V. THE ROLE THAT ALTERNATIVE INSTRUMENTATION AND/OR DATA ANALYTICS CAN PLAY IN THE FUTURE

A. Use of MEMS and Community Seismic Network in predicting ground and building responses

The current USGS ShakeMap/ShakeCast platform uses the ANSS network and its roughly XXX high fidelity sensors to create MMI intensity and ground motion contour maps following a detected earthquake. Studies by the USGS[i] indicate that the uncertainty associated with ShakeMaps grows significantly as the density of the sensor network decreases. ShakeMaps reside on the USGS website and can be emailed as notifications to subscribers; but these emails can be delayed significantly in urban areas, where many users are subscribed to the platform. MMI maps estimate damage to buildings generally and are based on relatively simple conversion equations from ground motion parameters. The performance of hospitals in particular is likely to be very different than these general MMI estimates, because of the complexity of hospital buildings and the high value of sensitive equipment and systems.

Having SMIP sensors directly in hospitals as part of the HBSB instrumentation program ensures that building specific ground motions are gathered; however the waveform data is not directly translatable into individual building damage without an estimate of an individual building's seismic vulnerability. Furthermore, the typically high cost of these sensors limits the number that can be placed in a hospital building or in other buildings on a hospital site. As hospitals often have complex configurations, consisting of setbacks, multiple wings and other irregularities, capturing their behavior is difficult with only one or two sensors.

A lack of real time earthquake data that is easily understood by non-technical hospital officials can result in poor decision making after an event. Following the 2019 Searles Valley Earthquake, the Ridgecrest Regional Hospital was evacuated by administrators who did not have data about potential damage to the hospital. Engineers later determined that the hospital did not suffer structural damage, and patients might have remained in place.[ii]

Additional use cases within hospitals for MEMS based sensors

An additional use case for lower cost MEMS based sensors is to provide situational awareness of an earthquake within the hospital environment to surgeons, operators of sensitive imaging equipment, etc. Sensors placed in operating and imaging rooms could audibly alert doctors to stop what they are doing when shaking exceeds a threshold that is likely to indicate a high intensity event is occurring.

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Another use case for a rapid web-based sensor platform is within community and regional emergency response offices. It will be critical in the minutes and hours after a large earthquake for police, fire and EMS to have good situational awareness within a city and particularly at essential facilities to aid their response.

B. Advancements in SHAKEALERT and the role of a robust earthquake early warning system for emergency response to hospital issues

Earthquake Early Warning System has been in operation in California for a few years now as a collaboration of the seismic networks (US Geological Survey, California Geological Survey, California Institute of Technology and University of California at Berkeley) and the California Governor's Office of Emergency Services. The earthquake early warning system detects initiation of earthquake motion and calculate size and location of earthquakes using a few seconds of P-wave arrival of waveforms recorded at seismic stations.

Several methods have been developed to apply earthquake early warning for structures. On-site measurement of ground motion was used to calculate arias intensity and spectral acceleration at a site and provide the information to automatically shut off gas valves, stop elevators, keep fire station garage doors open, slow down trains, stop traffic from entering tunnels, etc. The advantage of on-site methods is that such methods work with ground motion at the site and do not need to wait for information about earthquake size and location.

Some other simple methods use the size and location of earthquakes as soon as the information are available within a few seconds from the earthquake early warning systems and estimate ground motion at different distances and predict structural response to such ground motion models. This is a simple methods, but the results could be applied to multiple buildings quickly as the first estimate of structural response.

In some studies, structural drift has been estimated by using the first seconds of P-wave signal using machine learning and linear regressors. Recently some researchers have used structural response at the top of buildings to provide notifications when the response at the building's roof exceeds a threshold to provide notification to the occupants or to provide notifications for the like buildings at farther distances from the earthquake epicenter.

Wave propagation analysis has been used in some other methods to monitor changes in propagation of seismic waves in structures in real time to detect and localize damage in buildings automatically.

The application of earthquake Early Warning in structural health monitoring has been evolving recently. The applications can provide information to the property managers and earthquake emergency response teams. These methods are applicable to hospitals to make decisions at different levels from stopping an elevator or an operation to evacuating a building and bringing back the buildings to service as soon as possible.

C. Improvements to ShakeMap and the accuracy of hospital building damage assessment

There are several improvements that can be made to the current systems that provide earthquake data for use by hospitals, emergency responders and others.

1) **Improving damage estimates of hospital facilities and supporting buildings** – The current high fidelity sensors used as part of the SMIP and Shakemap platforms are relatively expensive and can be challenging to install in operating hospitals. The use of lower cost, MEMS based sensors will allow for installation typically without permanent anchorages to slabs, interconnection between stories, or a hardwired electrical supply. The ability to place many sensors in a large hospital building, at each floor, in wings, at locations of discontinuities or other structural irregularities, etc. will greatly improve the amount of useful data on the building's behavior. Combined with building specific vulnerability functions and the judgement of structural engineers, a denser network of sensors within a building will make it easier to estimate the locations and extent of damage.

