# Guidelines for Pre-processing Concrete Surface Images for Structural Health Monitoring (Theoretical Overview)

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**Abstract**

Damage detection based on computer vision and image processing in concrete surface images has been utilized these years and understanding the image processing methods in order to input the optimized images into the machine can further the perception of machine or it can reduce the computational cost or the CPU time of process. Or even in some cases it is so important to know that in some advanced machine some kinds of preprocessing are not imperative and understanding the importance of each preprocessing method and validate the efficiency of each preprocessing method can be crucial for the authors to avoid the redundant operations and process and for the reviewers to understand the true contribution of papers and researches in computer vision and SHM. So, in this theoretical overview the overall trends in the region of Techniques-Based Evaluation, Object-Based Evaluation, and Level-Based Evaluation will be explained. The aim of this file is to make you more familiar with the tasks you define and the process you need to conduct to have the best answer.

## 1. Introduction

Structural Health Monitoring (SHM) has become a cornerstone of modern civil engineering, where the timely detection of cracks, spalling, and other surface damages plays a crucial role in maintaining the safety and durability of concrete structures. Among the various approaches, computer vision and image processing have emerged as effective non-destructive tools, providing low-cost, scalable, and automated solutions for local damage detection. In recent years, the rapid evolution of image-based methods, coupled with artificial intelligence (AI), has introduced new possibilities for improving the accuracy, efficiency, and interpretability of SHM pipelines.

However, one critical aspect often overlooked in the research community is the pre-processing stage of image data. Pre-processing not only determines the quality of inputs fed into machine learning or deep learning models but also significantly affects computational costs, training time, and even the interpretability of results. While certain advanced AI architectures may bypass extensive pre-processing, an informed understanding of which pre-processing steps are necessary—and which may be redundant—is essential. This knowledge allows researchers to optimize their workflows, avoid unnecessary complexity, and demonstrate meaningful contributions in their studies.

The aim of this work is to present a theoretical overview of pre-processing methods and their evaluation in SHM image analysis, highlighting both classical image processing foundations and modern AI-driven approaches. Special attention is given to understanding the balance between process efficiency (e.g., CPU time reduction, data compression) and damage detectability (e.g., crack visibility, texture preservation). In this context, the review outlines the evolution of methods, the perspectives for data analysis, and strategies for evaluating preprocessing efficiency, aiming to provide both researchers and reviewers with a structured framework for assessing image-based SHM studies.

### 1.1. Pre-processing Importance

This section introduces the rationale for pre-processing in SHM imaging, emphasizing its role in contrast enhancement, noise reduction, dimensionality adjustment, and optimization of features for subsequent analysis. It will highlight cases where pre-processing is indispensable (e.g., low-quality field images) and cases where AI models can directly process raw data without extensive transformations.

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### 1.2. From Classical Image Processing to AI-Driven Methods

This section explains the progression from conventional image processing techniques to modern artificial intelligence (AI) methods for analyzing concrete surface images in SHM. Each approach has its unique role, depending on the task (e.g., crack detection, feature extraction, noise removal, or structural assessment).

- **Numerical Computation**
    - Definition: Techniques based on mathematical and statistical operations (e.g., Fourier transform, convolution, filtering) to extract low-level information from images.
    - Application: Used for basic tasks like noise filtering, edge enhancement, or frequency analysis of surface patterns in concrete imagery.
- **Pattern Recognition Process**
    - Definition: Methods designed to identify and classify recurring structures or features in images, often based on similarity measures or handcrafted descriptors.
    - Application: Helps in distinguishing cracks from background textures, detecting spalling regions, or separating damage from noise in heterogeneous concrete surfaces.
- **Edge Detection**
    - Definition: Algorithms (e.g., Sobel, Canny, Laplacian) that identify boundaries where pixel intensity changes sharply.
    - Application: Applied to locate crack edges, define boundaries of spalling, or highlight discontinuities in concrete imagery.
- **Morphology**
    - Definition: Operations based on set theory (e.g., dilation, erosion, opening, closing) that process image structures according to their shape.
    - Application: Effective in refining crack structures, filling small gaps, removing noise, or connecting broken crack segments.
- **Wavelet-Based Methods**
    - Definition: Multi-resolution analysis techniques that decompose images into different frequency components for localized feature extraction.
    - Application: Used to capture crack signatures at multiple scales, compress image data, or enhance fine texture details in concrete surfaces.
- **Data-Driven Based Methods**
    - Definition: Approaches where features are automatically learned from data, rather than manually defined, typically through machine learning algorithms.
    - Application: Applied in SHM to automatically detect damage patterns in diverse datasets without explicit feature engineering.
- **Machine Learning Methods**
    - Definition: Algorithms (e.g., Support Vector Machines, Random Forests, CNNs, U-Nets, YOLO) that learn from labeled or unlabeled data to perform classification, segmentation, or prediction tasks.
    - Application: Widely used for automated crack detection, damage segmentation, severity classification, and predictive analysis of concrete health conditions.

