# Development of a hybrid method for ground shaking map reconstruction in near-real time

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**Introduction**

Real-time seismic monitoring is of primary importance for rapid and targeted emergency operations after potentially destructive earthquakes. A key aspect in determining the impact of an earthquake is the reconstruction of the ground-shaking field, usually expressed as the ground motion parameter. Traditional algorithms (e.g. ShakeMap®) compute the ground-shaking fields from the punctual data at the stations relying on ground-motion prediction equations (GMPEs) computed on estimates of the earthquake location and magnitude when the instrumental data are missing. The results of such algorithms are then subordinate to the evaluation of location and magnitude, which can take several minutes.

Since machine learning techniques have already been proven capable of estimating the ground motion parameters (Fornasari et al., 2023), a hybrid method has been developed to integrate neural networks in the ShakeMap® workflow to speed up the current ground-shaking map evaluation process.

The core idea is to adopt the ShakeMap® multivariate normal distribution (MVN) method for the intensity measure (IM) interpolation and use a neural network, in place of the ground motion prediction equations (GMPEs), to estimate the IM conditional expected value and uncertainty at the target sites based only on data available in real-time and thus do not wait for the magnitude and location estimates.

Furthermore, by reusing the ShakeMap® framework, the complexity of the model is reduced with improvements in the interpretability of the results.

**Method**

The proposed hybrid method consists of two steps: first, the expected IM values (and their uncertainties) are computed at the stations and target locations; then the recorded and expected IMs are passed to the MVN to compute the ground-shaking map (and its uncertainty).

The approach adopted to replace the GMPE is called Convolutional Conditional Neural Process (ConvCNP, Gordon et al., 2019): starting from sparse randomly sampled observations, a functional representation of them is computed, discretized to a regular grid and fed to a backbone neural network whose outputs are converted from the function space to the original space of the intensity measures such that the output, for each target point, is a conditional distribution.

The input and output of the ConvCNP are expressed in log-units and thus assumed to be corrected for site effects: the effects of local geology are removed from the IMs recorded at the stations and reintroduced into the estimated IMs at the target points using the corresponding amplification factor by Falcone et al. (2021). The choice of using the amplification factors (instead of, for example, a Vs30-based approach) to address the site effects is double-fold: on one hand, it simplifies the ConvCNP process by operating on uniform inputs and outputs (which is especially useful since the encoder and decoder can seamlessly handle input and output points affected by different local effects); on the other hand, it improves the interpretability of the results by separating the contribution of local geology to the final results.

The implemented MVN is based on the formulation by Worden et al. (2018) and the correlation function by Loth and Baker (2013) is adopted: the choice of a correlation function independent of the epicentral distance and the event magnitude is required to obtain a workflow no longer dependant on the evaluation of the source parameters.

A flowchart of the hybrid method is shown in Fig. 1:

