Towards Video-Based System Identification and Finite Element Model Updating of Civil Structures and Infrastructures

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Abstract. Computer Vision in general and Phase-Based Motion Magnification (PBMM) in particular have been proved in recent years to be feasible and practical for the structural integrity assessment of simple laboratory models under controlled environment conditions. This technique has been partially tested for outdoor applications under natural illumination. In this paper, the potentialities of these enabling technologies for on-site surveying are highlighted, especially focussing on typical applications for Civil Engineering. These include two case studies, both of relevant interest due to their structural peculiarities: a 400+ meters high skyscraper and a concrete highway bridge. Advantages and limitations for both these applications are highlighted. The comments are then extended from these particular cases to some broader considerations valid for other structures and infrastructures.

Keywords: Phase-Based Motion Magnification; System Identification; Finite Element Model Updating; High Rise Buildings; Highway Bridges; Computer Vision.

1 Introduction.

The current form of Structural Health Monitoring (SHM) is described by the seminal works of several authors – most prominently C. Farrar and K. Worden [1] – relies on Statistical Pattern Recognition (SPR, [2]) to perform damage diagnosis as data-driven anomaly detection. In SHM, sensors (accelerometers, strain gauges, temperature sensors, etc.) are placed and critical locations of the structure and the data are recorded in real time. These measured data by the embedded sensors are used to monitor the real time performance of buildings and infrastructures. The measured data can be used to plan the maintenance schedule, predict structural life, enhance safety for the building etc. In SHM, the mathematical algorithms used to for the data analysis plays a vital role. Artificial Intelligence (AI) and Machine Learning (ML) is already creating more opportunities in data driven technology in general and SHM in particular.

However, application of a ML approach requires a large amount of experimental data to feed the algorithm. For this reason, continuous monitoring is the conventional approach, with large networks of accelerometers and/or other sensors physically attached to the target system (e.g. a structure or infrastructure of civil use). Nevertheless, the deployment of such large sensor arrays might not be feasible (or cost-effective) when applied at a large scale.

This is of the foremost importance for the sector of Civil Engineering, especially in rapidly developing countries. In the state of Kuwait, and particularly in the capital downtown area, vast and uninterrupted urban development has been underway for the last 15 years. These developments have been generally along two major lines: high-rise and tall buildings (especially including skyscrapers) and highway infrastructures [3].

Indeed, the Council on Tall Buildings and Urban Habitat (CTBUH) has enlisted thirteen buildings reaching or exceeding 150 meters in Kuwait City alone, accounting only for the completed ones (several others are under construction, approved, or proposed) [4]. The same list shows how 22 cities in 10 Middle Eastern countries have at least one structure above the 150 m threshold, for a total of 85 tall and very tall buildings. Many of these structures have been built very recently in Gulf Cooperation Council (GCC) countries, with multi-million private and public investments.

The issue is even more pronounced in the field of bridge monitoring. In Kuwait, it was estimated in 2013 that the total length of paved roads was about 5,000 km, with several roads and highways spanning over concrete bridges. As of 2019, 13 billion USD$ of projects were planned in the framework of the Kuwait Vision 2035 "New Kuwait" programme [5].

It must be remarked that these large structures and infrastructures all exist in a very peculiar region, with specific and compelling geotechnical, environmental, and seismic conditions. These include the presence of vast petroleum fields under exploitation, near and far seismic sources, and the seaside desert climate, with high maximum temperature in the daytime, substantial temperature drop at nighttime, and sustained winds [3].

1.1 The rationale for Computer Vision-based SHM.

For all the reasons enlisted above and due to the sheer number of systems to be monitored, it is not realistic to deploy and maintain embedded apparatus for each critical building or infrastructure. Video processing and Computer Vision techniques, on the other hand, allow for fast and flexible survey strategies. Video-extracted displacement time histories have been proved feasible for the SHM of large structures, utilizing recordings from both manned or unmanned platforms (e.g. [6]). It is thus possible, for example, to extract the structure's modal parameters from the extracted time series. This allows for both Frequency-Based Damage Detection (FBDD) and Mode-shape-Based Damage Detection (MBDD) [7], especially using a predictive, calibrated Finite Element Model (FEM).