### 1.3. Data Analysis Perspectives in Damage Detection

Building on the growing importance of analytics in SHM, this section frames image-based damage detection through four analysis types:

- Descriptive Analysis: Understanding features and their impact on crack morphology and damage assessment.
- Diagnostic Analysis: Identifying causes of damage based on image-derived patterns.
- Predictive Analysis: Forecasting damage evolution and structure lifetime.

- Prescriptive Analysis: Offering recommendations for material or structural enhancement based on detection outcomes.

### 1.4. Evaluation and Validation of Preprocessing

Finally, this section addresses the metrics and evaluation strategies used to validate preprocessing methods in SHM. Both quantitative (SSIM, FSIM, PSNR, confusion matrix, CPU-time, statistical measures) and qualitative (perception-based, neuro-scientific) criteria are discussed. Additionally, the role of Explainable AI (XAI) is emphasized to ensure interpretability in preprocessing evaluation and decision-making.

Three main steps are provided in this study: 1. Techniques-Based Evaluation, 2. Object-Based Evaluation, and 3. Level-Based Evaluation

### 1.5. Project Overview

This file presents a comprehensive overview of a wide range of preprocessing methods used in various tasks of structural health monitoring (SHM) for concrete surface images. Each method is introduced with a clear definition and its corresponding application, enabling readers to understand not only the operational principles but also the contexts in which each technique is most effective. By presenting these methods alongside practical examples and task-specific use cases, this overview aims to broaden the reader's perspective and provide a structured understanding of the realm of preprocessing in concrete surface image analysis.

It is important to note that the methods included here are illustrative rather than exhaustive. Not every preprocessing technique currently available in the literature has been covered. Instead, the focus is on providing sufficient diversity and practical relevance so that researchers can identify efficient methods, consider hybrid approaches, or select preprocessing steps that are best suited to their specific datasets, tasks, and computational constraints.

Furthermore, this file can serve as a useful reference for both authors and reviewers. For authors, it offers guidance in designing, implementing, and justifying preprocessing pipelines while avoiding redundant or unnecessary operations. For reviewers, it provides a structured framework for assessing the methodological soundness and true contributions of research works that employ preprocessing models. In this way, the content supports both the development and evaluation of preprocessing strategies within SHM.

Ultimately, this theoretical overview serves as a guiding framework, helping researchers and reviewers alike appreciate the rationale behind preprocessing choices, the potential benefits of combining methods, and the considerations necessary to enhance the effectiveness of image-based damage detection and assessment in concrete structures.

## 2. Initial Pre-processing methods

Initial pre-processing methods are essential for preparing raw images before applying advanced image analysis or machine learning algorithms. These techniques ensure that images are standardized, enhanced, and optimized for further processing, thereby improving the accuracy and robustness of detection tasks in SHM.

- **Image Resizing**
  - **Definition:** Adjusting the dimensions of the image to a desired scale without altering essential structural features.
  - **Application:** Ensures consistency across datasets, reduces computational cost, and aligns input sizes for deep learning models.
- **Normalization**
  - **Definition:** Scaling pixel values to a standardized range, typically [0, 1] or [-1, 1].
  - **Application:** Improves numerical stability, accelerates convergence in neural networks, and balances intensity variations across datasets.
- **Grayscale Conversion**
  - **Definition:** Converting a colored image to grayscale by eliminating color channels while preserving intensity information.

