Image Based Modelling and Prediction of Nonstationary Ground Motions

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Abstract

Nonlinear dynamic analysis is a required step in seismic performance evaluation of many structures. Performing such an analysis requires input ground motions, which are often obtained through simulations, due to the lack of sufficient records representing a given scenario. As seismic ground motions are characterized by time-varying amplitude and frequency content, and the response of nonlinear structures is sensitive to the temporal variations in the seismic energy input, ground motion nonstationarities should be taken into account in simulations. This paper describes a nonparametric approach for modelling and prediction of nonstationary ground motions. Using the Relevance Vector Machine, a nonparametric regression model which takes as input a set of seismic predictors, and produces as output a wavelet image showing the expected time-frequency distribution of energy, conditioned on the predictors, is developed. Demonstrative examples comparing the recorded and predicted ground motions in time, frequency, and time-frequency domains are presented.

Keywords: relevance vector machine, principal component analysis, wavelet transform, synthetic ground motion, eigenvalue problem.

1 Introduction

As performance-based concepts are being incorporated into seismic standards and code provisions, nonlinear dynamic analysis is becoming increasingly common in the current engineering practice. As sufficient records may not be available for a scenario dominating the seismic hazard at a given site, and a purely physics-based approach is not yet feasible, the input ground motions to be used in nonlinear dynamic analysis are often obtained by either modifying the recorded motions or generated synthetically, using time or frequency domain filtering procedures.

Because the behaviour of nonlinear systems is sensitive to local variations in the seismic energy input, when ground motion records are fit to a target response spectrum with little consideration given to the nonstationary character of ground motions, the accuracy of the resulting structural response estimates is questionable. Recent advances in computer technology and the growth in seismic databases have led to an increased interest in the characterization of ground motion nonstationarities and facilitated the development of new guidelines for selecting ground motion from strong motion databases and new techniques for simulations of nonstationary ground motions.

Performance assessment of structures can take three forms: intensity-based, scenario based, and time-based [1]. Recommended procedures for selecting and scaling ground motion records vary depending on the type of the assessment. To date, a variety of methods have been developed ground motion selection and scaling. A state-of-the-art review can be found in references [2-4]. Recently, engineering community has focused attention on the time-varying behavior of ground motions and its effects on seismic response of structures (e.g. [3, 5-13]).

This paper describes a data-driven method for modelling and prediction of ground motions in the joint time-frequency domain. The proposed method is intended to complement existing procedures for scenario-based seismic assessment of structures. The proposed procedure consists of three main steps: (1) Conversion of each acceleration record in the dataset into a wavelet image; (2) Determination of the eigen-images of the covariance matrix of the data matrix containing the norms of wavelet coefficients; (3) Estimation of combination coefficients of the eigen-images for a given earthquake scenario. The output of the model is a wavelet image describing the expected time-frequency distribution of energy, conditioned on the predictors. Once the wavelet image is obtained, acceleration records compatible with the predicted image can be synthesised using existing techniques.

Two recent studies are particularly relevant to the proposed method: Rezaeian and Kiureghian [12] and Yamamoto and Baker [13]. Rezaeian and Kiureghian [12] generate synthetic accelerograms by passing a Gaussian white-noise process through a filter with time-varying parameters. Yamamoto and Baker [13] use wavelet packets to describe the nonstationary behavior of accelerograms, conditioned on a set of predictors. For a given earthquake scenario, and without a seed ground motion, both models generate fully nonstationary ground motions. This study shares the same motivation as these two studies, but it introduces a new approach for modeling ground motion nonstationarities.

This paper is based upon Dak Hazirbaba and Tezcan [14], but the current paper identifies the wavelet coefficients inside the cone of influence (COI), where edge effects become important, and removes them from the regression algorithm. Removal of these coefficients not only prevents unreliable coefficients affecting the accuracy of the model, but also increases the computational efficiency of the algorithm by reducing the size of the data matrix. As the signals used in the study are centred during the pre-processing stage, most of the coefficients in the COI are already zero or negligibly small.

