Towards Collaborative Analysis of Computational Fluid Dynamics using Mixed Reality

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Abstract: Computational fluid dynamics is an important subtopic in the field of fluid mechanics. The associated workflow includes post processing simulation data which can be enhanced using Mixed Reality to provide an intuitive and more realistic three-dimensional visualization. In this paper we present a cloud-based proof of concept Mixed Reality system to accomplish collaborative post processing and analysis of computational fluid dynamics simulation data. This system includes an automated data processing pipeline with a ML-based 3D mesh simplification approach and a collaborative environment using current head mounted Mixed Reality displays. To prove the effectiveness and accordingly support the workflow of engineers in the field of fluid mechanics we will evaluate and extend the system in future work.

1 INTRODUCTION

In the field of fluid mechanics, computational fluid dynamics (CFD) represents an important subtopic to optimize product design workflows, reduce the need for costly prototypes and eliminate rework. With CFD simulations of either liquid or gas passing through or around an object, engineers can analyse the flow's impact on the object. Therefore, CFD simulations are used in several fields of application, such as aerodynamics and aerospace analysis, industrial system design and analysis, biological engineering as well as engine and combustion analysis. The process of CFD simulation and analysis consists of three main steps: Pre-processing, which includes identifying the fluid domain of interest and set up the geometry of the object, which will be analysed. The solving step to solve physical equations related to the fluid flow and the post processing step, where appropriate visual representations of the results are being generated for analysis purposes. The latter can be done by post processors to visualize the resulting solutions represented as contour and vector plots or 3D models. The analysis of this data is mostly done on pc monitors, which restricts the graphical representations on two dimensions. Thus, an intuitive and realistic data analysis is prevented. Additionally, these post processors and CFD simulation software often rely on proprietary data formats, so that incompatibilities on different systems can occur. Especially when distributed and interdisciplinary teams collaborate.

We suppose that current Mixed Reality (MR) systems can support and enable collaborative CFD post processing by outsourcing this process completely into mixed reality. Results of a CFD solver will be uploaded into our system in an open file format to process them further in three dimensions without restricting users to be completely separated from reality and manipulate data intuitively with hand gestures, eye gaze and speech control.

Current systems used for CFD post processing lack of collaborative features. Especially when it comes to multidisciplinary and distributed teams. It is not uncommon for third-party systems such as video conferencing tools to be used. Therefore, users share their desktop screens or presentation slides to present resulting data, which means, that the integration of new ideas and the communication of feedback is often limited through an abstraction of the actual three-dimensional data to static images or animations, based on pre-defined camera angles. As a result, individual inspection of components is restricted.

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With the help of cloud computing, AI technology and current MR hardware, a distributed MR environment can be implemented to accomplish collaborative and interdisciplinary post processing and analysis of CFD data. Thus, the workflow of engineers in the field of fluid mechanics can be actively supported by minimizing times of analysis and reducing travel costs. It also leads to enhanced coordination and collaboration between team members by providing natural exploration of multidimensional data paired with enhanced social interaction due to digital avatars and collaboration features like object annotations or digital whiteboards. Accordingly, we assume that this will result in a better product and system design.

In this paper we present a proof of concept system to manipulate and analyse the results of CFD simulations in a collaborative and distributed MR environment. The goal is to integrate this system in the daily workflow of engineers and scientists. To achieve this, a cloud infrastructure used for automated data computation based on an open data format is necessary, so that users can upload their simulation results and view them on an MR head mounted display (HMD). The latter can be computationally very intensive for complex CAD models due to the large number of polygons within the meshes. Accordingly, an artificial intelligence (AI) model, which can implicitly learn the shape and simplify the meshes in a goal-oriented manner, needs to be developed, so that also complex models can be computed by the HMDs. In the collaborative MR environment, users will be able to control the post computing process by intuitive interactions via gestures or speech, as they can set filters to redefine visualization results and move or scale an object freely. With the given cloud infrastructure, distributed collaboration including virtual avatars, can also be made possible as mentioned above. According to the sensor data of current HMDs, those avatars can be equipped with eye gaze and hand visualization as proposed in (Piumsomboon et al. 2017) and also spatial sound to enhance communication.