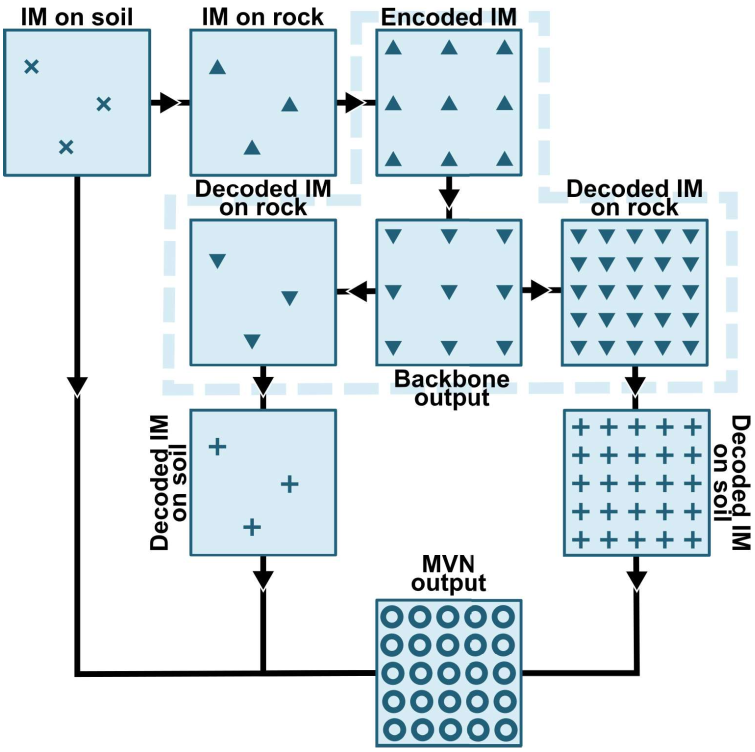


Fig. 1 – ShakeRec-hybrid flowchart: real-time data are corrected for the site effects with an amplification factor and passed to the ConvCNP (defined by the dashed line). IM values are estimated both at the station locations and the target points (here represented by a regular grid) and the soil effect is reintroduced by the corresponding amplification factors. These outputs and the real-time original inputs are then passed to the MVN to compute the ground-shaking maps.

The functional encoding and decoding are performed using rational quadratic kernels $k_{rq}$ based on the great distances $d_{ij}$ between the input and output points:

$$k_{rq}(d_{ij}) = (1 + \frac{{d_{ij}}^2}{2\alpha\lambda^2})^{-\alpha}$$

with $\lambda > 0$ and $\alpha > 0$ being two learnable parameters called length scale and the scale-mixture, respectively.

The backbone neural network has a custom architecture, shown in Fig. 2, consisting of a common sequential network that leads into two different branches for the evaluation of the mean IM values and the associated standard deviations, respectively.

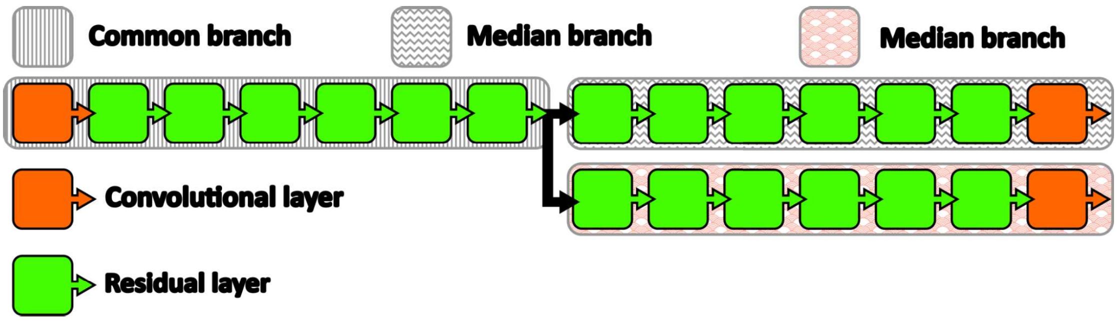


Fig. 2 – Schematic diagram of the ConvCNP backbone neural network architecture.

**Model training**

The model has been trained with a combination of synthetic and recorded data.

Numerical simulations provide a cost-effective way to acquire more data to train neural networks that allows building datasets whose dimension can meet the actual requirements for training and in which the distribution of the events can be balanced, generating more scenarios for rare events with high magnitudes (generally under-represented in recorded data). Furthermore, different scenarios can be generated including different noise levels in the input data leading to models more robust to input noise.

A synthetic dataset has been created by simulating multiple events over the Italian territory: the source characteristics have been taken within the ranges provided by the Database of Individual and Composite Seismogenic Sources, considering for each source multiple scenarios for different magnitudes.

The ShakeMap® INGV catalogue has been considered as the source for recorded data: specifically, the database considered contains 4925 events whose magnitude ranges between M3.0 and M6.5.

The model is trained to learn a conditional log-normal distribution over the expected GMPE output in two stages: first, a new model has been pre-trained on the synthetic dataset; then, the pre-trained model has been fine-tuned using the real data.

For each event (both synthetic or recorded), a variable number of context points (i.e., the IM values at the stations) and a fixed number of target points have been considered: the context points are corrected for the site effects using the amplification factors by Falcone et al. (2020) evaluated at the station locations.

The target points have been randomly selected with a radial uniform distribution around the epicentre.

To avoid any bias introduced by the training data, the "computational" grid is randomly shifted with respect to the epicentre position for each event.

The loss function $L$ used to train the model is a linear combination of negative log-likelihood (NLL) and Frechet inception distance ($FID$): $L = w_{NLL}NLL + w_{FID}FID$.

Effectively, the adopted loss can be seen as a Wasserstein distance with a negative log-likelihood penalty term introduced to regularise the results and provide a better connection between the mean and standard deviation.

