality of the generated meshes and helps to enable more realistic representations of movement sequences, such as sitting down on a stool or getting into a car. In addition, the modular structure of the evaluation algorithms makes it possible to adapt the approach to other areas of application with similar challenges.

2. Related Works

The analysis and processing of 4D body scans is an active field of research that is particularly important in digital clothing development, ergonomics and motion research [1]. A key problem here is the reliable segmentation of the human body from additional objects that are often present in the images.
Established methods for segmenting point clouds often use classic clustering methods such as DBSCAN or k-means [4, 5]. DBSCAN in particular has proven itself through its ability to segment point clouds based on density information without having to determine the number of clusters in advance. However, these approaches are mostly applied to individual static point clouds without explicitly considering temporal changes or dynamic objects in 4D datasets [4].
To separate people from aids such as chairs or stools, some studies also rely on color or intensity information to enable improved differentiation at close contact points [6]. The combination of geometric and visual features plays a decisive role here in order to avoid fusions in segmentation [7].
In the field of motion capture and analysis, methods have been established that use registration techniques such as Iterative Closest Point (ICP) or feature-based approaches (e.g. FPFH) to compare point clouds consistently over time and detect changes. However, such methods are computationally intensive and require careful parametrization, especially when removing dynamic objects [7, 8].
Specifically for applications in clothing production and pattern design, only limited work has been done to date on methods that address not only accurate body capture but also the easy removal of aids from 4D scan data.
This paper closes this gap by presenting three automated methods that combine clustering, color and registration approaches, enabling flexible and efficient removal of static and dynamic objects from 4D body scans.

3. Methods

In order to achieve error-free mesh generation of the 4D body scans, the auxiliary objects should be removed from the scans and only the human body should remain. Various methods have been developed for this purpose, enabling automated processing of the scans. Fig. 2 shows the data processing sequence.

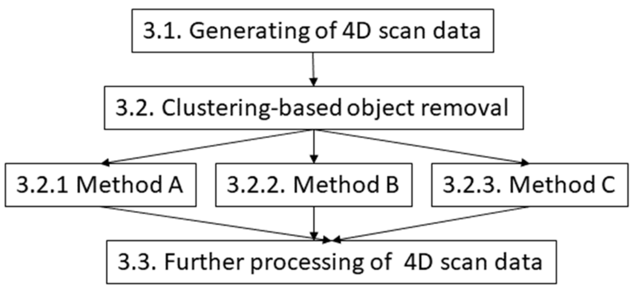


Fig. 2. Processing flow object removal.

After recording three movement sequences as 4D body scans (Section 3.1.), the auxiliary objects should be identified and deleted in an initial reference frame. This information was then transferred to all subsequent frames (Section 3.2). Three different methods were developed for this purpose (Sections 3.2.1, 3.2.2, 3.2.3). The various workflows were created in Python using common open-source libraries such as Open3D, NumPy and ply-file. Through parametrization and modularity, the methods can be adapted to different application scenarios. The final step was the further processing of the scan data (Section 3.3.).

3.1. Generating of 4D scan data

The scans were created using a Move4D body scanner from the Instituto de Biomecánica de Valencia (IBV). This consists of 12 cameras that are permanently installed in a room [3]. The scans were recorded at a frequency of 15 frames per second. The cameras are capable of generating a mesh of points, vertex coordinates and color (texture). The scans were then exported as ply files.

Three movement scenarios were created to evaluate and test the different methods. In scenario 1, a person is running on a treadmill. Due to the surface structure and coloring of the treadmill, only fragments of the treadmill are visible in the scan. This means that there is no contact between the person and the treadmill, which is to be removed. The treadmill is also static as an auxiliary object and only the person is in motion.

Scenario 2 involves a person stepping onto a step. This creates contact between the person and the auxiliary object (step), but the auxiliary object remains static.

Scenario 3 involves a person lifting a box. Not only is the person in motion, but the auxiliary object is also in motion. The box changes its position in several frames and also has contact with the body.

3.2. Clustering-based object removal

All three methods developed are based on an initial clustering step in the first frame of the 4D scans. The point cloud is segmented to separate different objects present in the scan (human bodies and auxiliary objects). Depending on the method, different segmentation methods are used, which either work exclusively on the basis of geometry or also take color information into account. In each case, the clustering is based on DBSCAN algorithms (Density-Based Spatial Clustering of Applications with Noise). The individual points of the point cloud are analyzed based on their spatial density. It is not necessary to specify the number of clusters in advance, as is the case with other clustering methods [4].

