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A Bayesian approach for NDT data fusion: The Saint Torcato church case study

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ABSTRACT

This paper presents a methodology based on the Bayesian data fusion techniques applied to non-destructive and destructive tests for the structural assessment of historical constructions. The aim of the methodology is to reduce the uncertainties of the parameter estimation. The Young's modulus of granite stones was chosen as an example for the present paper. The methodology considers several levels of uncertainty since the parameters of interest are considered random variables with random moments. A new concept of Trust Factor was introduced to affect the uncertainty related to each test results, translated by their standard deviation, depending on the higher or lower reliability of each test to predict a certain parameter.

1. Introduction

Characterization of engineering materials usually requires taking samples to laboratory in order to evaluate the mechanical properties. Nevertheless, sampling of masonry materials is often costly and, generally, prohibited in most historic buildings. Additionally, the heterogeneity of the material can lead to misunderstanding results when the sampling operation is not carried out properly and in sufficient number. In this way, non-destructive techniques are essential when the overall knowledge of the wall characteristics is needed [1].

Non-destructive techniques can be used for the following purposes: detection of hidden structural elements; cataloguing of masonry and masonry materials, mapping of heterogeneities of materials [2]; evaluation of the extent of mechanical damage in cracked structures; detection of voids and flaws [3]; evaluation of moisture content and capillary rise; detection of surfaced decay; evaluation of mortar, brick and stone mechanical and physical properties [4]; masonry durability problems [5]; and masonry creep (long-term) damage [6]. Up to now, most of the non-destructive techniques applied to historical structures are based in wave propagation and temperature detection [7], generally the same applied in concrete. Examples are [8,9]: infrared thermography, sonic tests [10,11]; and ground penetrating radar [12–15]. Geoelectrics, which is a technique mostly used in the geologic field [16,17], has been recently put in use for the structural diagnosis of old masonry structures [18,19].

As most of the non-destructive techniques give only qualitative results, it is desirable to test the same locations with more than one technique [8,20–23], although this requires a large knowledge of the investigator or a team of specialists to help in the interpretation of the results.

It is well known that data available from multiple sources underlying the same phenomenon can contain complementary information [3]. The idea of combining information from multiple sources is called data fusion [24–26], which have been studied by several researchers in the field of non-destructive testing. The key idea is to improve the quality of the non-destructive tests by taking advantage of their advantages and trying to overcome their limitations in a particular application. This combination of several techniques can give more reliability for the interpretation of results and for the detection of irregularities like voids, cracks, the presence of moisture, and better estimation of mechanical or structural properties.

The work presented in this paper addresses a methodology to overpass the difficulties of choosing the right value for a certain parameter when several non-destructive tests are carried out and

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when the majority of the gathered information is more qualitative rather than quantitative. The methodology is based on Bayesian methods [27,28] and provides a consistent and rational approach on the results' analysis. It starts from a range of values given by the literature and takes into account the history of testing, as well as the trust on the reliability of the results of each non-destructive method.

To analyze its applicability, the proposed methodology is applied to a real case study, Saint Torcato church, located in a town near Guimarães, Portugal. The historic building exhibits moderate to severe damage (including soil settlements and structural cracks), and several non-destructive tests have already been carried out in the church to characterize the mechanical properties of the materials and the existing damages, along circa ten years.

The paper is organized as follows: Section 1 introduces the aim of the paper; Section 2 presents the Bayesian methodology for data fusion applicable to the results analysis of different non-destructive tests; Section 3 describes the Saint Torcato church case study, including the non-destructive tests carried out with the results to be used as inputs for the Bayesian data fusion model to predict the Young's modulus of the stones used in the masonry walls; Section 4 presents the model for the Bayesian data fusion, including the introduction of a Trust Factor which was defined based on a survey carried out with several experts on inspection and diagnosis of historical constructions; Section 5 presents the results of the proposed methodology and its discussion; and finally, in Section 6 conclusions and future work are presented.

2. Bayesian methodology for data fusion

Data fusion is applied in different fields, such as civil, medicine, management, transportation systems, security and military, to mention a few of them. Among others, the purpose of application in each area ranges from surveillance and reconnaissance to wildlife habitat monitoring, including sensor networks management, robotics, detection of environment hazards, video and image processing [24–26]. Several methodologies have been proposed in the literature for the purpose of multi-sensor fusion and/or merging results coming from different testing methods. However, few applications were devoted to the evaluation of civil engineering structures and materials, especially to concrete structures [29–31], and non to historical masonry constructions.