   The efficient post-earthquake operation of a hospital site will be dependent on the performance of the many support buildings surrounding the acute care hospital. These include: central utility plants, medical office buildings, parking structures, records storage, imaging centers, etc. Use of lower cost sensors will make it more affordable for hospitals to install sensors in all important buildings on a campus.

2) **Creating a dedicated web based platform through which hospitals can access real time data on hospital impacts** – The current ShakeMap and SMIP networks do not provide information that is readily accessible and meaningful to hospital staff in the seconds and minutes after an earthquake. ShakeMaps provide shaking intensity information, which is not specific to the vulnerability of an individual structure, nor always timely; SMIP waveform data may be difficult to interpret by non-technical users. A web based platform that gathers sensor data and puts it into context would greatly aid emergency response. The platform would:

   a. be accessible to each hospital;

   b. gather data from multiple building sensors (high fidelity or MEMS based) and compare it to building specific vulnerability functions;

   c. display easy to understand damage estimates; and

   d. be available to structural engineers inspecting the buildings.

D. Use of displacement (e.g., laser interferometry) or velocity measurements to supplement accelerometer data

A correct understanding of a structure's displacement response to earthquake excitation becomes increasingly important as engineers, building owners and other stakeholders seek to implement vibration-based structural health monitoring strategies. Relative displacements which occur between adjacent floor levels of a building can be used to calculate interstory drift ratios by dividing the relative displacement at a floor level by its corresponding story height. The interstory drift ratio is a key parameter used in engineering practice to quantify both the system level demands on a building as well as the limit states commonly used in seismic design codes today. As a widely used and significant indicator of structural performance it highlights the importance of obtaining displacement response data.

The displacement response of a structure can be obtained by direct measurement using displacement transducers or it can be calculated by double integration of acceleration response measurements of accelerometers. Calculating displacements by double integration of acceleration is convenient because of the wide use of accelerometers in structural arrays; however, these calculated displacements suffer from errors and limitations caused by essential signal processing of the acceleration response data. Notable limitations include the loss of residual displacement information from the calculated displacements and the subjective nature of signal processing techniques. Additionally, Skolnik and Wallace (2010) found errors in peak displacement on the order of 12 to 15% for cases in which the calculated displacements included nonlinear response. For linear response, the results fared better with errors at less than 4%. See Skolnik and Wallace (2010) for additional discussion on the issues associated with obtaining displacements from acceleration measurements.

Another potential source of error occurs in cases where measurements – either acceleration or displacement – are not obtained at consecutive floor levels but are still desired for the purpose of estimating demands on the system (e.g., interstory drift ratios). In these cases, the responses at unmeasured levels must be determined by interpolation which is a subjective process and an additional opportunity to introduce errors into the response estimates of the structure. As a result, where practical it is recommended to install instrumentation and obtain response measurements at each floor level.

Historically, HCAI/CSMIP hospital instrumentation projects have predominantly used accelerometers, whereas displacement transducers have only been utilized in limited applications. For example, string potentiometers were installed at the Ontario – 5-story Hospital (CSMIP Station No. 23416) to measure the displacement response of selected buckling restrained braces in the building. Similarly, selected viscous dampers located at the isolation plane of the base isolated Loma Linda – 16-story Hospital (CSMIP Station No. 23M01) have been instrumented with string potentiometers. In addition, ultrasonic sensors have been used to measure global building displacements at the isolation plane of various base isolated hospitals (e.g., CSMIP Station Nos. 23M01, 58390, 57643, 58574, and 58623). To measure displacement, this style of sensor requires a target off which a sound wave can be reflected; in the case of base isolated buildings this target has typically been the moat wall.

A new laser-based optical sensor for measuring building displacement is discussed in McCallen et al. (2017). This technology appears promising for obtaining direct measurements of interstory drift in buildings. The optical sensor does require a clear line of sight between the laser source and position sensitive detector which could make its application in existing hospital buildings difficult.

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E. Remote Sensing methods:

Remote sensing represents various spaceborne and airborne imaging techniques that have been used after the moderate and large earthquakes to detect damage and assist emergency responders by providing estimate of the effects of earthquakes on structures.

The remote sensing techniques that are most applicable to earthquake and engineering are synthetic aperture radar (SAR) and light detection and ranging (LIDAR). The SAR technique uses electromagnetic waves with relatively long wavelengths. The LIDAR imaging technique collects reflected and scattered light from a laser source. The small size of LIDAR instruments can be mounted in small aircrafts for aerial surveys. Also, the Remote sensing imagery techniques have been applied for visualization of surface and structural deformation by using portable LIDAR system (Kayan and others, 2006).

