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# Fatigue analysis of concrete structures using AI with the introduction of fractal corrosion detection

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**Abstract.** The article is devoted to the study of fatigue of concrete structures using modern artificial intelligence technologies. The main attention is paid to the use of machine vision for the fractal analysis of reinforced concrete structures. The article presents models optimized for operation in machine vision conditions, which makes it possible to detect signs of corrosion and fatigue with high accuracy and speed. A feature of the presented method is the use of a unique method of infinite fractal discrimination, which allows you to analyze the concrete structure in detail at the micro level. This method reveals unique features and heterogeneities in the structure of the material, which contributes to a more accurate prediction of its behavior under various influences. The application of this approach can become revolutionary in the field of diagnostics and maintenance of infrastructure facilities.

## 1. Introduction

Concrete structures are an integral part of modern infrastructure and their durability and safety depend on many factors, including internal structural changes caused by various impacts. Modern methods of analysis, such as fractal analysis, provide unique opportunities to study the microstructure of concrete and identify potential threats to its strength.

One of the leading scientists in this area is Candidate of Physical and Mathematical Sciences Donenko I.L. and Doctor of Technical Sciences Donenko V.I. Their research in the field of fractal analysis and machine vision opens up new horizons in understanding the structure and properties of concrete materials. In the work [1] "Fractal Analysis of Microstructures in Reinforced Concrete Structures" Donenko considers the basic principles and methods of fractal analysis, as well as their application to the study of reinforced concrete structures. Also another study by Donenko I.L. [2] "Machine vision in the diagnosis of the state of concrete structures" delves into the application of modern machine learning methods for the analysis and diagnosis of the state of concrete structures.

This article aims to complement and expand on previous research by presenting new methods and approaches to fatigue analysis of concrete structures using artificial intelligence and fractal recognition.

## 2. Main part

Artificial intelligence (AI) in recent years has become one of the most promising tools in the field of construction and diagnostics of the state of infrastructure facilities. Its capabilities in concrete fatigue analysis open up new horizons for preventing accidents and extending the life of buildings and structures.

Let us consider the options and opportunities for implementing AI and machine vision:

1. Data collection and processing:

- Sensors: modern concrete structures can be equipped with a variety of sensors such as temperature, humidity, strain and pressure sensors. These sensors transmit real-time data to centralized servers or cloud platforms.
- Data Processing: AI systems can process this data using algorithms to detect anomalies such as unexpected changes in temperature or strain that may indicate the onset of a fatigue process.

2. Deep learning and neural networks:

- Convolutional Neural Networks (CNNs): These networks are capable of analyzing images and videos from cameras installed on or inside structures to detect cracks, corrosion, or other signs of fatigue.
- Data-based training: CNNs can be trained on large datasets containing images of concrete structures in various states to improve their ability to recognize signs of fatigue. [3]

3. Forecasting and modeling:

- Machine learning algorithms: used to create models that can predict the future state of a concrete structure based on current and past data.
- Scenario Simulation: AI can use simulations to simulate various scenarios, such as exposure to extreme weather conditions, to determine how a structure will react.

4. Visualization and interpretation of data:

- Graphic Interfaces: AI systems can provide intuitive graphical interfaces that visually demonstrate the state of the concrete structure.
- Analytical reports: systems can automatically generate reports, highlighting potential problem areas and providing recommendations for their elimination.

5. Integration with other systems:

- Building Management Systems (BMS): AI can be integrated with BMS to automatically control HVAC systems in response to changes in the state of the structure.
- Maintenance automation: When potential problems are detected, the system can automatically notify maintenance teams and even provide repair or maintenance recommendations.

These detailed points provide a deep understanding of how AI can be used to analyze the fatigue of concrete structures and highlight its potential to improve the safety and efficiency of modern construction sites.

Below is one of our finished 3D models showing the visualization of an old mall. To analyze this model, we use a neural network that works directly through a smartphone. An important feature of our approach is the use of a standard Android smartphone camera, which eliminates the need for expensive and complex sensors such as lidar.