Video acquisitions are not only fast and easy to perform on-site. They also require relatively inexpensive instrumentation and no particular training for the survey operators. More importantly, they are non-contact techniques, therefore, they are non-invasive and do not alter the structural configuration of the target system. They can operate from an arbitrary distance (as long as the line of sight is free), even reaching difficult-to-access areas such as bridge underdecks or the top floors of a skyscraper. Furthermore, with high pixel density, they can provide the spatial resolution needed for damage localisation, severity assessment, and other specific tasks which require a high spatial density of information. However, many Computer Vision techniques are still limited by their low precision for small and very small (barely visible) vibrations, such as the ones commonly encountered for massive concrete structures excited by low-amplitude Ambient Vibrations (AVs). In this regard, the Phase-Based Motion Magnification (PBMM; [8]) has been proposed in recent years as an enhanced video processing technique to deal with imperceptible movements.

The PBMM has been proved feasible for relatively simple laboratory models, as well as some more compelling outdoor applications [9, 10]. However, it has not yet been tested for Finite Element Model Updating (FEMU), let alone for high rise buildings with complex architectures. For bridge monitoring purposes as well, applications to relatively flexible steel-made railway and footbridges have been presented in the scientific literature [11]; nevertheless, concrete-made highway bridges present more difficulties due to their even smaller vibrations.

In the rest of this brief discussion, the theoretical background and main concepts of the PBMM and FEMU procedures will be recalled in Section 2. The two main case studies, a tall concrete building in Kuwait and a concrete highway bridge in Kuwait, will be presented (respectively in Sections 3 and 4). These will serve as the subjects of future studies for the applications of motion magnification to real-life, real-size structures and infrastructures of civil use. Their specificities will be highlighted, in particular from the point of view of the potential advantages offered by video-based measurements in general and PBMM specifically.

Finally, some Conclusions, valid for the specific case studies as well as for similar buildings, are discussed in Section 5.

2 Materials and Methods.

2.1 Phase-Based Motion Magnification (PBMM).

Motion magnification aims to post-process a video acquisition by modifying the spatial variations of its brightness profile, frame by frame. For a 2-dimensional frame with $w \times h$ pixels (width × height), considering the spatial coordinates $\boldsymbol{x} = (x, y)$ such that $x \in [0, w], y \in [0, h]$ at any instant t (expressed in terms of frame number), the brightness profile can be defined as $I(\boldsymbol{x} + \delta(\boldsymbol{x}, t))$, where $\delta(\boldsymbol{x}, t)$ is the time-varying, locally-defined displacement function. The aim of motion magnification is therefore to obtain a purposely manufactured video where, for a magnification factor α, the brightness profile becomes $I(\boldsymbol{x} + (1 + \alpha)\delta(\boldsymbol{x}, t))$.

This is doable as the motion $\delta(\boldsymbol{x}, t)$ can be assumed to be pixel-wise linear and therefore representable as a linear combination of harmonics. That is to say, the whole brightness profile can be well-approximated by a 2-dimensional Fourier series i.e.

$$I\big(\boldsymbol{x} + \delta(\boldsymbol{x}, t)\big) = \sum_{\omega=-\infty}^{+\infty} \sum_{\theta=+1}^{k} A_{\omega,\theta} e^{i\varphi_{\omega,\theta}(x,t)}, \tag{1}$$

where $A_{\omega,\theta}(\boldsymbol{x}, t)$ is the spatial amplitude at (x, y) and at the instant t, evaluated at the spatial scale ω and orientation θ, and $\varphi_{\omega,\theta}(\boldsymbol{x}, t) = \omega(\boldsymbol{x} + \delta(\boldsymbol{x}, t))$ is the corresponding spatial phase. Fleet & Jepson [12] and Gautama & Van Hulle [13] investigated the relationship between local phase differences and motions, proving that tracking the contours of constant phase in subsequent frames returns a good approximation of the motion field if the phase is properly spatiotemporally bandpassed in advance. Amplifying the motion means to shift accordingly these phase contours, defined as $\varphi(x, y, t) \equiv c$ for an arbitrary value of c.