The following sections are structured as follows: In section 2, we will present related work according to collaborative MR systems in the field of CFD and AI based mesh simplification. Section 3 will describe the overall system design including the automated data computation (Section 3.1), the AI based model optimization approach (Section 3.2) and the capabilities of the collaborative MR environment (Section 3.3). In section 4 we will conclude and present future work.

2 RELATED WORK

CFD simulations and analysis are widely used in the field of fluid mechanics. The visualisation of CFD results with MR technology was proposed in several projects. (J. Moreland et al. 2013) for e.g. developed an MR representation of simulated fluid flow within a power plant for training purposes. Vectors, streamlines and colour gradients were used to visualize CFD data. (Zhu et al. 2020) created a system, used in early building-design processes including the modelling of information about the building, mesh generation and CFD simulation to visualize animated thermal activities in a full-scale room using MR. Both studies rely on precomputed data, which must be manually changed on a desktop pc to visualize the MR projections. Functionalities to dynamically update models were proposed in (Malkawi und Srinivasan 2005). In this project different wireless temperature sensors were used to update the CFD simulation and visualize projections. These projects provide visualizations of simulation data but lack adequate user interfaces (UIs) and therefore an intuitive user experience while performing CFD post processing in MR in order to create new visualisations for HMDs.

As described in (Cheng et al. 2020), there is a lack of MR systems based on cloud storage and cloud computing, which are current trends for MR systems. They also mention that current systems are limited in terms of number of gestures or stability of voice recognition. Additionally, collaborative multiuser systems should be more promoted in the industry. For collaborative and distributed CFD analysis, cloud computing is also an essential part in order to accomplish efficient data manipulation, computation and visualisation. (García et al. 2015) presented a cloud-based system to monitor and alter CFD simulations for collaborative solution analysis. This includes pre-processing, solving and post-processing data within a server environment. The latter enables the user to set new basic filters such as stream tracers or colormaps to manipulate the simulations. Simulation results can be displayed in 3D environments, but are visualised on 2D screens, which, in contrast to MR systems, abstracts the outgoing data into unintuitive WIMP interactions. Furthermore, according to the literature research, there is a lack of MR environments to accomplish collaborative analysis of CFD simulation data by distributed working teams, which agrees with the statements provided by (Cheng et al. 2020).

Polygonal meshes effectively represent 3D shapes by capturing both surfaces and topology, and leverage non-uniform elements to represent large flat regions as well as sharp, intricate features. However, naive

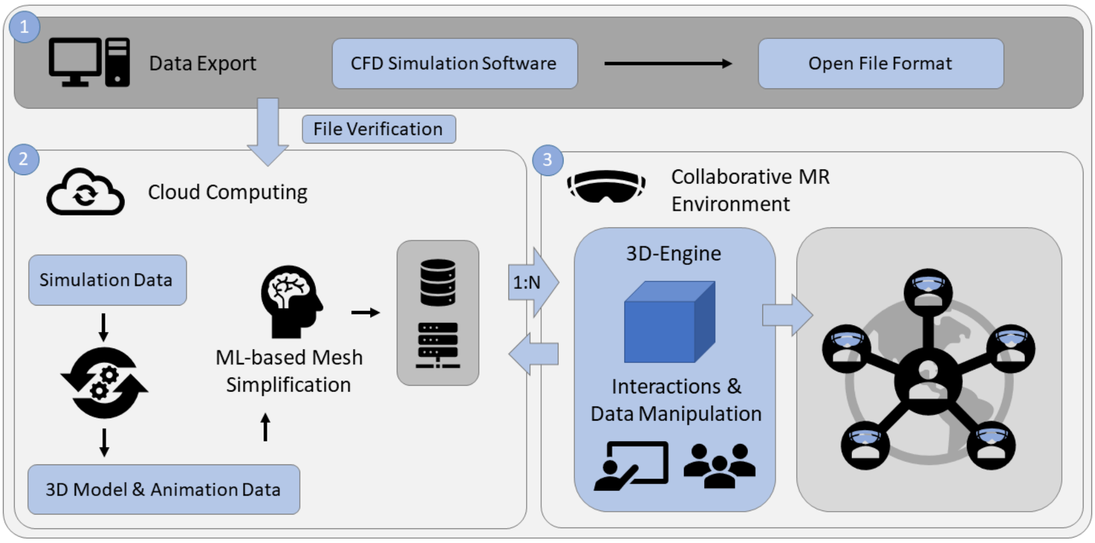

Figure 1: Architecture.