  - **Application:** Reduces computational complexity when color is not a critical feature, commonly applied in crack detection tasks.
- **Histogram Equalization**
  - **Definition:** Enhancing image contrast by redistributing pixel intensity values more uniformly across the histogram.
  - **Application:** Highlights subtle details and improves visibility of cracks and surface textures in concrete imagery.
- **Image Cropping**
  - **Definition:** Extracting a specific region of interest (ROI) from an image.
  - **Application:** Focuses analysis on relevant areas (e.g., cracks) while excluding irrelevant background content.
- **Color Space Transformation**
  - **Definition:** Changing the color representation of an image (e.g., RGB to HSV, YCbCr, or Lab).
  - **Application:** Improves segmentation, edge detection, and texture analysis by separating luminance from chrominance information.
- **Data Augmentation**
  - **Definition:** Generating modified versions of original images using transformations such as rotation, flipping, scaling, and noise addition.
  - **Application:** Expands limited datasets, improves model generalization, and prevents overfitting in machine learning.
- **Contrast Enhancement**
  - **Definition:** Adjusting image contrast using methods like linear stretching, adaptive histogram equalization, or CLAHE.
  - **Application:** Enhances fine structural details such as thin cracks that might otherwise be overlooked.
- **Brightness Adjustment**
  - **Definition:** Modifying the overall intensity of an image to make it appear lighter or darker.
  - **Application:** Compensates for lighting inconsistencies during data acquisition and improves visibility of local features.
- **Gamma Correction**
  - **Definition:** Applying a nonlinear transformation to pixel values to correct overall brightness and contrast.
  - **Application:** Improves perceptual quality of images and makes structural details more distinguishable under varying illumination conditions.
- **Sharpening**
  - **Definition:** Enhancing edges and fine details in an image using filters such as Laplacian, high-pass, or unsharp masking.
  - **Application:** Improves boundary clarity of cracks, spalling edges, or other damage patterns in SHM images.
- **White Balance Correction**
  - **Definition:** Adjusting the colors of an image to ensure that white objects appear white, compensating for illumination color cast.
  - **Application:** Normalizes color tones in field images captured under variable lighting conditions.
- **Image Inversion**
  - **Definition:** Reversing pixel values to create a negative image, where bright regions become dark and vice versa.

- **Application:** Used for contrast-based detection, making cracks and anomalies stand out in certain imaging scenarios.

- **Blurring**
  - **Definition:** Reducing noise or detail in an image using filters such as Gaussian, median, or average blurring.
  - **Application:** Smooths background variations and reduces irrelevant textures while preparing data for feature extraction.
- **Perspective Transformation**
  - **Definition:** Geometrically transforming an image to correct distortions or simulate a change in viewpoint.
  - **Application:** Aligns images for consistent analysis, especially when photos are taken from different angles in field inspections.

**3. Noise Removal Definitions and Application**

Concrete surface images acquired in real-world SHM often suffer from noise introduced by acquisition devices, environmental conditions, or structural surface irregularities. Noise reduction is therefore a crucial pre-processing step to ensure reliable feature extraction, segmentation, and crack quantification. Several classical and advanced denoising approaches are applicable depending on the type of noise**,** nature of the concrete surface, and target SHM task**.** Below, the most relevant methods are summarized with their definitions and applications.

- **Median Filtering**
  - **Definition:** A non-linear filtering technique that replaces each pixel with the median intensity value of its neighborhood.
  - **Application in SHM:** Effective for eliminating impulse-type noise (e.g., salt-and-pepper noise from sensor artifacts) in concrete surface images. Useful in crack segmentation where preserving edges is essential, especially in pavements and bridge decks subjected to dust, scratches, or digital sensor noise.
- **Gaussian Filtering**
  - **Definition:** A linear smoothing filter that reduces noise by averaging pixels with weights defined by a Gaussian distribution centered at the target pixel.
  - **Application in SHM:** Commonly applied for Gaussian noise reduction in images of concrete captured under low-light or fluctuating illumination. Supports general crack detection but may blur fine crack boundaries, requiring careful parameter tuning.
- **Wiener Filtering**
  - **Definition:** An adaptive filtering method that minimizes the mean square error between estimated and true image signals.
  - **Application in SHM:** Suitable for restoring degraded images where noise distribution is known or can be estimated (e.g., drone-based inspections of tunnels or bridge piers in low visibility). Balances noise reduction with detail preservation for quantitative crack width analysis.
- **Bilateral Filtering**
  - **Definition:** A non-linear filter that reduces noise while preserving edges by considering both spatial distance and intensity differences.
  - **Application in SHM:** Effective for concrete structures with textured surfaces (e.g., rough formwork finish or aged facades). Maintains sharp crack edges while reducing background variations from uneven lighting or surface roughness.
- **Anisotropic Diffusion**