The selection of the cluster to be removed or retained is semi-manual: users identify either the human body (method A) or the object to be removed (methods B and C) in the initial frame. The cluster is then used as a reference for processing all subsequent frames.

3.2.1. Method A – Geometry based Clustering with Open3D-DBSCAN

The first method is a robust method for removing static objects without contact with the body. The clusters of the point cloud are identified using DBSCAN from Open3D library [10]. The DBSCAN algorithm is applied to the 3D coordinates, using a minimum point distance (eps) of 0.03 m and a minimum number of points per cluster (minPts) of 30. These values were found to be suitable in a further series of tests.

After clustering, the human body is selected by manually selecting the corresponding cluster. All other points – such as those from the step or the treadmill – are removed. To transfer this separation to subsequent frames, the body cluster obtained is used as a reference, whose point distribution is mapped to the next time points using a cKDTree. Points that are not close to the reference cluster in the current frame are discarded.

3.2.2. Method B: Color weighted Clustering with sklearn-DBSCAN

This method also uses color differences to separate objects and people – particularly useful when the two are very close together or even touching. Segmentation is improved by an extended point description, in which the color values (RGB) of the point cloud are included as additional dimensions in the clustering. The DBSCAN algorithm from the sklearn library [11] is used here, as it allows explicit scaling of the feature dimensions. Geometry and color data are combined in a weighted manner, with color being weighted twice as heavily as spatial position. This allows two points with similar colors but further apart to be grouped together, while two points that are very close spatially but differ in color can be assigned to different clusters.

The auxiliary objects are removed based on reference proximity using KDTree matching. Points within a radius of a few millimeters around the original object cluster are removed. This method is suitable for static objects with physical contact, but is more computationally intensive.

3.2.3. Method C: Dynamic method with ICP-Registering

For more complex scenes with moving objects (e.g. lifting a box), a method is used in which the reference geometry is registered per frame using Fast Point Feature Histograms (FPFH) and can then be tracked over time using ICP (Iterative Closest Point). After registering the reference geometry, it is used as a mask and the corresponding points in the frame are deleted. In each frame, an independent registration and associated search for the reference geometry takes place. This method also makes it possible to delete objects moving in space, but the computing time is significantly higher.

3.3. Further processing of 4D scan data

After removing the auxiliary object from all frames of the respective scan, the cleaned point clouds are reloaded into the Move4D software and then processed.

4. Results

In the following chapter, the three object removal methods developed are applied to all three scanned movements and analysed to determine which method is suitable for which movement pattern.

4.1. Movement 1 – Treadmill

In Movement 1 – running on the treadmill – there is no contact between the moving person and the static auxiliary object. In the raw scan, there are artifacts from the treadmill, which cause problems when processing the scan. Using methods 1 and 3, these artifacts could be deleted from all frames of the scan series, allowing subsequent processing to proceed without errors. Method B is not suitable for this type of scan, as artifacts still remain in the scan after object removal. The results of the experiment are shown in Fig. 3.