application of MR for CFD data visualization to create an immersive design environment, for example for automobile shape designing, requires huge memory demand and accordingly it would be difficult to render those graphics in real-time. Numerous algorithms have been proposed for mesh simplification (aka polygonal simplification). Most of such conventional algorithms can be grouped under Manifold-only simplification and Nonmanifold simplification algorithms (D. P. Luebke 2001; P. Cignoni et al. 1998). Manifold-only algorithms are limited in their application, as they are not capable of handling nonmanifold meshes, which are typical for CAD models created manually (D. P. Luebke 2001). The most commonly used approach in simplifying nonmanifold meshes is to use a quadric error metric algorithm (QEM) (Garland und Heckbert 1997). Over the years, many variations to the original QEM algorithm (Garland und Heckbert 1997) were developed. Each of these variations are suitable for different and specialized applications, but produce undesirable results when used for other types of meshes (e.g., no boundaries, lots of boundaries, textured, etc.) (Bahirat et al. 2018). However, machine learning (ML) based techniques which implicitly learn how to retain or collapse edges, depending on the overall task being undertaken, are still in nascent stage. In the study (Hanocka et al. 2019), a novel convolutional neural network (CNN) called MeshCNN has been introduced. They have demonstrated the ability of MeshCNN in task-driven pooling to collapse redundant edges and expand important features on various 3D meshes. However, their approach works only on triangular meshes.

3 SYSTEM DESIGN

After considering the limitations of past and current systems, and future trends for MR in section 2, in this section, we propose a system which has the potential to overcome these limitations by providing a cloud based approach that makes dynamical CFD post processing, based on user inputs, possible. With this system, users can change the data and its visualization through a post processor working in the cloud and share all information and 3D components within an immersive and collaborative distributed MR environment. Including three-dimensional avatars and abilities to e.g. create annotations in the environment, we assume to improve efficiency of MR remote collaboration.

The overall system consists of three main components visualised in **Erro! A origem da referência não foi encontrada.**. First, resulting CFD simulation data is exported from the simulation software system to an open file format to ensure data compatibility. These files will then be uploaded to the cloud and verified to minimize computation errors. The second part includes the cloud based automated data computation, the interfaces for handling MR control commands and the ML based mesh simplification. The computed data will then be sent to the last component, a collaborative and distributed MR system. This includes UIs and interaction techniques for communication between users as well as for data manipulation.

3.1 Automated Data Computation

As described in section 1, the process of generating CFD simulations and analysing them is divided into three basic steps: Pre-processing, solving and post processing. Our system will be part of the post processing stage, in which simulation data is transferred into 3D data for computation in MR. Therefore, data must be exported from the CFD simulation software into an open file format. Proprietary data formats are difficult to handle when it comes to partners or team members with different software applications. Based on this, an open file format, which can be handled by different CFD applications such as STAR-CCM+, ANSYS or OpenFOAM, is required. The CFD General Notation System (CGNS) has established itself as such an open file format and data model to store CFD simulation results. It is capable of storing several types of auxiliary data, such as generic, discrete or integral data, dimensional unity and exponents or nondimensionalization information (Poirier et al. 1998). This also includes mesh data of CAD models.

In order to compute and visualise CGNS data models, a post processing software is needed. This software must be capable of converting CGNS into a readable data format for 3D engines in order to send this computable data to the HMD. Additionally, it must handle all necessary tools and commands which are required in the workflow of CFD engineers to perform CFD post processing. The post processing software should be included in the cloud infrastructure to directly connect it to the MR system and therefore, be able to benefit from cloud storage as well as cloud computing power in terms of CPUs, GPUs and RAM storage. A tool which is capable of these requirements is ParaView (Ahrens et al. 2005). As an open source post processing software, including the Visualization Toolkit, it provides a variety of algorithms to process CFD simulation data such as isosurfacing, cutting, clipping and streamlines. With the ability to access its filter pipeline by a Python API, ParaView can be run in a docker container. Based on this, resulting data can easily be processed on server side via HTTP requests.