The bandpassed phase can be obtained by simply temporally filtering the spatial phase with a DC balanced filter, thus removing the temporal mean and obtaining

$$B(\boldsymbol{x}, t) = \omega\delta(\boldsymbol{x}, t). \tag{2}$$

If needed, the temporally filtering step can be used as well for isolating a specific temporal frequency band of interest. The magnified phase shift is therefore

$$\widehat{S_\omega}(\boldsymbol{x}, t) = A_{\omega,\theta} e^{i\omega(x+\delta(x,t))} e^{i\alpha B_\omega} = A_{\omega,\theta} e^{i\omega(x+(1+\alpha)\delta(x,t))}, \tag{3}$$

which corresponds to a proportionately amplified motion (exactly $(1 + \alpha)$ times the original).

To apply the PBMM procedure described so far, it is necessary to decompose the 2D Fourier Transform of I into frequency bands that are localised in space (according to $\boldsymbol{x} = (x, y)$), scale (ω), and orientation (θ). The Complex Steerable Pyramid (CSP, [14]) is utilised to this aim as a set of orientable, spatially multi-scale, and spatially localised transform filters. An additional amplitude-weighted spatial smoothing can be performed at this point over σ adjacent pixels, to avoid unrealistic discontinuities due to excessive manipulation and/or noisy measurements.

The resulting amplified motions can be then used in several ways. Focussing on a single, (almost) pointwise pixel region will return a displacement time history which can be used as a single "virtual" output channel. This can be exploited e.g. as a single, virtual output channel [10]. However, considering the large quantity of spatial information captured by any single frame, it makes much more practical sense to perform these operations on many pixel regions, mimicking a multi-output acquisition procedure. This high spatial density of information grants several advantages; for instance, it can be exploited for robust measurements, comparing the response at several locations at the same time. It can be used as well to recreate the operational deflection shapes (that is to say, the full movement of the mode shapes during their natural period) of the target system with high spatial density. The flowchart of Figure 1 recalls the whole PBMM procedure for this specific application.