The rest of this paper is organized as follows. Section 2 describes the ground motion dataset and the procedures used in pre-processing of the data. Section 3

presents the proposed regression model and demonstrates two prediction examples. Section 4 concludes the paper.

2 Input data and pre-processing

2.1 Dataset

The dataset used in this study is a subset of PEER NGA (Pacific Earthquake Engineering Research Center Next Generation Attenuation of Ground Motion Project) database that Campbell and Bozorgnia employed in developing their NGA Ground Motion model [15]. The PEER-NGA database consists of ground motion recordings of shallow crustal earthquakes in Western United States and similar active tectonic regions. The dataset used in this study only considers recordings from free-field sites and excludes aftershocks.

A typical ground motion record has three orthogonal components, two horizontal and one vertical. In this study, we only use the horizontal components. In addition, we limit ourselves to recordings from large magnitude ($M > 6.0$), strike-slip earthquakes. Table 1 lists the selected earthquakes and the number of recordings from each earthquake. Total number of records used in this study is 345.

2.2 Data pre-processing

2.2.1 Rotation of ground motions to uncorrelated directions

The directions of the horizontal pairs of ground motions depend on the orientation of the accelerometers that record the ground shaking. This dependency is clear as these two orthogonal pairs are correlated along the direction of the sensor. To remove this dependency, we used Principal Component Analysis (PCA) [16] to rotate the two horizontal components of each record into its uncorrelated directions. The use of PCA to obtain uncorrelated ground motion components is a common task in seismic data processing (see e.g. [17-19]), and a detailed mathematical description of the PCA procedure can be found in any linear algebra textbook (e.g. [20]). Below is a summary of the procedure:

- Step 1. Given two components $q_1, q_2 \in \mathbb{R}^{N_t \times 1}$ of an acceleration record sampled at N_t time points, compute the sample covariance matrix, C . Since the q_1 and q_2 are zero-mean vectors, the covariance matrix is given by

$$C = \begin{bmatrix} q_1^T q_1 & q_1^T q_2 \\ q_2^T q_1 & q_2^T q_2 \end{bmatrix}, \quad (1)$$

where the superscript T denotes the matrix transpose operation.

- Step 2. Solve the eigenvalue problem $Cv = \lambda v$ to determine the eigenvalues (λ_1, λ_2) and the corresponding eigenvectors (v_1, v_2) of C . Here, we assume that eigenvalue-eigenvector pairs are ordered so that $\lambda_1 \geq \lambda_2$.

- Step 3. Project the data onto the first eigenvector, $v_1 = [v_{11} \ v_{12}]^T$. If v_1 is scaled to have unit length, i.e. $v_1^T v_1 = 1$, the projection can be computed as $q = v_{11}q_1 + v_{12}q_2$. We call q “the first rotated component” in this paper.

Earthquake ID in NGA Database	Earthquake Name	Earthquake Magnitude	Number of Records
25	Parkfield	6.19	4
31	Managua, Nicaragua-01	6.24	1
50	Imperial Valley-06	6.53	33
64	Victoria, Mexico	6.33	4
90	Morgan Hill	6.19	22
103	Chalfant Valley-02	6.19	10
115	Superstition Hills-01	6.22	1
116	Superstition Hills-02	6.54	11
121	Erzican, Turkey	6.69	1
125	Landers	7.28	67
126	Big Bear-01	6.46	38
129	Kobe, Japan	6.90	22
136	Kocaeli, Turkey	7.51	22
138	Duzce, Turkey	7.14	14
140	Sitka, Alaska	7.68	1
144	Manjil, Iran	7.37	7
158	Hector Mine	7.13	74
168	Nenana Mountain, Alaska	6.70	5
169	Denali, Alaska	7.90	9