For further processing in the 3D engine and for computation on the MR device, different export formats are available. Currently, the Wavefront OBJ format is used to send data from ParaView to the MR devices. Indeed, this data format is not directly capable of processing additional visualization data like surface textures. The GL Transmission Format is an open data format providing efficient transmission of 3D scenes and models between applications. It is capable of handling large datasets such as needed for CFD data processing and supported by ParaView. Also it includes binary files such as images and shaders (Schilling et al. 2016) and therefore makes it suitable for our approach.

To visualize the resulting data from ParaView, the Mixed Reality HMD HoloLens 2 from Microsoft is used. With its hand- and eye-tracking capabilities as well as voice recognition and spatial audio within a stand-alone device, it provides a variety of different visualization and interaction possibilities for the user. Although it has some limitations as mentioned in (Cheng et al. 2020), it is still the most advanced standalone MR device with improved performance, wearing comfort and especially an renewed interaction design compared to its predecessor.

In order to connect the MR device to the cloud, the game engine Unity 3D is used. Based on its modular structure, open accessibility by utilising .NET scripting with either C# or JavaScript and together with the Mixed Reality Toolkit, which provides a variety of predefined interaction scripts and connection services, the engine is a good matter of choice for this system.

The 3D engine establishes a connection to the cloud, as the user logs into the system. After logging in, its uploaded and optimized models will automatically be fetched and loaded. Therefore, a network manager receives the optimized meshes from the cloud. These meshes will be included in the following interaction sequence.

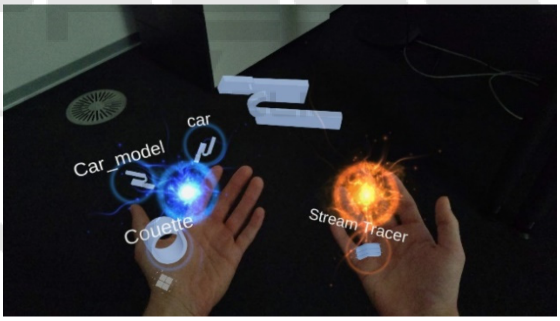

Figure 2: Hand menus.

To facilitate a user-centred object interaction and provide a good ease of use, we have designed two hand menus (see Figure 2). The object menu on the left hand provides the processed meshes as 3D objects around a sphere. The second menu on the right hand lets the user access the current implemented filters of ParaView. This is a modular approach in which more filters can be added in future versions. The interaction sequence is visualized in Figure 3, pictures (a) to (f). In order to apply one or more filters to an object, the user can place objects into the room via drag and drop with hand gestures (a). Also, the scale of an object can easily be changed by grabbing the object with both hands (thumb and forefinger) and move the hands away from each other. After the object is placed, a