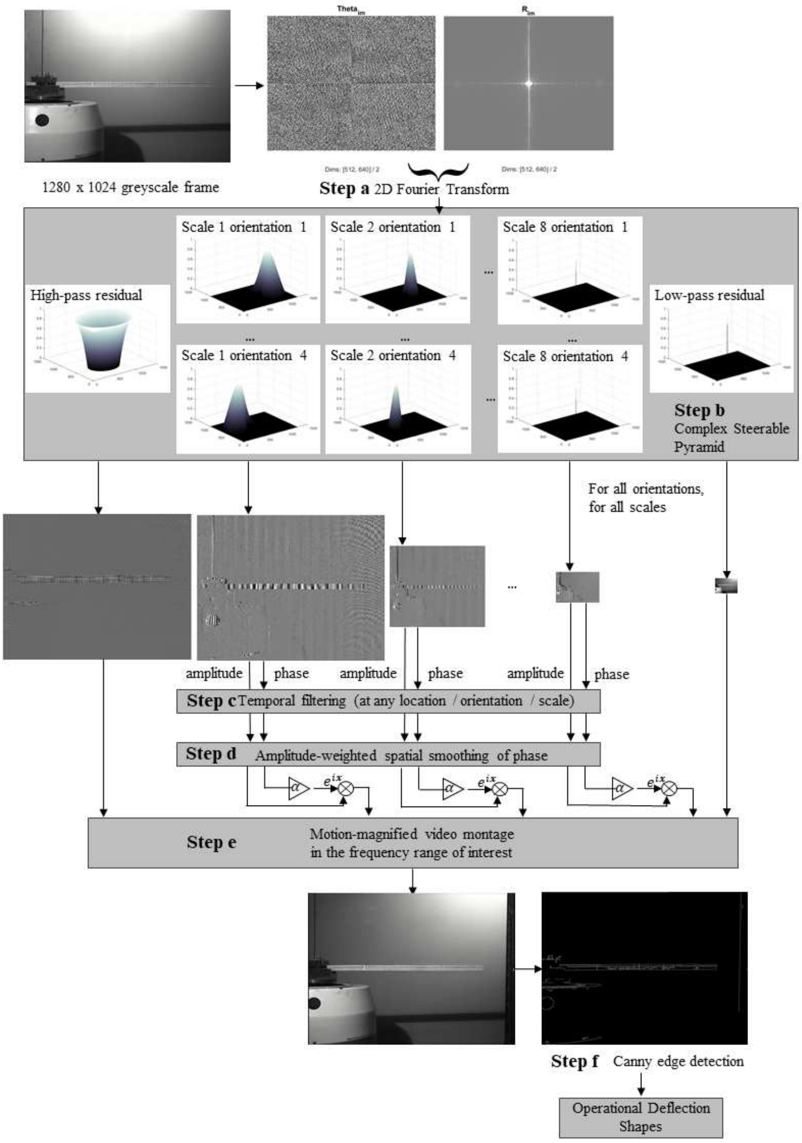

Fig. 1. Flowchart of the PBMM approach for mode shapes estimation. From Civera et al. [15]

2.2 Finite Element Model Updating (FEMU).

Once the time histories are obtained and validated through comparison against the known ground truth, they can be then used for Finite Element Model Updating. FEMU approaches may be mainly classified as direct and indirect methods; the members of this latter group are also known as sensitivity-based techniques [16]. For direct methods, the individual elements in the system matrices of masses and stiffnesses are adjusted through comparison between the initial model prediction and the experimental data, generally without recurring to iterative algorithms. In the case of indirect techniques, the adjustments are applied not directly to the system matrices but rather to some specific physical property of the model elements. In turn, this causes a variation of the resulting matrices and brings the predicted output closer to the measured data.

An indirect method will be applied in this study, varying Young's modulus and density of the most relevant macro-elements (selected according to the preliminary sensitivity analysis) until the error between the estimated modal parameters (natural frequencies and mode shapes) and their experimental counterparts (extracted from video recordings via PBMM) is minimized under a properly selected threshold. The whole algorithm is pictorially depicted in Figure 2 (accounting for both output-only Operational Modal Analysis, as it will be performed here, or input-output System Identification, i.e. Experimental Modal Analysis). A similar approach was tested on displacements extracted from video recordings in [17], even if without applying the PBMM in that previous study.