Table 1: Selected records from Campbell-Bozorgnia NGA dataset

2.2.2 Resampling and time-domain shifting

Different accelerometers may record ground motions in time domain at different sampling rates. As a first step, we resampled the acceleration records at sampling interval $dt=0.02$ second, using an infinite-impulse-response Butterworth filter of order 4 and cut-off frequency 25 Hz. Next, we set the duration of each record equal to 40 seconds by shifting it in the time domain and using truncation and zero-padding as needed, so that the energy contained in the first 20 seconds equals 50% of the total energy. The energy contained in the record was measured using Arias intensity, defined as [21]:

$$I_a = \frac{\pi}{2g} \int_0^T q^2(t) dt \quad (1)$$

where I_a denotes the Arias Intensity in dimensions of length per time, T is the duration of the ground motion, $q(t)$ is the acceleration record in units of acceleration of gravity.

During preprocessing, it is possible that small amplitude p-wave arrival be truncated. While this is an issue from the geophysical point of view, it will not affect seismic performance evaluations where peak structural responses are of interest.

2.2.3 Conversion of acceleration records to wavelet images

To retain the nonstationary character of ground motion records, we use Continuous Wavelet Transform (CWT). Given a mother wavelet $\psi(t)$, the CWT coefficients of a time domain signal $q(t)$ can be computed using [22]:

$$Q(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} q(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (2)$$

where $\psi((t-b)/a)$ is a shifted and scaled wavelet and the operator $*$ represents complex conjugation. In this study, we use the Morlet wavelet defined as:

$$\psi(t) = \left(e^{-2i\pi t} - e^{-\frac{z_0^2}{2}} \right) e^{-2\pi^2 \frac{t^2}{z_0^2}}. \quad (3)$$

In Equation (3), the second term inside the parenthesis, called the correction term, serves to make $\psi(t)$ an admissible wavelet, i.e. a zero-mean function localized in both time and frequency domains. Without this correction, the mean of $\psi(t)$ is not zero, and thus $\psi(t)$ is not admissible. However, for $z_0 \geq 5$, the correction term is negligible and can be ignored. In this paper, we use $z_0 = 6$. Note that if the correction term is ignored, Equation (3) reduces to a complex exponential multiplied by a zero-mean Gaussian envelope of standard deviation $z_0/(2\pi)$. The envelope factor z_0 controls the number of oscillations in the envelope.

For each record in the dataset, after obtaining the first rotated component $q(t)$ as described in Section 2.2.1, and shifting it in the time domain as described in Section 2.2.2, we performed CWT to determine the wavelet coefficients $Q(a, b)$. Using 6 scales to span an octave (the frequency shift achieved by a dilation of the wavelet by 2), and descending from the Nyquist frequency $f_{Nyq} = 25 \text{ Hz}$, we used a total of 65 scales. The scales (a) and the corresponding frequencies (f) are calculated as follows:

$$a_i = 2^{(i-1)/6}, \quad i = 1, 2, \dots, 65, \quad (4)$$

$$f_i = f_{Nyq}/a_i, \quad i = 1, 2, \dots, 65. \quad (5)$$

With 65 scales and 2000 translations, the wavelet transform of each record produces a matrix of size 65×2000 . We define the “wavelet image” of a record as the matrix I containing the absolute values of the wavelet coefficients. That is, the $(i, j)^{th}$ term of the wavelet image is

$$I_{ij} = |Q(a_i, b_j)|, \quad i = 1, 2, \dots, 65, \quad j = 1, 2, \dots, 2000. \quad (6)$$

Figure 1 shows the two horizontal components of a sample record (NGA Record #839) recorded during the 1992 Landers Earthquake before pre-processing. Figure 2 shows the first rotated component of the same record and its wavelet image.