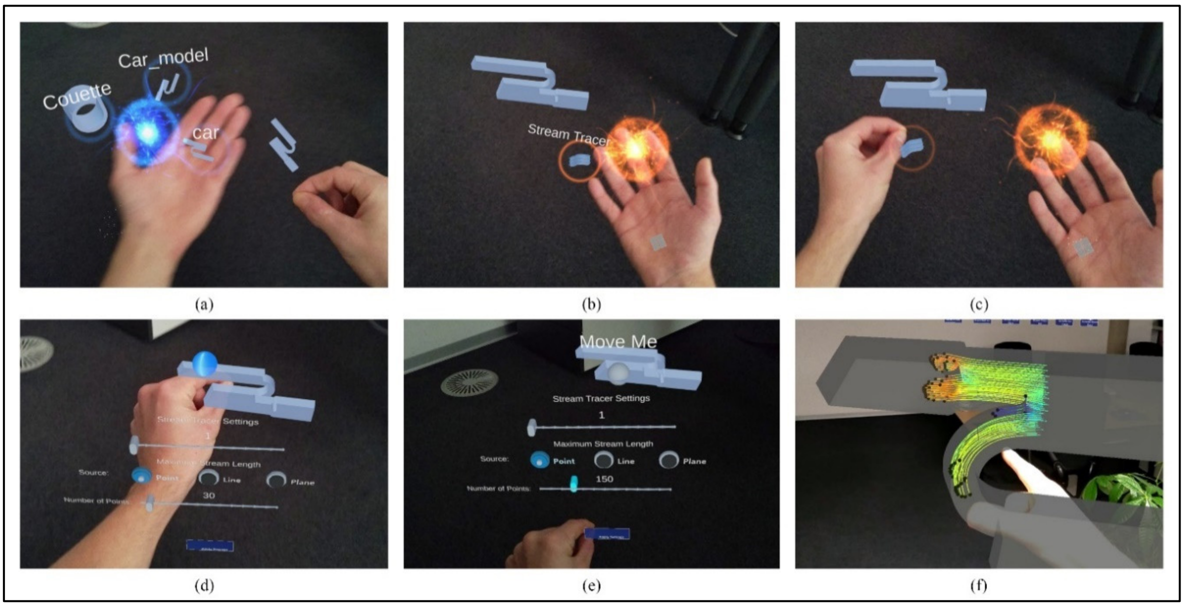

Figure 3: MR interaction sequence to apply filters.

filter from the filter menu can be selected (b) and applied onto the object, utilizing the drag and drop method (c). With adjusted filter settings via a menu near the current selected object (d, e), a new mesh including the resulting data is generated by ParaView and Unity (f). If the user wants to remove an object, it can be dragged and released into the object menu again. Additionally, filters like the stream tracer can be animated to allow the visualization of a local stream flow (f). Besides the stream tracer, also filters like the clip, slice and contour (isosurfaces) filter together with colour gradients are implemented in a simple form.

3.2 AI for Model Optimization

With reference to section 2, another edge collapsing algorithm which works effectively and efficiently on big CAD files, is NSA (Silva 2007). Unlike other QEM based methods, which are based on minimization of error associated with each new vertex, the NSA algorithm follows a geometric criterion which implies, that the region around the collapsing edge be nearly coplanar. An edge is only collapsed if the variation of the face normal around the target edge is within a given tolerance. This makes NSA to arrive at a good compromise between shape preservation, time performance, and mesh quality (Silva 2007).

Another interesting approach for mesh simplification would be, to use neural mesh autoencoders, which have been recently applied for many 3D tasks (Ranjan et al., 2018). With this approach, the task is, that the autoencoder implicitly learns the mesh structure and the encoder component of the autoencoder compresses the input mesh into a latent space representation. Later, the decoder component of the autoencoder decodes / reconstructs the latent representation into a mesh structure, neglecting the redundant elements from the original mesh. (Ranjan et al. 2018) for example, proposed such a convolutional mesh autoencoder called CoMA, which used spectral convolution layers accompanied by quadric up-and-down sampling methods to achieve promising results in aligned data of a 3D human face. However, such learning-based methods would also require additional heuristics (or operators) to make them work with different number of neighbouring elements, yet maintaining the weight sharing property of CNNs. In this direction, the study (Zhou et al. 2020) has proposed a template-free fully convolutional autoencoder, empowered by novel convolution and (un)pooling operators, which works for arbitrary registered meshes like tetrahedrons and non-manifold meshes. The spatially varying convolution kernel is especially interesting for our application, as every vertex will have its own convolution kernel, which accounts for irregular sampling and connectivity in the dataset. Their method of jointly learning the global kernel weight basis and a low dimensional sampling function for each individual kernel, would greatly reduce the number of parameters and accordingly would be less computationally expensive (Zhou et al. 2020). Although, our task here is restricted only to carry out mesh simplification with this approach based on an autoencoder, the capability of obtaining semantically meaningful localized latent codes would further assist in better semantic manipulation of the given original 3D mesh, if desired by the designer. Although the application of autoencoder based algorithms seems very interesting, owing to goal-oriented mesh simplification, the main drawback here is, that the technique requires a sufficient number of datasets for each kind of mesh and long training times to be effective. However, the research in this direction is ongoing and with recent advances, particularly in hardware technology, learning based algorithms have a great potential for this application.