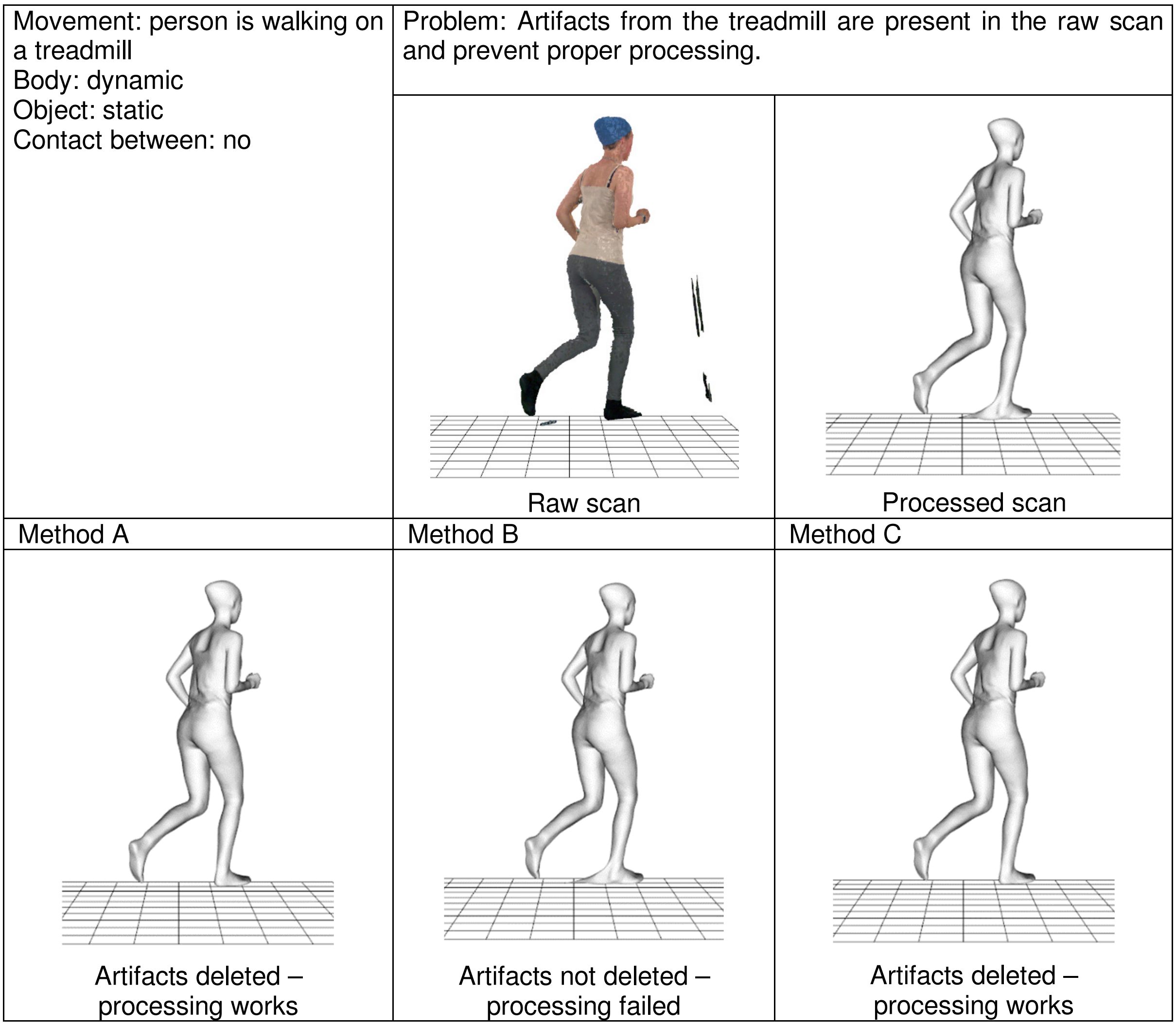


Fig. 3. Overview object removal process movement 1 – treadmill.

4.2. Movement 2 – Step

Movement 2 – Stepping onto a step – involves a moving person stepping onto a static auxiliary object, whereby the person and object come into contact during the movement. Due to the artifacts of the step, which are present in the raw scan, error-free processing of the scan is not possible. Methods B and C are suitable for completely removing the point cloud of the step from all frames of the scan and ensuring subsequent processing. Method A is not suitable for this application, as artifacts remain in the scan and hinder processing. The test results are shown in Fig. 4.

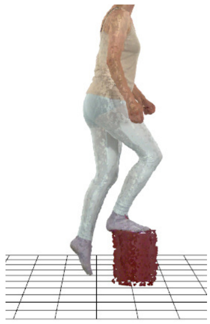
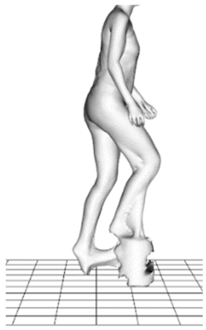
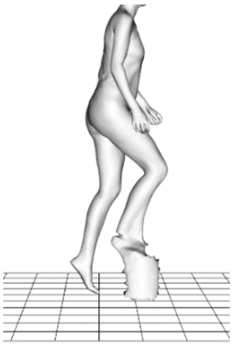
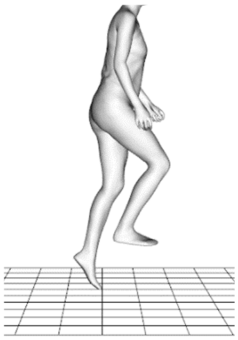
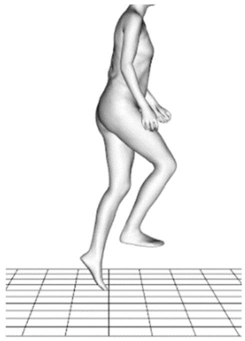
<table>
<tr><td rowspan="2">Movement: Person climbs onto a step
Body: dynamic
Object: static
Contact between: yes</td><td colspan="2">Problem: Artifacts from the step are present in the raw scan and prevent proper processing.</td></tr>
<tr><td>
Raw scan</td><td>
Processed scan</td></tr>
<tr><td>Method A</td><td>Method B</td><td>Method C</td></tr>
<tr><td>
Artifacts not deleted – processing failed</td><td>
Artifacts deleted – processing works</td><td>
Artifacts deleted – processing works</td></tr>
</table>