  - **Definition:** A variational filtering technique that smooths images selectively in homogeneous regions while preventing diffusion across edges.
  - **Application in SHM:** Enhances micro-crack detection in high-resolution concrete imagery by reducing background noise without blurring thin cracks. Especially useful in microscopic studies of cementitious composites.
- **Non-Local Means Denoising**
  - **Definition:** A patch-based algorithm that denoises by averaging similar patterns across the image rather than only local neighborhoods.
  - **Application in SHM:** Useful for images of large concrete surfaces with repetitive patterns (e.g., block masonry, panel joints) under noisy acquisition conditions. Helps retain surface texture while suppressing sensor noise.
- **Total Variation (TV) Denoising**
  - **Definition:** A noise reduction method that minimizes total variation, enforcing piecewise smoothness while retaining edge sharpness.
  - **Application in SHM:** Suitable for concrete crack mapping and segmentation where sharp discontinuities (cracks, joints) must be preserved. Applied in bridge decks and slabs to enhance binarization-based crack detection.
- **Fourier Transform Filtering**
  - **Definition:** Noise removal in the frequency domain by attenuating high-frequency components associated with noise.
  - **Application in SHM:** Effective against periodic or structured noise (e.g., vibration-induced scanning artifacts during robotic inspections). Supports global image cleaning before applying deep learning models.
- **Wavelet Transform Denoising**
  - **Definition:** A multi-resolution technique that decomposes the image into different frequency bands, selectively removing noise while reconstructing details.
  - **Application in SHM:** Widely applied for multi-scale crack analysis, as cracks appear at different resolutions depending on width and length. Supports hierarchical processing for detecting cracks in dams, retaining walls, and large bridge girders.
- **Kalman Filtering**
  - **Definition**: A recursive estimator that predicts and corrects pixel intensity values by modeling noise as a dynamic process.
  - **Application in SHM**: Useful for **video-based monitoring of concrete structures** (e.g., UAV inspections), where temporal noise reduction across frames is important.
- **Non-Subsampled Contourlet Transform (NSCT) Denoising**
  - **Definition**: A multi-resolution, multi-directional transform that captures edge and texture information more effectively than wavelets.
  - **Application in SHM**: Suitable for **highly textured concrete surfaces**, improving crack visibility under complex aggregate patterns.
- **K-SVD (Sparse Representation Denoising)**
  - **Definition**: Learns a dictionary of image patches and reconstructs the image with sparse coding, suppressing noise in the process.

    - **Application in SHM**: Effective for **fine crack enhancement** when images are degraded by strong noise, though computationally more demanding.
- **Machine Learning-Based Denoising (Case Study: Shadow Removal)**
    - **Definition:** Data-driven methods that learn to distinguish noise (e.g., shadows, illumination artifacts) from structural details through supervised or unsupervised learning.
    - **Application in SHM:** Shadow removal in outdoor concrete structures (e.g., bridge columns, pavements under sunlight) improves segmentation accuracy by reducing illumination bias. Beneficial in deep learning crack classification and quantification tasks where shadows mimic crack patterns.

4. **Data Reduction Methods**

Concrete surface imaging often generates **large datasets** due to high-resolution acquisition, multiple inspection angles, or continuous monitoring systems (e.g., UAV or robotic inspections). Processing such data directly is computationally demanding and may not always be necessary. **Data reduction methods** allow the removal of redundant or less-informative image content, thereby reducing storage, bandwidth, and computational complexity while maintaining essential structural features.

- **Image Compression**
    - **Definition**: Reduces the amount of data required to represent an image using coding algorithms (lossy or lossless).
    - **Application** in SHM: Employed when transferring or archiving large image datasets from UAV surveys of bridges or dams. Lossless formats (PNG) are used where fine crack detail must be preserved, while lossy formats (JPEG) may be acceptable for broad condition assessment where minor detail loss is tolerable.
- **Downsampling**
    - **Definition**: Reducing the resolution of an image by decreasing the number of pixels.
    - **Application** in SHM: Applied in real-time monitoring systems (e.g., surveillance cameras on bridge decks or tunnels) to lower computational cost. Care must be taken, as excessive downsampling can obscure micro-cracks but may suffice for detecting large-scale spalling or delamination.
- **Quantization**
    - **Definition**: Reducing the number of distinct intensity or color levels in an image.
    - **Application** in SHM: Useful in texture-based classification of concrete surfaces where high color resolution is unnecessary. Supports compression and pattern recognition tasks, e.g., distinguishing cracks from stains under different lighting conditions.
- **Principal Component Analysis (PCA)**
    - **Definition**: A dimensionality reduction technique that transforms data into orthogonal components emphasizing variance and minimizing redundancy.
    - **Application** in SHM: Applied to multispectral or hyperspectral imaging of concrete surfaces to extract the most relevant components for crack detection or material characterization, while discarding redundant channels. Improves efficiency in machine learning pipelines.
- **Subsampling**
    - **Definition**: Selecting every nth pixel (or block) to generate a lower-resolution version of the image.

- **Application** in SHM: Common in video-based concrete monitoring (e.g., surveillance of tunnels or bridges) where processing every frame at full resolution is unnecessary. Helps in long-term condition assessment while reducing data storage.