**Results and Conclusions**

The proposed hybrid method implements a multi-step approach in which the neural network performs a very specific task: while it still maintains some aspects of a black box-like algorithm, the results of this implementation are much more interpretable, specifically with the possibility to address the role of the different components in the final result.

The use of data augmentation is beneficial even in cases where a good amount of recorded data is available to train the models, because the greater control over synthetic data could allow the development of more balanced datasets that can, in turn, promote the model to learn more useful low-level features while the fine-tuning phase using real data seems promising in training models able to generate more realistic results.

The proposed method proved to be robust to network geometry changes (both in terms of the number of stations and their spatial distribution) and to noise.

The 30 October 2016 $M_w$6.5 Norcia earthquake has been chosen to benchmark the method against ShakeMap®.

Even though it doesn't represent an exhaustive analysis, the Norcia event, which required mobilisation of emergency response, is indicative of the behaviour of the method for the archetype of the seismic event it has been developed for, being a strong event recorded by a high number of stations with good coverage.

In Fig. 3, the PGA median and standard deviation obtained with the proposed method and ShakeMap® are compared. In the epicentral area, thanks also to the high density of stations, both methods provide similar results in terms of median values (panels a) and c) in Fig. 3). Considering the standard deviations, the hybrid method generates values that are overall more similar, although consistently greater, than ShakeMap® (panels b) and d) in Fig. 3). Given the PGA probability distributions at each target point from the hybrid method $f_H$ and ShakeMap® $f_{SM}$, the map of the overlapping coefficient $OVL = \int_R min(f_1(x), f_2(x))dx$ has been computed (panel e) in Fig. 3) showing great compatibility between the two methods and thus the quality of the hybrid method.

Despite being non-predictive (i.e. it reconstructs the ground-shaking field to be consistent with the values recorded until that moment rather than foresee future ones), the hybrid method allows to update the ground-shaking maps every few seconds and to obtain the final ground-shaking map for inland events within a minute of their origin time.

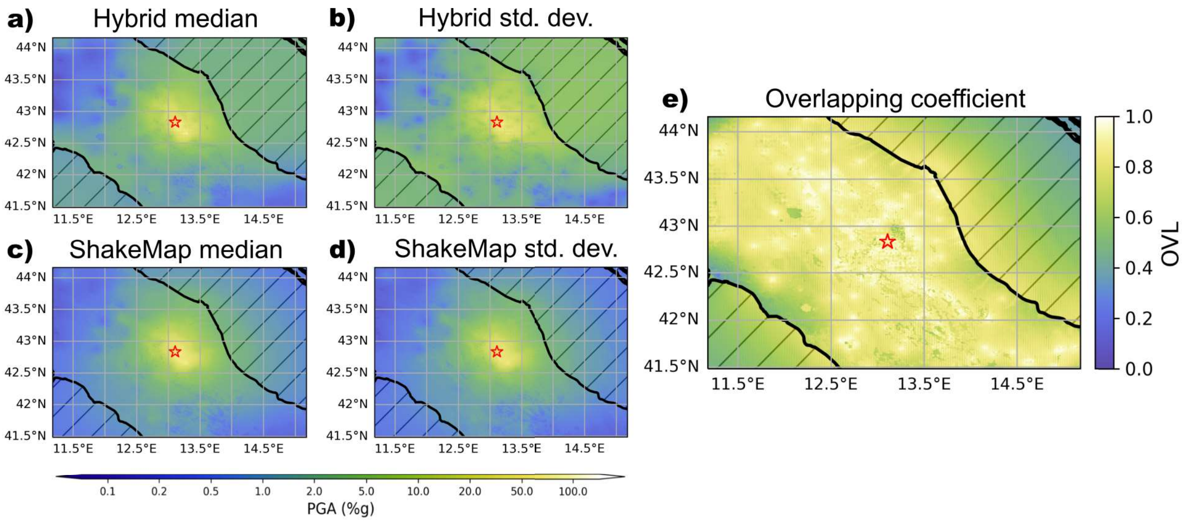


Fig. 3 – Reconstruction of the PGA median and standard deviation using the hybrid method (panels a) and b), respectively) and using ShakeMap® (panels c) and d), respectively) for the $M_w 6.5$ Norcia earthquake. Panel e) shows the overlapping coefficient between the PGA reconstructions obtained with the two methods.

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