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Exploration of Transfer Learning, Co-Kriging and Control Variates for Early-Phase Crashworthiness Analysis

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Abstract

This work aims to propose an exploration of Transfer Learning (TL), Co-Kriging and Control Variates for crashworthiness analysis. This industrial scenario, characterized by uncertainties and lack of knowledge, provides an interesting challenge to these three bi-fidelity predictive techniques. Investigating their potential and exploring their performance becomes an appealing task to address.

The development of a vehicle is a complex task. Car manufacturers need to satisfy strict safety requirements. Assessing vehicle safety in an early stage of the development, they need to face the challenge of low data availability. In the early-phase of the vehicle development, indeed, the ultimate geometrical and material data of the product are not yet available. Moreover, in the industry, most new product designs are obtained by partially modifying some existing ones and it is rare that entirely new products have to be designed from scratch.

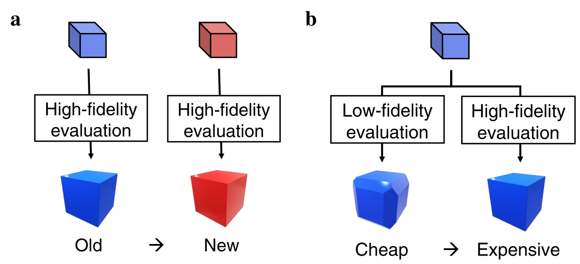

Figure 1: Representation of two bi-fidelity problems.

Given these reasons, a task worthy of pursuit, in this context, is exploiting the data coming from past development processes to infer knowledge on forthcoming situations. This problem can be visualized as a bi-fidelity one, see Figure 1a. The numerous data (e.g. simulations, hardware tests) from the already developed products can be seen as the low-fidelity information, while the few data belonging to the product under current development take the role of the high-fidelity counterpart.

Possible solutions to tackle this challenge are techniques that enhance the learning on the high-fidelity model by exploiting a large number of additional cheap measures. Although serving different needs, examples of these techniques are TL, Co-Kriging, and Control Variates. In the following, we propose an overview of the three, highlighting their differences and exploring their potential for crashworthiness analysis.

TL is a type of machine learning algorithm that leverages the knowledge from a related source domain to improve the learning performance in a target domain [5]. TL helps to relax the need of having big amounts of high-fidelity target data. By exploiting the knowledge acquired from pre-accomplished tasks, TL becomes a promising approach in situations where only a limited amount of high-fidelity data is available for a specific target task [4].

TL can be employed in a past-to-future configuration for crashworthiness, where the numerous low-fidelity data from past vehicles represent the source domain, and the limited high-fidelity instances available for the new vehicle constitute the target domain. As represented in Figure 1a, the old and new data can belong to different mechanical systems. The similarity between the two influences the performance of the TL methodology: the higher the correlation between source and target domain, the easier the network learns the basic features from the former and transfers them to the latter. Another technique where the success of the performance highly depends on the correlation between low- and high-fidelity data is Co-Kriging.

Co-Kriging is an extension of ordinary Kriging in which additional low-fidelity variables are used to improve the precision of the interpolation of the high-fidelity variable of interest [1]. In other words, Co-Kriging is a surrogate modeling technique that allows an enhanced prediction of the output of a complex system by incorporating auxiliary fast-to-obtain data of lower fidelity. As well as TL, Co-Kriging can be used to improve the prediction of a variable of interest at unobserved locations. In addition to TL and Co-Kriging, a further technique worth of being investigated for the same crash analysis past-to-future challenge is Control Variates.

While Co-Kriging and TL are aimed at improving the accuracy of the high-fidelity — or target domain — prediction, Control Variates is instead used to reduce the second order statistics of the response of interest [3]. By introducing an additional variable, called control parameter and correlated with the outcome of interest, Control Variates reduces the variance of the estimates, leading to more accurate results. The key advantage of this method is that it allows to aggregate estimates generated using the high- and low-fidelity models to enhance the estimated second order statistics of the high-fidelity one [2].

Control Variates and Co-Kriging are generally employed in situations similar to the one represented in Figure 1b, where the low- and the high-fidelity evaluations refer to the same system. As an example, a crash analysis where the system under investigation is, on the one hand, approximated to an analytical function, and, on the other, simulated through finite element (FE) analysis. The same system is evaluated in a cheap – analytically – and expensive – FE – way. Regardless their usual employment, in this work we attempt to utilize Co-Kriging and Control Variates in a past-to-future configuration. We plan to apply these techniques and TL to an industrial problem in which the low- and high-fidelity data belong to different, yet similar, physical mechanical systems. High quantities of data coming from old products are exploited to gain knowledge on a new one, characterized by low data availability.

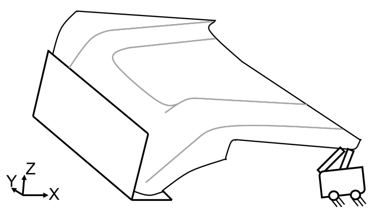

Figure 2: Bonnet load case.

For the purpose of this study, we consider the bonnet case as an explanatory example. Considering the bonnet in a situation of full frontal impact towards an L-shaped rigid barrier, see Figure 2, our goal is to gain insights about the relation between the variations in panel thickness and the structural safety performance. Specifically, we focus on how the uncertain thickness value of the lower panel influences the intrusion of the bonnet into the window frame. Ideally, for occupant safety reasons, a crash should cause no such intrusion. This type of investigation is effectively tackled in industry during the architecture development of a new vehicle, e.g. in the body-in-white development process. Two bonnet geometries are considered for the study: a low-fidelity and a high-fidelity one. To one of the variants is assigned the role of predecessor, from which the mentioned techniques are supposed to learn the thickness-intrusion relationship; the other variant is assumed to be the new product under development, which is the one to which the knowledge has to be transferred.

The results of this work suggest that Control Variates can be employed first to explore the high-fidelity space. Not being influenced by the level of similarity between the low- and high-fidelity data, Control Variates is expected to provide robust prediction of the mean and variance of the high-fidelity quantity of interest. Co-Kriging can be used to predict the crash performance of a new product when the correlation between old low- and new high-fidelity data is high. TL, instead, provides a more robust outcome regardless the correlation between source and target domain. Moreover, Co-Kriging is awaited to perform worse in high-dimensional situations.

In summary, given their unique characteristics, TL, Co-Kriging, and Control Variates, can be considered powerful techniques for crashworthiness analysis in different scenarios. By harnessing information from past already developed products, they can serve to extend the acquired knowledge to forthcoming cases. In this way, they can provide the engineers with useful tools to support their expertise and automatize the early-stage development operations.

Key words: Transfer Learning; Co-Kriging; Control Variates; crashworthiness

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