# Improving the Realism of Mixed Reality through Physical Simulation


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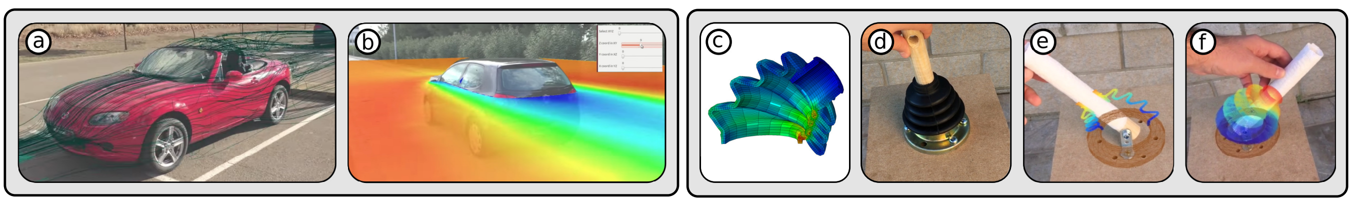

**Figure 1: Left: CFD simulation of the aerodynamics of a car, evaluated in real time and showed with augmented reality over the proper cars. Results involve (a) particle tracing and also (b( flux velocity of the air allowing an interactive visualization. Right: mechanical simulation of the deformation in an automotive rubber dust boot: (c) result of the simulation for a particular angle, showing stresses; (d) original piece; (e) augmented reality techniques projecting the virtual piece to interact with users, showing displacements only in the middle plane, and (f) in the whole piece.**


## ABSTRACT

We present a new way of adding augmented information based on the computation of the physical equations that truly govern the behavior of objects. In computer graphics, it is common to use big simplifications to be able to solve this type of equations in real time, obtaining in many occasions behaviors that differ remarkably from reality. However, using model order reduction (MOR) techniques we are able to pre-compute a parametric solution that is only evaluated in the visualization stage, greatly reducing the computation time in this on-line phase. We present also several examples that support our method, showing computational fluid dynamics (CFD) examples and deformable solids with nonlinear material behaviors. Since it is a mixed-reality implementation, we decided to create an interactive poster that allows the visualization of augmented reality videos using augmented reality techniques, what we call $(AR)^2$.


## CCS CONCEPTS

• **Human-centered computing → Mixed / augmented reality**;



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## KEYWORDS

Mixed Reality, Physical Augmentation, Computational Mechanics, Model Order Reduction.

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## 1 INTRODUCTION

Concepts of virtual, augmented and mixed reality are suffering a strong development in some fields such as entertainment, social media, marketing, design or optimization in the Industry 4.0. It is, therefore, a revolution with great interest in many fields and with many people involved. That is why we are seeing increasingly better implementations and developments that allow the interaction with virtual objects, although there are still some deficiencies in such interactions. Our goal is to allow a user to interact with virtual objects as he would do in reality, so we need to model the physical behavior of objects in order to perform tasks such as moving or deforming them. This behavior is usually modeled by *physics engines* that provide an approximate simulation in real time of some of these actions, but of course, making great simplifications. We cannot expect the behavior of a solid object with a highly non-linear material law (such as a piece of rubber or a cushion) and a complex geometry to be simulated in real time. Great simplifications are

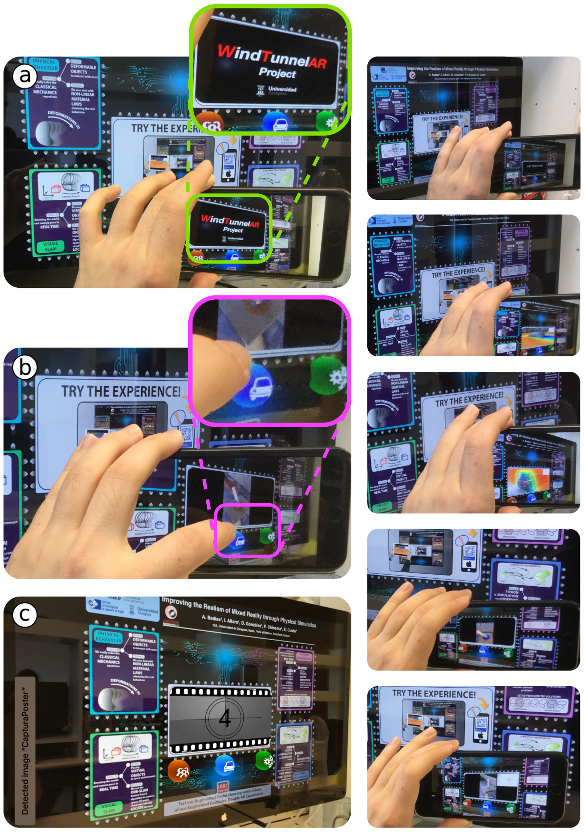


**Figure 2: Examples of the augmented poster. (a) An app working in a smartphone allows the user to watch some videos of our work in the central part of the poster. (b) User can interact with 3D virtual objects to select a video to reproduce. (c) Screenshot of the device. (https://bit.ly/2HY30fk).**