Figure 1: Sample record (NGA #839) before pre-processing

Similar to Fourier analysis, wavelet transform suffers from the edge effects due to the finiteness of the signal. The region in the time-scale domain where such effects become dominant is called the cone of influence (COI). The way the COI is identified depends on whether the wavelet has compact support. The support of a wavelet is the set of points in the time domain where the wavelet has nonzero values. A wavelet is said to be compactly supported if it is zero outside a finite time interval. For compactly supported wavelets, the cone of influence of $t = t'$ is defined as the set of points in the time-scale plane such that the support of the translated and scaled wavelet covers the point $t = t'$ [22]. Since Morlet wavelet is not compactly supported (due to the Gaussian envelope which approaches zero at plus and minus infinity), the definition of its COI is less precise. For such wavelets, the COI can be defined as the envelope for some low threshold of wavelet

coefficients of a Dirac function at position t_0 or t_{N-1} [23]. In this study, we set the threshold value to 2%.

Figure 2: Sample record (NGA #839) after pre-processing and its wavelet image

Figure 3 shows the first rotated component of a sample record (NGA #931) and its wavelet image where the COI is shown as the white region.

2.2.4 Principal Component Analysis (PCA) of wavelet images

To perform PCA, we first combined the wavelet images of the 345 records into a single data matrix $\tilde{D}$, where each row contains the wavelet image of a record in vectorized form. The row vector corresponding to a wavelet image I of size $r \times c$ is obtained by stacking the entries I_{ij} according to the index map:

$$\begin{array}{cccccccccccc}
 (1,1) & \dots & (1,c) & (2,1) & \dots & (2,c) & \dots & (r,1) & \dots & (r,c) \\
 \downarrow & \dots & \downarrow & \downarrow & \dots & \downarrow & \dots & \downarrow & \dots & \downarrow \\
 1 & \dots & c & c+1 & \dots & 2c & \dots & (r-1)c+1 & \dots & rc
 \end{array} \quad (7)$$

With $N = 345$ records, the data matrix $\tilde{D}$ has 345 rows and (65×2000) columns.

Next, we centred the data matrix by subtracting the mean vector (the row vector containing the mean value of each column of $\tilde{D}$) from each row of $\tilde{D}$. The centered data matrix D can be computed as follows:

$$D_{ij} = \tilde{D}_{ij} - \frac{1}{N} \sum_{k=1}^N \tilde{D}_{kj}. \quad (8)$$

Figure 3: The processed acceleration record (NGA #931) (top) and its wavelet image with COI coefficients removed (bottom)

The mean vector can be recast into a matrix for visualization using the index map given in Equation (7). We refer to the mean vector as the “mean image” when it is in matrix form. The mean image $\bar{I}$ can be computed directly as the average of the N wavelet images. The $(i, j)^{th}$ term of the mean image is

$$\bar{I}_{ij} = \frac{1}{N} \sum_{k=1}^N I_{ij}^{(k)}, \quad (9)$$

where $I_{ij}^{(k)}$ is the $(i, j)^{th}$ term of the wavelet image of the k^{th} record. Next, we determine the eigenvalues and eigenvectors of the covariance matrix $D^T D$. Since $D^T D$ is a very large matrix compared to DD^T we use a linear algebra trick that allows us to work with the matrix DD^T instead. Note that if λ is an eigenvalue of DD^T , and v is the corresponding eigenvector, we write $DD^T v = \lambda v$. Pre-multiplying both sides by D^T , we get

$$D^T DD^T v = \lambda D^T v, \quad (10)$$

which shows that the nonzero eigenvalues of $D^T D$ are the same as those of DD^T , and that the eigenvector of $D^T D$ corresponding to eigenvalue λ is $\tilde{e} = D^T v$. To normalize the eigenvector to unit length, we use

$$e = \frac{\tilde{e}}{\sqrt{\tilde{e}^T \tilde{e}}}. \quad (11)$$

While perfect reconstruction of the data matrix D is possible using all the eigenvectors, retaining only the eigenvectors corresponding to large variance (measured by the size of the eigenvalue) allows reducing the dimension of the data at the expense of reconstruction quality. In determining the number of eigenvectors to be retained, a useful metric is the Cumulative Variance Ratio (CVR), which shows the percentage of total variance retained using the eigenvectors corresponding to largest z eigenvalues. If the eigenvalues are sorted in descending order, $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_d$, the CVR corresponding to the first z components is computed as

$$CVR(z) = \frac{\sum_{k=1}^z \lambda_k}{\sum_{k=1}^d \lambda_k}. \quad (12)$$

For the dataset used in this study, the first 66 components retain 95 % of the total variance, allowing 80% reduction in the dimension of the data.