3.3 Distributed and Collaborative XR Environment

Due to complex characteristics of the human body, the human perception of physical quantities like the behaviour of light as well as social interaction between multiple users, creating collaborative and distributed MR environments is a challenging task. They have to provide different key aspects, such as telepresence via co-present active communication, immersion achieved through interactivity or include tacit knowledge such as cultural and contextual cues to enhance distributed collaboration (Raybourn et al. 2019). Although collaborative MR environments have been developed and studied in different fields of application like architectural design (Ahn et al. 2019) or analysis of geo-spatial data (Mahmood et al. 2019), currently there is a lack of such systems for collaborative CFD analysis as proposed in section 2. In order to close this gap and extend the MR system, we propose a cross reality (XR) system to achieve collaborative CFD post processing and data analysis, in which additional features like virtual whiteboards will be provided, in order to enhance collaboration.

Indeed, the system will also be capable of including other devices, such as Virtual Reality (VR) headsets to make the system accessible for different team members, who prefer to view the simulation data in a fully immersed environment. Advanced Mixed Reality hardware like the HoloLens 2 is currently quite expensive (3500€) but offers more functionalities like hand and eye tracking in standalone devices and advanced communication aspects based on see-through displays in comparison to VR systems. Nevertheless, VR headsets can also provide adequate and immersive environments for CFD analysis. To accomplish such analysis, the user, according to section 3, must be able to upload the CGNS data for further computation. This can be done by a web application, including a user management system. In order to do so, the user can sign up to the system, which generates a unique user ID and a certain amount of cloud storage for the simulation data. After this step, the files can be uploaded and verified to ensure for e.g. that the data format is correct, which minimizes further computation errors. After the file upload is completed, an automated mesh generation process will be initiated to create the basic meshes for the 3D objects in the object menu by ParaView. Further processing is described in section 3.1.

To enhance user collaboration and provide telepresence, automatically generated 3D avatars of each connected user will be included. Based on the sensor technology of current MR headsets, these avatars and the MR environment can be equipped with different kinds of features to enrich collaboration and communication of distributed users. Hand recognition and eye tracking can be used to create realistic hand and finger movement as well as eye gaze visualizations, which enhanced multi-user collaboration (Piumsomboon et al. 2017) and create significantly stronger sense of co-presence (Bai et al. 2020). With spatial audio, the task of finding points in three dimensions, that are located outside the users Field of View (FoV), is less time consuming (Hoppenstedt et al. 2019). This can help users to find avatars of currently speaking team members, which can't be seen in the FoV at that moment, and therefore improve communication.

To further enhance virtual collaboration, annotations can be added to the virtual scene by the user. When it comes to CFD analysis and workflows of engineers, it is important to show other team members, at which point a simulation is defective or where enhancements can be applied. Especially, interdisciplinary teams can benefit from annotations as the task of collaborative CFD analysis in expert to non-expert relationships can be accomplished faster (Gauglitz et al. 2014). Therefore, an annotation system with simple annotations will be implemented to visualize important or critical parts of objects. Thereby, users will be able to mark objects partially or in complete in an annotation mode using their hands in MR or controllers in VR systems.

4 CONCLUSION AND FUTURE WORK

The paper proposes a proof of concept for collaborative post processing and analysis of computational fluid dynamics using Mixed Reality. It recommends a cloud based and automated data computation pipeline with a user management system to allow CFD engineers uploading simulation results in the open data format CGNS. With a CFD post processing software, which is located in the backend, and an MR application for visualization, analysis of resulting 3D fluid flow models is possible. The system is partially implemented in the ongoing project.

For future work, we plan to implement a first working prototype and evaluate the collaboration aspects and effectiveness of the proposed system with different user tests. This includes implementation of the ML algorithms for mesh simplification as well as the collaboration aspects such as avatars and the annotation system. Additionally, it is planned to examine if GLTF, as an internal format for 3D data exchange, is an appropriate alternative for simple data formats such as the Wavefront OBJ format.

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