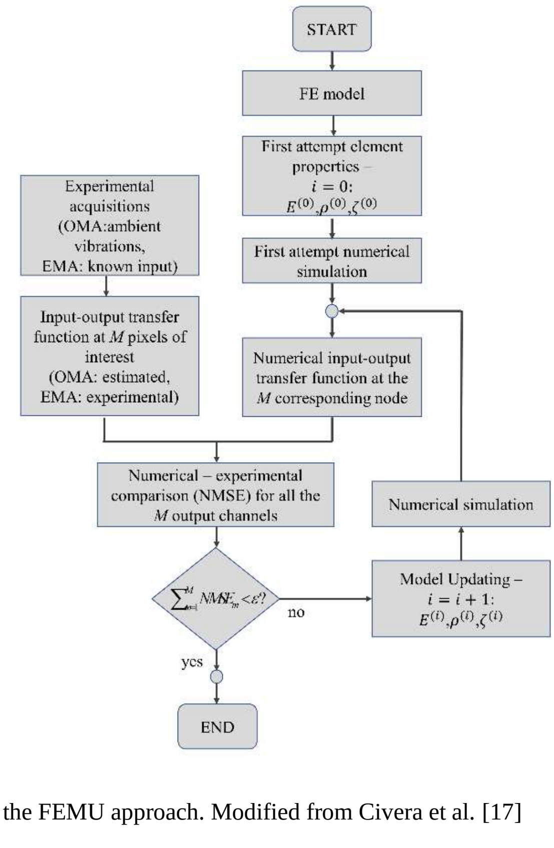

Fig. 2. Flowchart of the FEMU approach. Modified from Civera et al. [17]

3 Case Study #1: SHM of High Rise Buildings.

The SHM of high rise buildings involves some specific challenges and requirements. For instance, it needs to cover a large structure, with surfaces exposed to environmental effects on all sides; these not only changes over time but also according to the positions due to the different heights, resulting in gradients of temperature, wind speed, etc. Furthermore, tall and supertall buildings are mainly located in an urban context, with a high density of other human-made structures (that can affect the boundary conditions) and varying traffic loads (that can affect the ambient vibration measurements).

Apart from these general considerations, the specific case study will present some peculiarities as well.

For instance, the tallest building in Kuwait City, Kuwait, stands at 414 m (83 floors; see Figure 3). The structure is permanently monitored and has been largely studied in the last years [18, 19]. This and other tall buildings in the city (as mentioned, 12 other structures rise above 150 m within the city limits) are subject to harsh environmental conditions, typical of the Middle Eastern desertic climate, with temperatures ranging from a record minimum of -4 °C (at night in wintertime) to a record maximum of more than +50 °C (on summer days). Due to the city close proximity to the seaside, these structures are subject as well to almost constant windy conditions, with an all-year-round mean wind speed of about 20 km/h (at surface level). However, on the other hand, the site presents very few rainy days, with good visibility and natural illumination; these are therefore ideal conditions for outdoor video-based remote sensing, especially involving PBMM, which can be performed even with commercial smartphone cameras under such conditions [20].

Fig. 3. The skyline of Kuwait City, Kuwait.

4 Case Study #2: Bridge Monitoring.

Bridge monitoring is essential for many different reasons, ranging from safety to economic and practical concerns (i.e., to avoid traffic disruptions). For historical bridges, the preservation of the cultural and architectural heritage is another key factor [21]. In Kuwait, there are over 350 highway bridges; most of them are modern concrete bridges. Therefore, developing an easy and cost effective methods for concrete highway bridge monitoring has its own importance.

For this project, the highway bridge in Kuwait on the Faheel highway near Cairo street (Figure 4) is considered. This bridge is an example of a concrete-made highway bridge subject to high traffic and extremely hot weather conditions. Continuously monitored by both the Kuwait Institute of Scientific Research (KISR) and the Public Authority for Roads and Transportations (PART). This bridge is currently undergoing exacavation to expand the traffic laned below the bridge.

Fig. 4. The monitored concrete highway bridge.

5 Conclusions.

Computer vision in general and Phase-Based Motion Magnification (PBMM) in particular offer a valid remote sensing alternative to physically-attached sensors for vibration-based inspection.

This can be applied for the structural integrity assessment and health monitoring of both high rise buildings and critical infrastructures (such as highway bridges). The video-based technique has never been validated in detail for SHM purposes on large case studies in arid, extreme environmental conditions such as the ones of Middle Eastern desert zones.

In this paper, the general methodologies and framework for a future project have been presented. These future researches are intended to fill the highlighted research gap, especially evaluating the potentialities of video-extracted displacement time histories to produce damage-sensitive features (including but not restricted to modal parameters) and to use them for damage diagnosis under large temperature changes and strong wind loads.

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