Each eigenvector can be reshaped into a matrix using the index map given in Equation (7). We refer to an eigenvector recast into the matrix form as an eigen-image. Figure 4 shows the mean image $\bar{I}$ (average of the 345 wavelet images) on the upper left corner and the first eight eigen-images. The same color scale has been used in all 9 images.

Figure 4: The mean image (upper left) and the first eight eigen-images

Once the eigen-images are identified, each wavelet image in the dataset can be expressed as a linear combination of the eigen-images plus the mean image. The reconstructed image $\hat{I}$ using z eigen-images can be calculated as

$$\hat{I} = \bar{I} + \sum_{j=1}^z w_j E_j, \quad (13)$$

where $\bar{I}$ is the mean image, E_j is the j^{th} eigen-image with coefficient w_j . Figure 5 illustrates the reconstruction process.

Figure 5: Reconstruction of a wavelet image using z eigenvectors

3 Relevance Vector Machine (RVM) Regression

The central part of this study is the estimation of the combination coefficients (w_j in Equation (13)) for a given set of seismological predictors. We use the Relevance Vector Machine (RVM) [24] to create a regression model which takes as input a set of predictors and produces as output the combination coefficient associated with a given eigen-image.

The Relevance Vector Machine (RVM) constructs a data-driven, nonparametric model using Bayesian inference. Assuming an unknown function $f: x \rightarrow y$ exists between the vector input x and scalar output y , RVM predicts the output as:

$$\hat{f}(x) = \sum_{r=1}^{N_r} b_r K(x, x_r) + b_0. \quad (14)$$

where x is the input vector for which the output is to be predicted, x_r , $r = 1, 2, \dots, N_r$ are the relevance vectors (a subset of the input vectors selected during training), b_0 is the intercept term, b_r is the coefficient of the r^{th} relevance vector, and K is a kernel function. In this study, we use the Radial Basis Function (RBF) kernel:

$$K(x_i, x_j) = e^{-\gamma(x_i - x_j)^T(x_i - x_j)}, \quad \gamma > 0 \quad (15)$$

where γ is the kernel width parameter.

3.1 Input and target variables

We used three predictors as input to the RVM regression model: moment magnitude (M), closest distance from the recording site to the rupture area (R_{rup}), and the shear wave velocity averaged over the top 30 meters of the soil (V_{s30}). The input vector corresponding to record i has the following form:

$$x_i = [M_i, \log_{10}(R_{rup}), V_{s30i}] \quad (16)$$

The target variable is the combination coefficient associated with an eigen-image. Since the RVM regression model given in Equation (14) produces a scalar output, a separate RVM model is trained for each retained eigen-image. After the coefficients w_j , $j = 1, 2, \dots, z$ are predicted, the resulting wavelet image is obtained using Equation (13). Figure 6 depicts the procedure for predicting a wavelet image composed of z retained eigen-images.

Figure 6: Composite RVM model with z retained eigenvectors

Once the wavelet image is obtained, acceleration records compatible with it can be simulated using existing procedures (e.g. spectral decomposition).

3.2 Model selection and training

In this study, we set apart 30% of the dataset for testing, and used the remaining 70% for model selection and training. Selection of a proper γ value is essential to the accuracy and the generalization capability of the model. As γ increases, so does the model's susceptibility to overfitting. On the other hand, too small γ values are associated with underfitting and lead to large training errors. In this study, we set the value of γ using five-fold cross validation [25].

Five-fold cross validation involves randomly partitioning the data into five folds of approximately the same size, training and testing the model five times, each time retaining one fold for testing, and using the remaining four folds for training.

Referring to Equation (14), training of an RVM corresponds to selecting the relevance vectors x_r , $r = 1, 2, \dots, N_r$, their coefficients b_r , and the intercept term b_o . Tipping [24] provides a detailed description of the training algorithm.