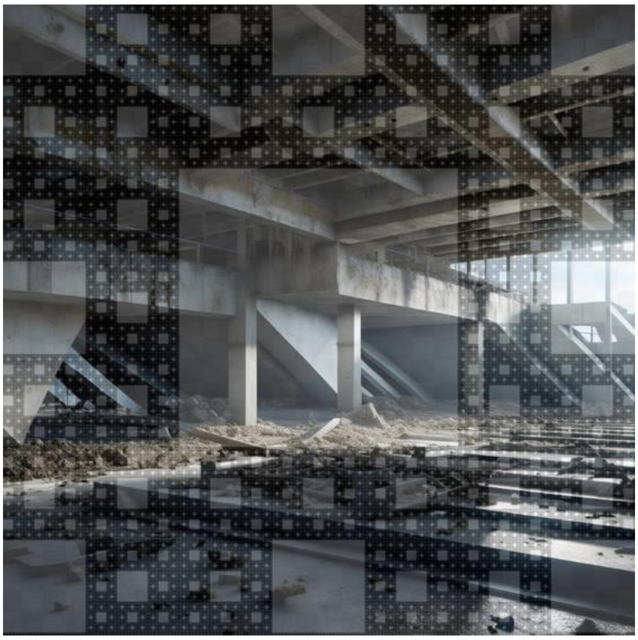

**Figure 1.** Visualization of machine vision and fatigue search.

Advantages and features of the system:

- Accessibility: Most modern smartphones are equipped with high-quality cameras, which makes our system accessible to a wide range of users without additional investment in equipment.
- Mobility: Since the system is based on a smartphone, it can be easily carried and used anywhere analysis is required [4].
- Ease of use: No specialized training is required to operate the system. The user can easily scan the object and get real-time analysis results.
- Flexibility: Neural networks can be trained to recognize and analyze different types of objects, making the system versatile for various tasks.

Resource savings: Eliminating expensive sensors reduces the cost of the system, making it more attractive to small and medium enterprises [5].

Integration with Other Applications: Thanks to the Android core platform, the system can be easily integrated with other applications and services, extending its functionality.

Fast update: Since most of the data processing takes place on the server, users can receive system updates and enhancements without having to change hardware.

Overall, our system offers a revolutionary approach to 3D modeling and object analysis, combining ease of use, affordability and high functionality [6].

The analysis presented in this paper is based on the fundamental properties of self-similarity of the original fractal. These properties can be expressed in terms of the transmission function of the vector coordinate p in the object plane. In accordance with the Fourier transform theory and similarity properties, the intensity distribution I(q) in the observation plane can be written as a vector coordinate in this plane. This equation indicates the presence of self-similarity in the diffraction distribution with a scaling factor.

$$\mathrm{A(p)} \propto A(p\mu) \tag{1}$$

This analysis opens up new ways to understand the structure of objects and use self-similarity properties for deeper analysis. The results of this work have significant potential in the field of optical and diffraction studies, as well as in the application of the Fourier transform theory to the analysis of complex structures.[7] The shape factor corresponds to the diffraction pattern generated by the unit cell of the fractal structure, while the structure factor is determined by the algorithm for constructing this fractal. In other words, the diffraction pattern can be conditionally divided into two regions - fractal and periodic [8].

$$A(x,y) = A_0 \exp\left[\frac{i\pi}{\lambda d}(x^2 + y^2)\right] \quad (2)$$

Further processing of the fractal region in the Fraunhofer diffraction distribution makes it possible to estimate one of the main parameters of fractal structures - their fractal dimension. The Fraunhofer diffraction pattern that appears in the plane of observation is the result of an optical Fourier transform of a grating with a fractal pattern. Let the grating be illuminated by a spherical wave incident on the screen. Then the amplitude of the propagating wave in front of the grating:

$$A'(x,y) = A(x,y)T(x,y) \quad (3)$$

This description emphasizes the importance of shape and structure factors in the analysis of diffraction patterns of fractal structures and their influence on the characteristics of the results obtained.

This refers to a lattice representing the structure of concrete structures. In the plane of this grating, the wave amplitude takes on a different value, where T(x, y) is the transmission function of this grating. In the plane of observation, the amplitude of the wave that has been diffracted by this grating is determined using the Fresnel diffraction formula. This makes it possible to obtain a diffraction pattern that reflects the structural features of concrete structures and their effect on the distribution of light intensity.

$$A(p,q) = \frac{A_0}{i\lambda d} exp[i\pi\lambda d(p^2 + q^2)] \int_{-\infty}^{\infty}\int_0^{\infty} T(x,y) exp[-2i\pi(px + qy)]dxdy \quad (4)$$

In equation (1.4), where p=u⁄λd,q=v⁄λ drepresent the spatial frequencies, d is the distance from the grating to the viewing plane, and A is the wavelength of the incident radiation on the structure when scanning for corrosion. Without the factor exp[iπλd(p^2+q^2 )], which determines the phase of the wave, equation (1.4) is a Fourier transform with a low lattice transmission function T(x, y). This factor in the equation introduces a phase shift in the diffracted wave, which is an important aspect when analyzing diffraction patterns and determining material structure characteristics such as corrosion in this case.