- **Region of Interest (ROI) Coding**
  - **Definition**: Selectively encoding areas of importance at higher quality while compressing less critical regions more heavily.
  - **Application** in SHM: Highly relevant for targeted crack monitoring, where cracks or spalling zones are retained at full fidelity, while background concrete surfaces are compressed. Useful in autonomous inspection systems focusing only on defect-prone regions.
- **Vector Quantization (VQ)**
  - **Definition**: A compression approach that represents image blocks (vectors) with a finite set of representative vectors (codebook).
  - **Application** in SHM: Effective for large datasets of repetitive concrete textures (e.g., precast panels, patterned masonry). Reduces storage without significantly affecting recognition of crack patterns in repetitive surfaces.
- **Discrete Cosine Transform (DCT) Based Reduction**
  - **Definition:** Transforms image data into frequency components and discards less significant coefficients.
  - **Application in SHM:** Widely used in JPEG compression; applicable for reducing storage of large crack image datasets while retaining important structural details.
- **Singular Value Decomposition (SVD) Reduction**
  - **Definition:** Factorizes the image matrix into singular values and vectors, allowing approximation with fewer components.
  - **Application in SHM:** Useful for pattern recognition of cracks and dimensionality reduction in large inspection datasets, preserving dominant structural patterns while minimizing redundancy.
- **t-SNE and UMAP (Manifold Learning Reduction)**
  - **Definition:** Non-linear dimensionality reduction techniques that preserve local or global data structure in lower dimensions.
  - **Application in SHM:** Applied in deep learning feature space analysis (e.g., clustering crack vs. non-crack regions) to reduce high-dimensional representations from CNNs while preserving separability.
- **Block Truncation Coding (BTC)**
  - **Definition:** Divides images into blocks and represents each block using a small number of intensity values.
  - **Application in SHM:** Lightweight method for compressing large-scale video inspections of pavements or tunnels, reducing storage while keeping overall defect visibility.

5. **Optimization methods for color contents (Texture)**

Concrete surfaces exhibit diverse **color and texture variations** due to cement matrix heterogeneity, aggregate exposure, carbonation, efflorescence, stains, and environmental factors such as shadows or moisture. These variations complicate automated crack detection and segmentation. Optimization methods for color and texture aim to enhance **structural damage visibility** (e.g., cracks, spalling, scaling) while suppressing irrelevant surface variations.

- **Local Binary Methods (e.g., Local Binary Patterns, Watershed Algorithm)**
  - **Definition:**
    - Local Binary Patterns (LBP) describe local texture by encoding neighborhood intensity differences into binary patterns.

        - The Watershed algorithm segments images based on topographic representation, identifying region boundaries as watershed lines.
    - **Application in SHM:**
        - LBP assists in texture classification of concrete surfaces, separating cracks from pores or rough textures.
        - Watershed segmentation helps to separate overlapping or connected cracks, particularly in bridge decks, pavements, and tunnel linings where stains or moisture complicate crack boundaries.
- **1D Multi-Level Thresholding**
    - **Definition:** A histogram-based segmentation approach that divides grayscale intensity levels into multiple thresholds, segmenting the image into different regions.
    - **Application in SHM:** Suitable for grayscale concrete imagery, particularly when cracks appear under varying illumination. Applied in pavement inspections and surface evaluations where cracks must be isolated from background shading.
- **3D Colored Multi-Level Thresholding (Metaheuristic Optimization Methods)**
    - **Definition:** Extends multi-level thresholding into 3D color spaces (RGB, HSV, or Lab), where multiple thresholds are selected across channels. Due to the high dimensionality, metaheuristic optimization algorithms are employed to identify optimal thresholds efficiently. Key algorithms include:
    - **Genetic Algorithm (GA):**
        - Based on evolutionary principles of selection, crossover, and mutation.
        - **Application in SHM:** Effective for optimizing color thresholds in highly variable concrete surfaces with stains and weathering. Improves crack vs. background discrimination in outdoor bridge and tunnel inspections.
    - **Particle Swarm Optimization (PSO):**
        - Inspired by swarm intelligence, where particles explore threshold space guided by local and global best solutions.
        - **Application in SHM:** Provides efficient convergence for large UAV image datasets of concrete dams and bridge decks. Reduces computational time while preserving crack boundary accuracy in color-texture segmentation.
    - **Sine Cosine Algorithm (SCA):**
        - A mathematical function-based optimizer that updates solutions using sine and cosine components to balance exploration and exploitation.
        - **Application in SHM:** Useful for complex background conditions (e.g., shadows, efflorescence, surface staining), where cracks must be clearly separated from color-intensity variations. Enhances segmentation robustness in tunnel linings and retaining walls.
    - **Jaya Algorithm:**
        - A parameter-free optimization method that iteratively moves candidate solutions toward the best solution and away from the worst.
        - **Application in SHM:** Well-suited for computationally constrained crack monitoring systems (e.g., embedded inspection units in smart bridges). Balances accuracy and efficiency in color-based crack segmentation and damage quantification.
    - **General Application in SHM:** 3D CMLT with metaheuristic optimization is highly effective for complex concrete surface imagery, where cracks coexist with noise from shadows, stains, or heterogeneous textures. It provides enhanced contrast for segmentation, supports machine learning pipelines (CNN, U-Net, YOLOv8), and improves quantitative crack analysis under varying environmental conditions.