These most common techniques applied for data fusion are: artificial intelligence [32], pattern recognition [33], statistical methods [34], fuzzy sets and neural networks [35], Kalman Filters [36], and probabilistic methods such as the Bayesian approach [29,37]. In the next section only the Bayesian approach will be discussed because it was the chosen technique to fuse data in the present paper.

2.1. Bayesian data fusions and uncertainty

Uncertainties may be represented in terms of mathematical concepts from the probabilistic theory [29,32]. In many cases it is enough to model the uncertain quantities by random variables with given distribution functions and parameters estimated on the basis of statistical and/or subjective information [38]. The principles and methodologies for data analysis and fusion that derive from the subjective point of view are often referred to as Bayesian statistics. In this approach the knowledge about an unknown parameter is described by a probability distribution function which means that probability is used as the fundamental measure of uncertainty.

Bayesian techniques allow fusing or updating random variables when new data is available using a mathematical process to deal with uncertainties.

In a Bayesian approach, the data fusion process starts with a given probability distribution. Its parameters may be chosen or estimated based on previous experimental results, experience and professional judgement. This distribution is called prior distribution and translates the uncertainty about the parameter value. When additional data becomes available it can be integrated to update this prior distribution into a posterior distribution using the Bayes theorem which weighs the prior information with the evidence provided by the new data. The posterior distribution is a compromise with reduced uncertainty between the prior information and the one contained in the new data [39]. Fig. 1 resumes this overall process.

The prior distribution represents a population of possible parameter values and should include all plausible ones. The parameters of the prior distribution can be chosen or calculated in such a way that the prior reflects: (a) known initial observations of the random variables (for instance test results) and (b) subjective knowledge (for instance professional judgment) [21]. It is possible to choose a prior distribution, which reflects a range of situations from very good prior knowledge (small standard deviation) to limited knowledge (large standard deviation) or even no knowledge.

The property that the posterior distribution follows the same parametric form as the prior distribution is called conjugacy. Conjugate distributions present computational advantages since they simplify calculations and can be often translated in analytical form. For example, if the prior and likelihood functions are Gaussian this will ensure a Gaussian posterior. This happens to all members of the exponential family.

If the prior distribution of a parameter θ, with k possible outcomes $(\theta_1, \ldots, \theta_k)$, is continuous and new information x is available, then the Bayes theorem is translated by:

$$p(\theta|x) = \frac{p(\theta)p(x|\theta)}{\int p(\theta)p(x|\theta)d\theta} \quad (1)$$

where $p(\theta)$ is the prior distribution of θ which summarizes the prior beliefs about the possible values of the parameter, $p(x|\theta)$ is the conditional probability (or likelihood) of the data given θ and $p(\theta|x)$ is the posterior distribution of θ given the observed data x.The prior and posterior distributions of θ are represented by density functions. The joint probability distribution of the data and the parameter is given by $p(x|\theta)$ which is called the likelihood and is defined by:

$$p(x|\theta) = L(\theta) = \prod_i p(x_i|\theta) \quad (2)$$

where i is the number of outcomes of the new data. Bayes theorem is applied multiplying the prior by the likelihood function and then

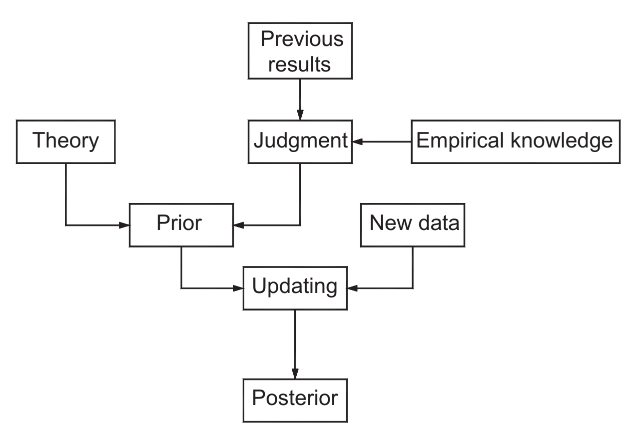

Fig. 1. Scheme of the fusion process (adapted from [29]).