Structural Health Monitoring and model updating with distributed optic fiber measurements

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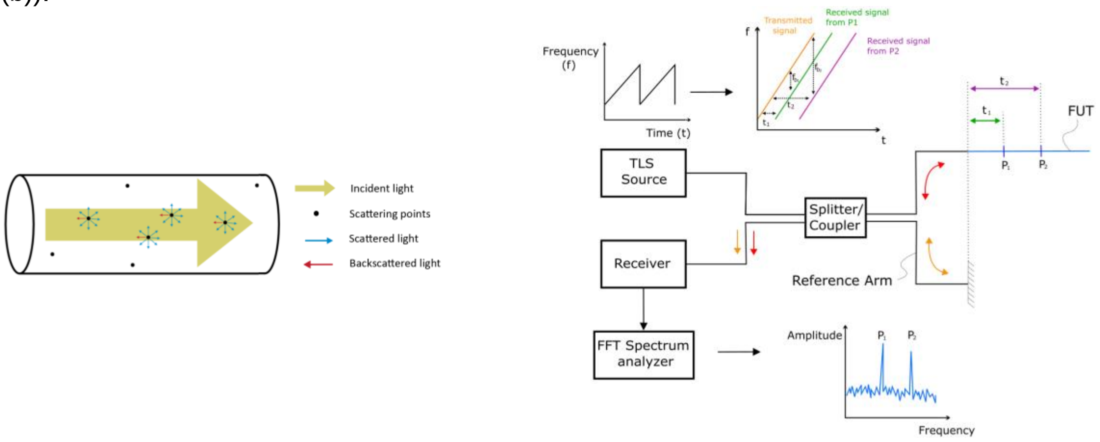
The detection of damage in its early stages is of great interest in mechanical systems and structures. Sensor-equipped structures provide information regarding the system state and damage progression, leading to their increased safety and durability by adapting the service load and thus, limiting the damage progression. Distributed Optic Fiber Sensors (DOFS), providing highly time and space resolved measurements along the fiber, are therefore an efficient tool that is more and more utilized for structural health monitoring. A typical high end optic fiber setup nowadays provides accurate measurements (around 10^{-5} strain uncertainty) with a spatial resolution as high as 1500 points per meter [1]. Furthermore, the DOFS immunity to electromagnetic fields, their high resistance and long life cycle, along with their simplicity of use when installed, makes them a proper candidate in various environments [2].

In this study, DOFS based on Rayleigh backscattering and Optical Frequency Domain Reflectometry (OFDR) are used to provide strain measurements. While considered a disadvantage in optical fiber telecommunications, backscattering is the essential principle based on which the optic fiber sensors operate. It is defined as the interference of light with inevitable inhomogeneities that were produced in the fiber core during the manufacturing process (Fig. 1(a)). The perturbed light and its backscattered fraction preserve the same frequency as the initial travelling light. This characteristic is exploited to develop the OFDR technique, which employs interferometry and a frequency-modulated optical wave to gain measurements [3].

The frequency difference between the backscattered light from the Fiber Under Test (FUT) and the reference light in the interferometer defines the measurement position on the optic fiber sensor. With the same process being applied on all the backscattered lights from different positions on the fiber, it results in a full profile of the measurement along the sensor. Each DOFS has a unique signature profile, and changes in the said profile specify changes in the measurements of the surveyed system. The interferometry in OFDR sensors is showed in (Fig. 1(b)).



(a) (b)

Figure 1-(a) Rayleigh backscattering in the optical fiber core; (b) The interferometry in OFDR sensors

The specimens used in this work are cement-base mortar beams reinforced with polyamide fibers and different percentages of steel fibers. The samples undergo a four-point bending test, while a single optic fiber sensor is passed through the sample in a 4-way path, providing measurements in both parts under tension and compression. Sample dimensions, sensor position and the test layout are presented in (Fig. 2).

The measurements provided during the quasi-static tests can then be used to build a digital twin of the structure. The numerical model is updated with the sequentially assimilated measurements by solving an ill-posed inverse problem. A powerful method for model updating using experimental data is the modified Constitutive Relation Error (mCRE) [4].

This energy-based functional is developed by strongly imposing the reliable information, such as equilibrium equation, known boundary conditions, and sensor positions, on the minimization functional.

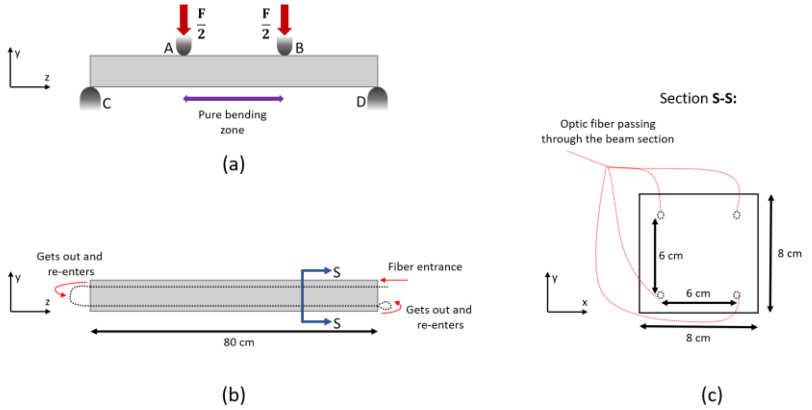


Figure 2 – (a) Schematic set-up of a four-point bending test; (b) and (c) Dimensions of samples and positioning of the embedded fiber inside the samples

On the contrary, unreliable information such as constitutive relation, unknown boundary conditions and sensor measurements, are relaxed. Thus, mCRE can be seen as a least squares minimization problem regarding the measurement error, that is regularized by modeling error term, aka Constitutive Relation Error (CRE). This implies that mCRE is by definition a compromise between measurement and model error, which is adjusted regarding the level of confidence in each of these terms. Hence, it provides an updating method with a strong physical sense that is also relevant when confronting noisy or corrupted measurements [5]. Moreover, analysing the CRE part of the mCRE functional permits detecting areas with large modelling error, and correspondingly adapting the parametric space.

As mCRE lacks a sequential framework, and can become computationally expensive, it is reasonable to use it within a sequential data assimilation method such as Kalman filters to comply with real-time applications.

Kalman filters are a common prediction method for evolving systems. These filters are based on incrementally correcting the predictions by acquired measurements [6], and are sensitive to noisy data [7,8]. Although Kalman filter was initially developed for linear systems, several extensions of it have been introduced throughout the years for solving nonlinear inverse problems [9,10]. Coupled by the mCRE, it can provide a robust and sequential model updating method called Modified Dual Kalman Filter (MDKF) which improves the features of both mCRE and Kalman filters, separately [11,12]. In this work, the acquired measurements are implemented in the MDKF framework so as to identify model parameters such as local Young's moduli of the material, and detect possible damage occurance throughout the tests. Several numerical illustrations will be shown on the capabilities of the proposed technique, with different fiber reinforcement percentages.

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