Fig. 4. Overview object removal process movement 2 – step.

4.3. Movement 3 – Lifting a box

In Movement 3 – Lifting a Box – a moving human body comes into contact with an auxiliary object that is also moving dynamically. The artifacts of the box in the raw scan prevent error-free processing. Method C is suitable for removing the box point cloud. Methods A and B are not able to completely remove the point cloud of the box. The test results are shown in Fig. 5.

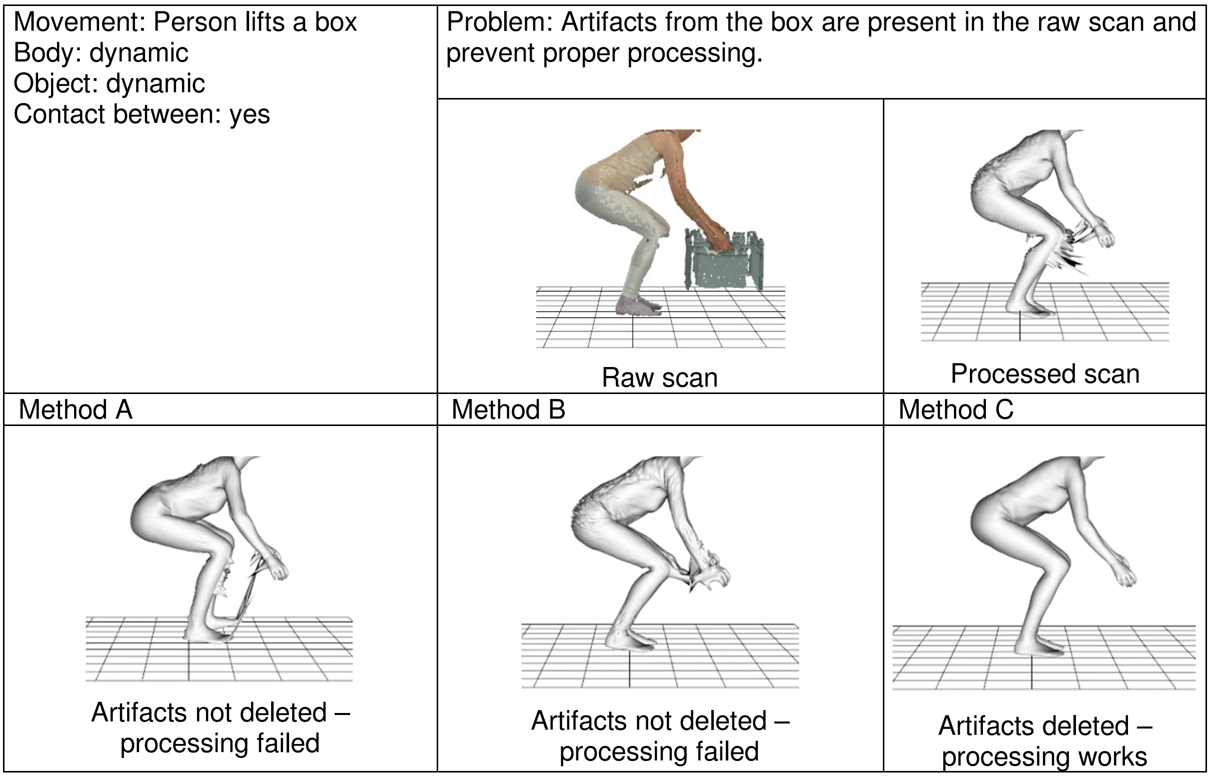


Fig. 5. Overview object removal process movement 3 – lift.