Some algorithms have been proposed for performing unsupervised building segmentation and damage assessment using airborne light detection and ranging (LIDAR) data. One example is the study by Alex and Van (2017), in which Local surface properties, including normal vectors and curvature, were used along with region growing to segment individual buildings in LIDAR point clouds. Damaged building candidates were identified based on rooftop inclination angle, and then damage was assessed using planarity and point height metrics.

During the last decade, artificial intelligence and machine learning methods have been developed for the vision-based structural health monitoring using imagery data. In general, one limitation for applying imagery data to structural damage detection is lack of imagery benchmark datasets. Recently, there have been efforts and progress to compile such datasets (e.g., https://apps.peer.berkeley.edu/phi-net/).

One challenge with LIDAR and SAR image acquisition is that it requires time and may not happen quickly after an earthquake. Airborne image acquisition needs available service to schedule flights over the area, and spaceborne image acquisition depends on satellite location, acquisition angle and cloud cover (Rathje and Adams, 2008). Also, the damage level resolution by such methods is limited to external damage in larger scale.

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F. ARTIFICIAL INTELLIGENCE-ENABLED STRUCTURAL HEALTH MONITORING

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State of Knowledge

In this data explosion epoch, artificial intelligence (AI)-enabled structural health monitoring (SHM) using the state-of-the-art machine learning (ML) and deep learning (DL) technologies has become of great interest in civil engineering. Based on data type, it can be further classified into two major directions, namely vision-based [9] and vibration-based [4] SHM.

The goals of vision-based SHM is to automatically detect presence, type and severity of damage from images. A critical aspect that is needed to be addressed to achieve these goals is the lack of benchmark[2] datasets with well-labeled large amounts of data. To address this issue, an automated and hierarchical framework, called PEER Hub Image-Net (PHI-Net or simply ϕ-Net), was developed [10]. The framework consists of eight basic benchmark detection tasks based on current domain knowledge and past reconnaissance experience. These tasks are: (1) scene level (structural, component, or material), (2) damage state, (3) concrete cover spalling condition (material loss), (4) material type, (5) global collapse mode, (6) component type, (7) damage level, and (8) damage type. According to the ϕ-Net framework, many structural images was collected, preprocessed, and labeled to form the ϕ-Net dataset, an open-source online large-scale multi attribute image dataset, which currently contains 36,413 images of structures and structural components with multiple labels. However, compared to the general computer vision benchmark dataset, ImageNet containing 15 million labeled images, the size of ϕ-Net is still not large enough. Thus, different techniques are used to address the lack of useful labeled data.

Through the development and application of ϕ-Net, promising results were achieved and reported, which provide the reference for future DL applications. The well-trained models in these applications are named Structural ImageNet Models (SIMs) and they serve as benchmarks for future development of classification algorithms. Moreover, the direct application of these SIMs was further performed, namely image-based post-disaster assessment of the 1999 Chi-Chi earthquake, Taiwan, which revealed the high potential and contribution of the ϕ-Net in vision-based SHM [10]. The SIMs also detected the collapse and partial collapse of cripple wall houses in the 2014 South Napa earthquake [16]. In other studies, DL was employed to classify materials and lateral resisting systems of buildings [12] and detect damage levels of buildings due to earthquakes using aerial photographs [22]. Similarly, DL was used in [24][25] for image classification in building reconnaissance after various hazards (e.g., earthquake, hurricane, and

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[2]A benchmark is defined as a standard by which all others are measured.

tornado). The dataset used in this study consisted of 90,000 colored structural images for training the network for scene classification and component detection. For classifying building damage due to service conditions (not extreme events), the possibility of detecting common building defects caused by dampness, such as mold, deterioration, and staining, was explored using images trained with DL [23]. This type of studies can be helpful for detecting issues on time to avoid any catastrophic failures, e.g., the collapse of Champlain Towers South in Florida due to deterioration [17].