## 6. Data Reconstruction Methods

In SHM, concrete surface images are often degraded due to noise, occlusion, missing data, or limited acquisition conditions such as shadows, low resolution, or motion blur. Furthermore, in cases where inspection is performed using UAVs, robotic systems, or tomographic imaging, incomplete or sparse data collection is common. To ensure accurate crack detection, surface texture analysis, and structural feature extraction, data reconstruction methods are employed. These techniques restore missing or degraded information, enhance resolution, and allow for consistent structural analysis. Both traditional mathematical methods and modern deep learning-based approaches are widely adopted depending on the inspection conditions and computational constraints.

- **Interpolation**
  - **Definition:** A family of techniques used to estimate missing or unknown pixel values based on the values of nearby pixels.
  - **Types:**
    - **Nearest Neighbor: Assigns the value of the closest pixel.**
    - **Bilinear: Uses a weighted average of the four nearest pixels.**
    - **Bicubic: Uses up to 16 neighboring pixels for smoother results.**
  - **Application:** Applied in resizing concrete surface images, filling missing regions in UAV inspections of bridges, or reconstructing incomplete crack patterns.
- **Radon Transform and Inverse Radon Transform**
  - **Definition:** Mathematical transformations used for tomographic reconstruction by mapping spatial data into projection space and vice versa.
  - **Application:** Useful in SHM tasks involving cross-sectional imaging of concrete cores or detecting internal voids/cracks from projection data.
- **Filtered Back Projection (FBP)**
  - **Definition:** A reconstruction algorithm that filters projection data before back-projecting it across the image space.
  - **Application:** Commonly used in CT-based structural imaging to reconstruct cross-sections of concrete specimens and detect internal damages.
- **Iterative Reconstruction Algorithms**
  - **Definition:** Techniques that progressively refine image estimates by iteratively comparing reconstructed and observed data.
  - **Types:**
    - *Algebraic Reconstruction Technique (ART).*
    - *Simultaneous Iterative Reconstruction Technique (SIRT).*
  - **Application:** Applied when projection data is sparse or noisy, e.g., in non-destructive testing (NDT) of large concrete structures.
- **Sparse Representations**
  - **Definition:** Methods exploiting the fact that images are sparse in certain transform domains (e.g., wavelets, Fourier) for efficient reconstruction.
  - **Application:** Useful in compressive sensing for reconstructing structural images from limited or compressed inspection data.
- **Non-Local Means (NLM)**
  - **Definition:** A reconstruction and denoising method that averages similar patches across the image, regardless of location.
  - **Application:** Effective for enhancing noisy SHM images while preserving fine crack details and textures.
- **Multiscale Approaches**
  - **Definition:** Reconstruction techniques that operate across multiple resolutions, progressively adding detail.
  - **Application:** Beneficial for scalable reconstruction in UAV-based inspections, where global structures and fine cracks must both be preserved.
- **Optical Flow-based Methods**

  - **Definition:** Algorithms estimating pixel motion between consecutive frames to reconstruct or enhance image sequences.
  - **Application:** Useful in video-based SHM for tracking crack growth, corrosion spread, or spalling progression over time.
- **Wavelet Transform**
  - **Definition:** A multi-resolution analysis tool that decomposes images into different frequency bands for reconstruction.
  - **Application:** Used in denoising, edge enhancement, and compressive reconstruction of concrete surface textures.
- **Autoencoders**
  - **Definition:** A type of neural network consisting of an encoder (compresses image data into a latent representation) and a decoder (reconstructs the image).
  - **Application:** Applied to reconstruct missing crack segments, recover degraded images from noisy environments, and enable SHM image compression.
- **Deep Learning-Based Methods**
  - **Definition:** Advanced reconstruction approaches using CNNs, GANs, and transformers to learn reconstruction mappings from training data.
  - **Application:** Increasingly applied for super-resolution of UAV images, crack inpainting, and enhancing low-light or shadowed structural inspection images.

## 7. Assessment Process in Local Damage Detection Process

Accurate detection of local damage, such as cracks, spalling, or corrosion on concrete surfaces, requires a robust assessment process to evaluate the effectiveness of image preprocessing and AI-based analysis. This process ensures that algorithms generalize across different structures, environmental conditions, and imaging devices while preserving the critical structural information. The assessment typically integrates theoretical evaluation, critical scenario analysis, and quantitative metrics, often supported by explainable AI (XAI) frameworks for interpretability.