4.4. Compare methods

Table 1 provides an overview and comparison of the respective characteristics, advantages and areas of application of the evaluated methods.

Table 1. Overview table of the three methods for object removal from 4D body scans.

	Method A	Method B	Method C
Use case	Static objects without contact to human	Static objects with contact to human	Dynamic objects
Clustering method	DBSCAN (Open3D)	DBSCAN (sklearn) with color-based clustering	DBSCAN (Open3D)
Object selection	Keep-cluster (human)	Delete-cluster (object)	Delete-cluster (object)
Use of color	No	Yes, with color weighting	No
Cluster data transfer	KDTree (Index Mapping)	KDTree + Distances	ICP Registration
Subsequent frames	Transfer via cluster mapping	Removal based on reference proximity	Removal based on registered reference
Objects	Static	Static	Static and dynamic
Advantages	Simple, robust for static objects	Considers color differences, better separation when object and human touch in the first frame	Suitable for more complex, dynamic objects
Disadvantages	No object movement possible, no contact between object and human allowed	No object movement possible	Higher computational costs as each file must be registered

The three methods presented cover different application scenarios.
Method A is particularly efficient in processing and is well suited for scenes in which the object does not come into contact with the body and does not move over time. Here, the object is selected with just one click on the human body to be retained, which is very time-efficient. However, its weakness becomes apparent when there is little distance between the body and the object or when objects are moving, as geometric separation becomes unreliable in these cases.
Method B is also suitable for static auxiliary objects that are in direct contact with the human body, as color characteristics are also included in the clustering. Selecting the object to be deleted is somewhat more time-consuming here, as several clusters of the auxiliary object must be selected.
Finally, method C extends the scope of application to fully dynamic scenes in which the auxiliary object is moving. This offers the highest flexibility and accuracy, especially in realistic motion scenarios in which humans and objects move or touch each other simultaneously. However, the implementation effort is higher than with the other two methods.
As already explained in Table 1, the overview of the tests in Table 2 shows that method A is suitable for detecting and removing static auxiliary objects that do not come into contact with the test person. Method B is suitable for detecting and removing static auxiliary objects that come into contact with the test person. Method C is suitable for detecting and removing static auxiliary objects that may or may not come into contact with the test person. However, it should be emphasized here that, in contrast to the other two methods, it is also suitable for detecting and removing dynamic auxiliary objects. However, the computing time for Method C is higher than that for the other variants, so it is worth checking what scenario is involved and selecting the appropriate variant accordingly.

Table 2. Method-Movement Matrix.

Variant	Body	Object	Contact	Method A	Method B	Method C
Treadmill	Dynamic	Static	No	✓	✗	✓
Step	Dynamic	Static	Yes	✗	✓	✓
Lift	Dynamic	Dynamic	Yes	✗	✗	✓

5. Conclusion and Discussion

In this paper, three modular automated methods for removing static and dynamic auxiliary objects from 4D body scans were developed and evaluated. The aim was to improve the quality of mesh generation and enable the most realistic and error-free representation of human motion sequences possible. Each method addresses specific challenges. Method A is quite simple and time-saving, but only suitable for static objects that do not come into contact with the body. Method B, on the other hand, is also suitable for static objects that come into contact with the body, as color characteristics were included in the clustering process. Method C is more flexible and is the only one that is also suitable for dynamic objects, but it is also more computationally intensive. The tools thus enable flexible adaptation to different application scenarios and offer a significant improvement over the previously purely manual object removal.
The methods presented represent an important step towards automated processing of 4D scan data. Nevertheless, there is further potential for optimization and expansion. In particular, the dynamic-capable method C could be further developed to reduce computing time through more efficient approaches. Similarly, the selection and removal of objects with different shapes and textures, different and, above all, larger contact surfaces or deformable objects could be addressed. This would also be exciting in terms of separating two human bodies in motion. Another promising approach for future work is the integration of machine learning methods for the automatic recognition and classification of auxiliary objects directly in the point cloud data set. This would eliminate the need for manual selection of a reference cluster and fully automate the process. Further development of the methods is conceivable in various directions.

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