Attention has been given to the applications of DL in practical bridge health monitoring (BHM) projects. In such AI-enabled BHM, crack identification and width measurement are two of the important metrics for evaluating the functionality of bridges. However, some problems still exist in extending previously developed ML/DL methods to practical applications, such as data annotation difficulty, limited ability of the models to be generalized for all cracking types and distributions, and inaccuracy of the DL identification of the actual crack width measurement. An application-oriented multistage crack detection framework is recently proposed and called Convolutional Active Learning Identification-Segmentation-Measurement (CAL-ISM) [26]. The performance of the CAL-ISM framework is validated from two practical applications: (i) a test bridge column specimen, and (ii) a BHM field project. The results from these applications demonstrated the effectiveness of these approaches and their recommendation for future BHM deployments. Because of its potential widespread application under serviceability and extreme event conditions, crack identification using images have also been explored in other studies, for bridges, historical structures, and others, e.g., [1][8][13][15]. Datasets in these studies consisted of images from masonry structures containing cracks that were acquired using a digital camera and an unmanned aerial vehicle [8]. An image dataset of 11,000 pixel-wise labeled images, called the "Bridge Crack Library," has been developed as a dataset with adequate numbers of pixel-wise labeled crack images and a rich diversity of on-site scenarios [24]. In other efforts of using adequate number of images, a wall-climbing unmanned aerial system was used in [14] to acquire real-time videos. The video data were then converted to 1,330 crack images, and a DL model was trained.

In the direction of vibration-based SHM, vibration data, especially acceleration, plays the major role [5][6][18]. Since the turn of this century, time series (TS) modeling of vibration signals using a family of auto-regressive (AR) models, defined as statistical models predicting future values based on past values, was found to be effective in damage detection and has been used to capture damage features in structures [5][6][11]. However, for these models to be successful with conventional methods, elaborate data pre-processing is inevitable to remove trends and noise. To facilitate this need, making use of the learning capability of ML approaches, a systematic framework, namely Auto-Regressive Integrated Moving-Average Machine Learning (ARIMA-ML), was developed to combine TS modeling techniques and ML approaches for detecting structural damage [11]. The performance of the framework was validated using data from full-scale shaking table tests of a three-story steel frame. The validation experimental results demonstrated the robustness and accurate performance of the ARIMA-ML.

There are a few studies that combined vision-based and vibration-based approaches. As a unique example, the acceleration data from a long-span bridge were first converted into images in [7] that were then transformed into grayscale image vectors for training a deep neural network (DNN) considering six different anomalies such as missing, minor, outlier, square, drift, and trend data points.

Even though the number of AI-enabled SHM studies and applications is rising in the past five years, very few of them bridge the gap between ML/DL results and the final decision-making procedure. In one of our ongoing projects for developing the “Bridge Rapid Assessment Center for Extreme Events (BRACE2)”, we developed a post-earthquake damage and functionality assessment framework and implemented it on Route 580/238 Separation in Hayward. The developed framework uses the data to provide a real-time estimate of the bridge damage that can be used to inform decisions concerning whether to close the bridge to traffic and where to expect damage. At the core of the framework is a decision-making platform (DMP) that utilizes (a) data streamed in real-time from accelerometers, (b) response from a global bridge model subjected to the recorded ground motion signals, (c) damage states from component models, e.g., [19], and (d) ML/DL rapid recognition results; refer to [20][21] for an earlier development of this DMP.

Future Directions

In summary, the developed advances and obtained promising results in AI-enabled SHM studies shed light on the high potential of these state-of-the-art methodologies in practical structural engineering applications. In future pursuits, improved monitoring, learning, maintenance, and ultimately effective decision-making, regarding the conditions, replacement, or retrofit of key elements of the built environment can be reliably achieved. Among the AI-enabled SHM studies in literature, there is a lack of studies that focus on hospital buildings. Future directions towards filling this gap are discussed below.

1. <u>Use of images for evaluation of damage on a structural level</u>: Images collected in hospital buildings during earthquake reconnaissance can be used to develop algorithms for characterizing the damage at the structural level and for tagging purposes. This can be performed using approaches similar to those in FEMA-P58 [2] or ATC-138 [3] that relate component damage to structural level damage and recovery states. This can be facilitated by a building information model (BIM) of a hospital facility that provides critical locations of images for identifying component and structural level damage. Such application is not limited to extreme events and can also be used for regular maintenance and identifying any issues under service conditions. Platforms like ϕ-Net & SIM can be expanded for this purpose and key hospital facilities selected as prototypes for development.
2. Hybrid methods that use vibration-based data and vision-based images can be developed. These methods can benefit from (a) sensors at floor levels and the use of methods, such as ARIMA-ML [11] or other techniques as in [20] to detect presence, severity, and location of damage, and (b) images of non-structural components, specialized equipment, and local damage that cannot be identified by sensors, to provide a holistic damage evaluation of hospitals.
3. Early-stage warning applications, similar to DMP in BRACE2 described above, that use the results of vision- & vibration-based SHM can be developed to recommend actions of hospital operations.

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Important Links

[1] PEER Hub ImageNet (ϕ-Net or PHI-Net)

[2] Structural ImageNet Model (SIM) app [This uses http protocol not https.]

[3] Upload Images and Label Images apps

[4] PHI Challenge