In the context of the study of corrosion of concrete structures, as in many diffraction experiments, the intensity of the diffracted wave is determined by several factors that play a key role in the analysis and detection of corrosion processes. Let's look at this aspect in more detail:

Form factor F(q): a diffraction experiment makes it possible to analyze the scattering of light from a unit cell of a structure. In this case, the unit cell may be, for example, a rectangular slot with a width ε=1. The shape factor F(q) reflects the intensity of light scattered from a given structural feature. In the context of corrosion of concrete structures, this factor can help reveal changes in the structure of the material associated with corrosion processes.

Structure factor S(q):the structure factor S(q) is determined by the fractal construction algorithm. In this context, this may reflect changes in the structure of the concrete structure associated with corrosion and the formation of corrosive products. This factor describes how the elements of the structure interact with the light wave during diffraction. In the context of corrosion, changes in the structure factor can indicate the occurrence of defects and changes in the microstructure of the concrete.

$$F(q) = \frac{sin^2(\pi q)}{(\pi q)^2} \quad (5)$$

The structure factor is a key metric that describes how a fractal object, such as a concrete structure, is built and what changes occur at each iteration of the build. In this case, the iterative construction method reflects how the larger structural elements connect and form the entire concrete structure. The fractality of concrete structures lies in the fact that similar elements are repeated at different scales and have similar shapes. Using an iterative way of building, the structure factor describes the rules by which elements are connected and form larger components. This factor determines the degree of complexity and detail of the fractal structure, which in the context of concrete structures can be associated with different levels of reinforcement, material distribution and other characteristics.

$$S_n(q) = 2^{2n}\left(\prod_{i=1}^{n-1} \cos\left(2\pi 3^i q\right)\right)^2 \quad (6)$$

The study of the structure factor (if it is possible to extract it from the intensity expression) shows that the distribution S_n (q) is self-similar, and with an increase in the generation order of the fractal, new frequency bands appear in the intensity spectrum, which are scale invariant with respect to the factor 1/3 and represent inclusions of corrosion of the material.

```python
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPRegressor

# generation of corrosion and structural data
num_samples = 1000
corrosion_data = np.random.uniform(0, 1, num_samples)
structural_properties = np.random.uniform(0, 1, num_samples)

# creation of a fractal feature based on structural characteristics
fractal_feature = structural_properties ** 2

# combining features into a data matrix
X = np.column_stack((corrosion_data, structural_properties, fractal_feature))

# creating a target variable (corrosion value)
y = corrosion_data + 0.1 * np.random.randn(num_samples)

# dividing data into training and test samples
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42

# data scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# creation of an artificial neural network model
model = MLPRegressor(hidden_layer_sizes=(64, 32), max_iter=1000, random_state=42)

# training the model on the training set
model.fit(X_train_scaled, y_train)

# evaluation of the model on a test sample
test_score = model.score(X_test_scaled, y_test)
print("evaluation of the model on a test sample ", test_score)
```

**Figure 2.** An example of using AI for fractal analysis of concrete structures is implemented in python.

By solving these equations, taking into account the structure factor, we create the following 3D model of the structure of concrete elements. This model is used in subsequent analysis using artificial intelligence (AI) to detect corrosion of materials. Visually, this 3D model represents a complex spatial representation of the structure, including details and features associated with the structure factor. AI-assisted analysis reveals peaks in the intensity of radiation penetration through the structure. These peaks correspond to the regions where the waves interact most intensively with the material. In the case of materials corrosion studies, such intensity peaks may indicate the presence of corrosion defects, changes in microstructure, or other anomalies.

This approach allows more accurate and visual representation of information about the state of materials and their structure. The combination of structure factor and AI analysis allows not only to detect corrosion, but also to provide additional information about the location, nature and extent of damage, which is important for making decisions on the maintenance and repair of concrete structures.

**Figure 3.** Visualization of the structure by machine vision in 3D.

## 3. Conclusion

This article presented a method for studying the fatigue of concrete structures using artificial intelligence and fractal corrosion recognition. Based on the analysis of diffraction patterns and structural characteristics, models and approaches were developed to assess the state of materials and identify corrosion processes. The use of self-similarity properties and transmission functions made it possible to create 3D models of concrete structures and conduct analysis using artificial intelligence. The results of the study confirm the effectiveness of the proposed method in the field of identifying corrosion processes and assessing the stability of structures.

An important contribution of this work is the development of algorithms and models that contribute to a more accurate and detailed analysis of the state of concrete structures. This method can be used for real-time monitoring, inspection and decision-making on the maintenance and repair of infrastructure. Despite the successful results, it should be noted that this area of research remains promising and requires further development and improvement of methods. In the future, we see the potential to expand this approach to other types of materials and structures, which improves the safety and durability of engineering structures.

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