To assess the performance of the model on the test set, we used the Nash-Sutcliffe model efficiency coefficient [26] which measures the dispersion about the 1-to-1 line. The Nash-Sutcliffe model efficiency coefficient (C_{NS}) is given by

$$C_{NS} = \left[1 - \frac{(y - \hat{y})^T (y - \hat{y})}{(y - \bar{y})^T (y - \bar{y})} \right], \quad (17)$$

where y , $\bar{y}$ and $\hat{y}$ are the column vectors containing the observations, the average of the observations and the predictions, respectively. The coefficient C_{NS} can take values between $-\infty$ and 1, with 1 corresponding to 100% prediction accuracy. A model with $C_{NS} = 0$ achieves no improvement over using the average of the observations, and when $C_{NS} < 0$, the model's performance is worse than using the average of the observations. Figure 7 shows the change in the model efficiency coefficient C_{NS} as the number of retained eigen-images is increased. The broken lines represent the average C_{NS} of folds, and the thick line is the combined average obtained from the five folds. As the number of retained eigen-images increases, so does the model's performance, albeit at a decreasing rate. In this study, we constructed the final model using 66 eigen-images. Further increasing the number of retained eigenvectors is unlikely to increase the model's performance.

3.3 Prediction results

In this section, we present results from two prediction cases, using records from the test set. Figure 8 shows a comparison of the recorded and predicted wavelet images, acceleration signals and the 5%-damped pseudo-acceleration response spectra for the acceleration record (NGA #920) from the 1992 Big Bear Earthquake, recorded at Shore-Salton Sea station. To simulate acceleration time series from the predicted wavelet image, we applied the procedure described in Cacciola and Deodatis [10]. Comparison of the recorded (left column) and predicted (right

column) wavelet images, accelerograms, as well as the 5% damped elastic spectral accelerations shows reasonable match.

Figure 7: Model efficiency coefficient (C_{NS}) versus the number of retained eigenimages

Figure 8: Test record (NGA #920) from 1992 Big Bear Earthquake, Shore - Salton Sea station

Another prediction instance is presented in Figure 9, with the same quantities plotted as in Figure 8 has been shown in the same order. This record (NGA #1827) was recorded at the San Bernardino, Fire Station #4 during the 1999 Hector Mine Earthquake.

Figure 9: Test record (NGA #1827) from 1999 Hector Mine Earthquake, San Bernardino - Fire Station #4

4 Conclusion

This study proposes a novel, data-driven procedure for modeling and prediction of nonstationary ground motions. The proposed method uses Principal Component Analysis to decompose each record in the training dataset into a linear combination of eigen-images, the combination coefficients of which are predicted using the Relevance Vector Machine. Once the predicted wavelet image is obtained, acceleration signals representative of a particular earthquake scenario described by a set of seismological predictors can be generated using existing methods. Two prediction examples are presented, where recorded and predicted ground motions are compared in time, frequency and joint time-frequency domains. The comparisons

between the recorded and predicted quantities indicate reasonable agreement, showing the promise of the model.

The proposed procedure is intended to be a part of a scenario-based seismic assessment framework. The main contribution of this work is that it describes a systematic way to incorporate nonstationarities into ground motion models. One advantage of the proposed model over existing nonstationary ground motion prediction models is that there is no need to specify parameters such as a significant duration, as the prominent energy distribution patterns are learned directly from the records.

As with any regression model, the model presented in this paper should not be used for cases not represented by the training data. In addition, for cases with very few data points, the predictions should be interpreted with caution. Another potential limitation of this work is due to the use of a small set of predictors (magnitude, distance and shear wave velocity). Since a small set of predictors cannot satisfactorily describe complex scenarios, the model constructed in this paper should not be used for predicting ground motions whose characterization requires more predictors than the ones used in this study, e.g. near-fault ground motions. For such cases, the proposed methodology can still be used, provided that the set of predictors are adjusted accordingly.

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