applied to reach real-time frequencies, in some cases very effectively, but in others with an unnatural behaviour, so properties of materials are extremely important. That is the reason why we propose in this work the use of the true physical equations that govern the behavior of objects, even though they are highly non-linear material laws. We use dimensionality reduction techniques allowing us to work in a reduced subspace.

## 2 MODEL ORDER REDUCTION METHODS

MOR methods applied to continuum mechanics are based on the projection of the solution with dimension $D$, in another space of dimension $d$, expecting $d << D$. The greatest advantage is obtained in the projection of parametric solutions with an important number of parameters $M$, since as $M$ grows, the well-known *curse of dimensionality* appears, where the amount of data grows exponentially with the dimensionality. It can be mitigated using MOR techniques.

Several methods have been developed to reduce the dimensionality of the PDE equations that govern the behavior of a physical problem. We can find *a priori* implementations applied directly to the equation (e.g. Proper Generalized Decomposition [Chinesta et al. 2011]) or *a posteriori* methods aplied to the data once the equation has been solved (e.g. Proper Orthogonal Decomposition [Berkooz et al. 1993]). Other techniques allow to face non-linear equations (e.g. Discrete Empirical Interpolation Method [Chaturantabut and Sorensen 2010]), and also there exist some methods to generate a non-linear reduction of the dimensionality (e.g. local implementations of the PGD method [Badías et al. 2017]).

In general words, the reduction is based on the projection of the whole solution into functions $F$ depending on separate parameters $\boldsymbol{\mu}$, and approximated with finite element methods. Therefore, the solution $\boldsymbol{u}$ can be expressed as a finite sum of the product of *modes* with separate dependency

$$\boldsymbol{u}(\mu_1, \mu_2, \ldots, \mu_M) \approx \sum_{i=1}^{N} F_i^1(\mu_1) \circ F_i^2(\mu_2) \circ \ldots \circ F_i^M(\mu_M)$$

being $\circ$ the Hadamard product. The parametric solution is pre-computed and stored in a compressed way (projected) to ensure a fast evaluation in the on-line step with low cost of memory storage.

## 3 DATA ASSIMILATION

Data coming from video sequences is used to feed the parametric solution and solve the inverse problem to estimate the parameters, fulfilling time rates of the video sequence (30 fps). The functional to minimize is

$$\mathcal{J}(\boldsymbol{\mu}) = \sum_{j=1}^{\mathrm{n_{meas}}} \left( \boldsymbol{u}_{\mathrm{pix}}^{\mathrm{meas}}(\boldsymbol{x}_j) - \Pi_t \left( \boldsymbol{u}^{\mathrm{MOR}}(\boldsymbol{x}_j, \boldsymbol{\mu}) \right) \right)^2 \qquad (1)$$

being $\boldsymbol{u}_{\mathrm{pix}}^{\mathrm{meas}}$ the set of points measured in pixel coordinates, $\Pi_t$ the projection in 2D image coordinates and $\boldsymbol{u}^{\mathrm{MOR}}$ the displacements estimated by the precomputed solution depending on parameters $\boldsymbol{\mu}$. We use the well-known Levenberg-Marquardt (LM) algorithm [Levenberg 1944] to minimize functional of Eq. 1. The expression of the solution in a separate variables way provides a great advantage, since the jacobian matrix in LM is defined as

$$J_k = \frac{\partial \boldsymbol{u}(\boldsymbol{x}, \boldsymbol{\mu})}{\partial \mu_k} = \sum_{i=1}^{N} \boldsymbol{F}_i^1(\mu_1) \cdot \ldots \cdot \frac{\partial \boldsymbol{F}_i^k(\mu_k)}{\mu_k} \cdot \ldots \cdot \boldsymbol{F}_i^{\mathrm{n_{param}}}(\mu_{\mathrm{n_{param}}})$$

being $\boldsymbol{J}_k$ the $k$ jacobian component of matrix $\boldsymbol{J}$ related to parameter $k$. Derivative terms of functions $\boldsymbol{F}_i^k$ with respect each parameter (sensitivity) are computed very fast due to the separate variables fashion, saving the computational effort of estimating derivatives in the whole parameter space.

Some examples can be seen in Fig. 1, and also in the augmented information added to the poster (see Fig. 2).

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