- **Theoretical Evaluation**

  Theoretical evaluation provides the foundational understanding of how preprocessing and detection methods affect local damage assessment.
  - **Generalization Perspective in AI**
    - Evaluates how well-trained models perform across different concrete structures, surface textures, or lighting conditions.
    - Ensures robustness of local damage detection beyond the training dataset.
  - **Image Processing Basis**
    - Assesses the effect of preprocessing techniques (noise removal, data reduction, color optimization) on feature visibility and segmentation accuracy.
    - Evaluates preservation of critical structural details such as micro-cracks and edges.
  - **Color Science Basis**
    - Considers the impact of color space transformations, contrast enhancement, and color normalization on detecting damage under variable lighting or environmental conditions.
  - **Neuro-Science Basis**
    - Studies the human visual system and perception to guide feature enhancement and attention mechanisms.
    - Supports algorithmic decisions in highlighting relevant areas while suppressing irrelevant textures.
  - **Critical Scenarios Introduction**
    - Critical scenarios simulate real-world challenges in SHM to test algorithm resilience:
      - **Noise Defining**
        - **Environmental:** Variations in illumination, shadows, rain, dust, or surface contamination.
        - **Structural:** Surface texture irregularities, rough aggregates, or material heterogeneity.

      - **Imaging Defects:** Motion blur, sensor artifacts, low resolution, or compression-induced noise.
   - **Damage Definition**
      - Establishes criteria for what constitutes local damage, including cracks, spalling, delamination, or stains, often using ground truth labeling or expert assessment.

Here is the list of some critical scenarios in concrete surface images:

Table 1. Critical Phenomena

| Damage Types | Misleading Phenomena | Imaging Challenges |
|---|---|---|
| Deep Crack | Pseudo Bug-hole | Blurry Image |
| Surface Crack | Rebar Exposure | Low Contrast |
| Hairline Crack | Honeycomb | Overexposed (High Brightness) |
| Edge Crack (near joint or edge) | Paint Spatter | Underexposed (Low Brightness) |
| Longitudinal Crack | Dirt or Mud Accumulation | Shadowed Image |
| Transverse Crack | Staining or Discoloration | Flash Reflection / Glaring |
| Deep Bug-hole | Formwork Markings | Watermark or Wet Surface |
| Surface Bug-hole | Non-concrete Object | Colorful Background or Annotations |
| Wide Bug-hole | Texture Misinterpretation | Noisy Image (sensor or compression noise) |
| Clustered Bug-holes | - | Low Resolution / Pixelated Image |

- **Quantitative Metrics for Assessment**
   - Structural Similarity Measures:
      - SSIM (Structural Similarity Index), FSIM (Feature Similarity Index) – measure perceptual similarity between reference and processed images.
   - Pixel-Wise Metrics:
      - PSNR (Peak Signal-to-Noise Ratio) – evaluates signal fidelity after preprocessing or reconstruction.
      - Mean, Std – measure average and variability of pixel intensities or feature maps.
   - Classification Performance Metrics:
      - Confusion Matrix, Z-Score, P-Value – assess the accuracy, statistical significance, and reliability of damage detection models.
   - Computational Efficiency:
      - CPU-Time – evaluates algorithm runtime for real-time or large-scale SHM applications.
- **Explainability Metrics (XAI):**
   - **Definition:** Provides interpretable explanations for AI decisions in damage detection, highlighting why certain regions are classified as damaged and ensuring reliability for engineers.
   - **Types:**
      - **Feature Attribution (Global/Local Importance)**
         - **Application:** Identifies which features (inputs) most influenced the model's decision.
         - **Common methods:**
            - **LIME (Local Interpretable Model-Agnostic Explanations):** Perturbs inputs locally and fits a simple interpretable model to approximate decisions.
            - **SHAP (SHapley Additive exPlanations):** Based on Shapley values from game theory; quantifies each feature's contribution to the output.
      - **Saliency & Gradient-based Explanations**
         - **Application:** Highlights which parts of the input (pixels, regions) influenced the prediction most.
         - **Common methods:**
            - **Grad-CAM (Gradient-weighted Class Activation Mapping):** Produces a heatmap overlay showing "where the model looked" in an image.

- **Integrated Gradients:** Computes contribution of each input pixel by integrating gradients along the input path.

- **Rule-based & Surrogate Models**
  - **Application:** Replace complex models with interpretable approximations.
  - **Common methods:**
    - **Decision Trees / Rule Extraction:** Represent black-box model decisions as logical "if–then" rules.
    - **Surrogate Linear Models:** Use a simpler model trained to mimic the black-box locally/globally.
- **Prototype & Example-based Explanations**
  - **Application:** Explains decisions by comparing with similar instances.
  - **Common methods:**
    - Case-based reasoning (finding the closest example in the dataset).
    - Prototypes & Criticisms (examples that strongly represent or contradict a class).
- **Visualization & Human-Centric Approaches**
  - **Application:** Uses visual tools to make decisions interpretable.
  - **Common methods:**
    - Heatmaps, attention maps, hierarchical clustering of features.
    - Interactive dashboards for inspection.

## 8. Method Selection

Selecting an appropriate computational method is a critical step in image-based SHM of concrete surfaces. The choice of method influences accuracy, robustness, computational efficiency, and interpretability. The following considerations can guide method selection:

### 8.1. Dataset Characteristics

- **Definition:** The size, quality, and annotation of the dataset determine the suitability of different methods.
- **Application:**
  - Small datasets → Classical machine learning (ML) models like SVM, Random Forest, or k-NN.
  - Large datasets → Deep learning (DL) models such as CNNs, U-Net, or YOLO for automatic feature learning.

### 8.2. Task Type

The type of damage detection task determines which computational approach is most suitable. In SHM of concrete surfaces, tasks can be broadly classified into:

- **Presence of Damage**
  - **Definition:** Determining whether a damage (e.g., crack, spalling) exists in the concrete surface image.
  - **Application:**
    - Typically formulated as a binary classification problem.
    - Can use ML classifiers (SVM, Random Forest) or DL models (CNNs).
    - Object detection methods like YOLO can be applied to flag damaged regions.
- **Damage Localization**
  - **Definition:** Identifying the precise location of damage on the concrete surface.
  - **Application:**
    - Achieved through segmentation models (e.g., U-Net, DeepLab) or bounding-box object detection (YOLO, Faster R-CNN).
    - Useful for highlighting specific cracks or spalling areas for maintenance.
- **Damage Quantification (Severity, Size, and Extent)**

  - **Definition:** Measuring characteristics of damage, including length, width, area, and severity.
  - **Application:**
    - Segmentation outputs can be analyzed to compute geometric properties.
    - ML regression models or DL-based quantification networks can estimate severity levels.
    - Provides critical data for structural assessment and repair prioritization.
- **Damage Prognosis (Types and Causes)**
  - **Definition:** Predicting the type of damage (e.g., fatigue, corrosion, spalling) and potential causes.
  - **Application:**
    - ML classification models or DL architectures can be trained to classify damage types.
    - Combined with environmental and material features, it can support etiology analysis and preventive maintenance planning.

**8.3. Preprocessing Requirements**

- **Definition:** Some methods require careful preprocessing; others can work directly with raw images.
- **Application:**
  - ML models → Need feature engineering (e.g., noise removal, edge detection, color normalization).
  - DL models → Can often process raw or minimally preprocessed images but benefit from preprocessing for faster convergence and robustness.

**8.4. Computational Resources**

- **Definition:** Available CPU/GPU resources and time constraints influence method feasibility.
- **Application:**
  - ML models → Lightweight, fast training, suitable for real-time or resource-limited environments.
  - DL models → Require GPUs, longer training, but scale better for large datasets and complex patterns.

**8.5. Generalization and Robustness**

- **Definition:** The ability of the model to perform well across different structures, environmental conditions, and imaging devices.
- **Application:**
  - Hybrid pipelines (preprocessing + DL) → Improve robustness in real-world field conditions.
  - ML models with engineered features → Provide reliable performance in controlled scenarios.

**8.6. Explainability and Interpretability**

- **Definition:** The extent to which model predictions can be understood and justified.
- **Application:**
  - Classical ML → Easier to interpret using feature importance or rule-based decisions.
  - DL → Requires Explainable AI (XAI) techniques such as Grad-CAM, SHAP, or attention maps to explain crack detection results.

**8.7. Evaluation and Validation**

- **Definition:** The process of verifying model suitability using quantitative and qualitative metrics.
- **Application:**
  - Metrics: SSIM, FSIM, PSNR, confusion matrix, CPU-time, Z-score, P-value.
  - Ensures chosen method balances accuracy, efficiency, and interpretability.

Method selection in SHM is task-, data-, and resource-dependent. Classical ML models are suitable for small datasets or controlled environments, while DL models excel in large, complex datasets with automatic feature extraction. Hybrid approaches often provide the best trade-off between accuracy, robustness, and explainability, especially for real-world concrete surface inspection.

**References**

See the file **“REFERENCES”**