Automatic Focal Mechanism Computation for Small-Magnitude Earthquakes in NE Italy

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1. Introduction

This study presents a workflow to automatically compute focal mechanisms for new earthquakes by integrating machine learning-based polarity picking with advanced focal mechanism determination methods. The approach is applied to events in northeastern Italy, a seismically active region of the Southeastern Alps, where understanding earthquake mechanics and stress distribution is crucial.

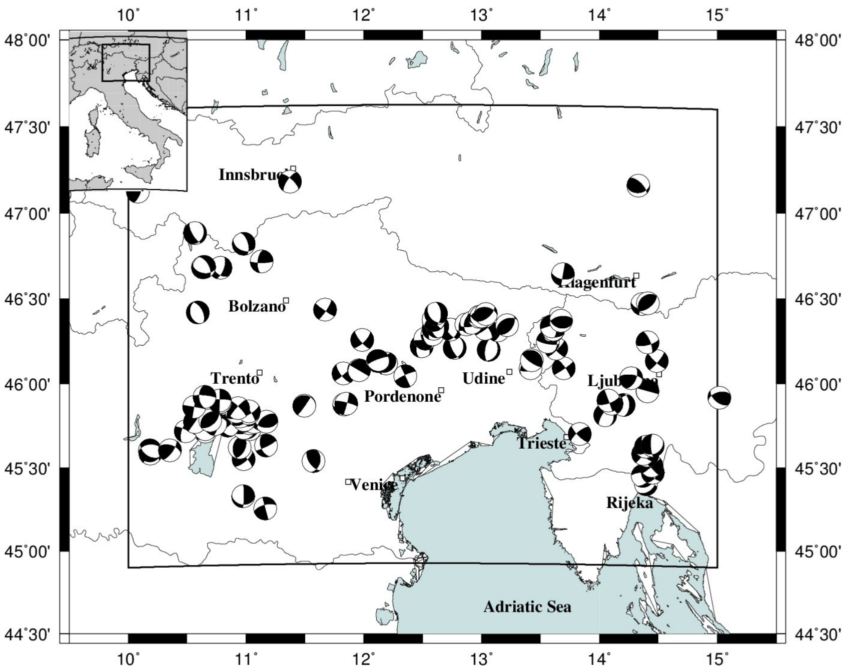

Fig. 1 – Dataset of focal mechanisms for study area. Modified from Sugan et al., (2024).

The workflow was developed using the earthquake catalogue from 2014 to 2023 (Sugan et al., 2024), which contains 162 focal mechanisms derived from manually picked polarities and computed using the FPFIT method (Reasenberg and Oppenheimer, 1985). From this catalogue, 101 events (magnitude range 2.8–3.6) were selected for the validation and tuning of two innovative tools, the Convolutional First Motion (CFM) neural network, a deep learning model for automatic polarity picking (Messuti et al., 2023) and SKHASH, a grid searching tool for focal mechanism determination that integrates ray tracing, misfit minimization, and polarity uncertainty modeling to enhance accuracy (Skoumal et al., 2024, Hardebeck and Shearer, 2002; 2003).

2. Method

The Convolutional First Motion (CFM) neural network is a robust tool based on Convolutional Neural Network (CNN) architecture to automatically classify first-motion polarities in seismic waveforms. By leveraging CNNs, the CFM network can automatically extract relevant features from seismic waveforms, making it well-suited for tasks like first-motion polarity determination. Trained on a large dataset of over 140,000 seismic waveforms, the CFM network achieved high accuracy (97.4% and 96.3%) on two independent test sets (Messuti et al., 2023). The CFM model outputs a prediction score ranging from 0 to 1, where values near 0 indicate downward first motions, and values near 1 represent upward first motions. The threshold for classifying polarity as upward or downward is flexible and can be adjusted based on the data characteristics. Scores in the range of 0.6-0.4 are considered less reliable, often due to inaccuracies in P arrivals picks or the presence of very noisy waveforms. The CFM is sensitive to the P-wave arrival picking in the input traces. When the P-wave is accurately picked, the model performs exceptionally well, delivering precise and reliable predictions. The CFM network processes a 1.6 second window (160 samples at 100Hz) centered on the provided arrival time, and it is designed to tolerate arrival time inaccuracies of approximately ±0.1 seconds. It focuses on this ±0.1 second window, where polarity is most likely to be accurately detected. Beyond this margin, prediction reliability decreases significantly. The noise level present in seismic data also influences the model's accuracy. High levels of noise can adversely affect prediction quality, resulting in inconsistencies or errors. To mitigate this, we calculated the Signal-to-Noise Ratio (SNR) for each record to assess the impact of noise on the predictions.

Using the automatically classified polarities as inputs, we applied SKHASH to compute focal mechanisms. SKHASH is a new grid-search approach based on HASH (Hardebeck and Shearer, 2002; 2003; Williams, 2014) designed to enhance focal mechanism determination for smaller earthquakes. It integrates machine-learning detected, and cross-correlation consensus polarities, as well as traditional and relative S/P ratio measurements. SKHASH incorporates three-dimensional uncertainty in hypocentral locations further refining accuracy. Additionally, it allows custom weighting of polarity measurements (ranging from -1 to 1) to adjust their significance, making it highly compatible with CFM prediction results. A key advantage of SKHASH is its ability to compute focal mechanisms using data from multiple earthquakes to address poor coverage. Furthermore, it automatically reports misfits for both individual and collective measurements, providing a clear assessment of the reliability of the solution.

3. Analysis and Results

The CFM neural network was validated for application in the study area against the manually assigned polarities from Magrin et al. (2024) and achieved an 87% agreement. Fig. 2 (a) illustrates the prediction probability distribution for all analysed polarities, highlighting the model's strong confidence in most classifications. The majority of polarities were assigned probabilities close to 0 (Down) or 1 (Up), indicating high certainty in the predictions. Fig. 2 (b) further emphasizes this, showing the number of predictions in agreement and disagreement with the manually assigned polarities. Notably, both Up and Down polarities show a substantial proportion of correct classifications, validating the efficacy of the CFM model in this specific region.

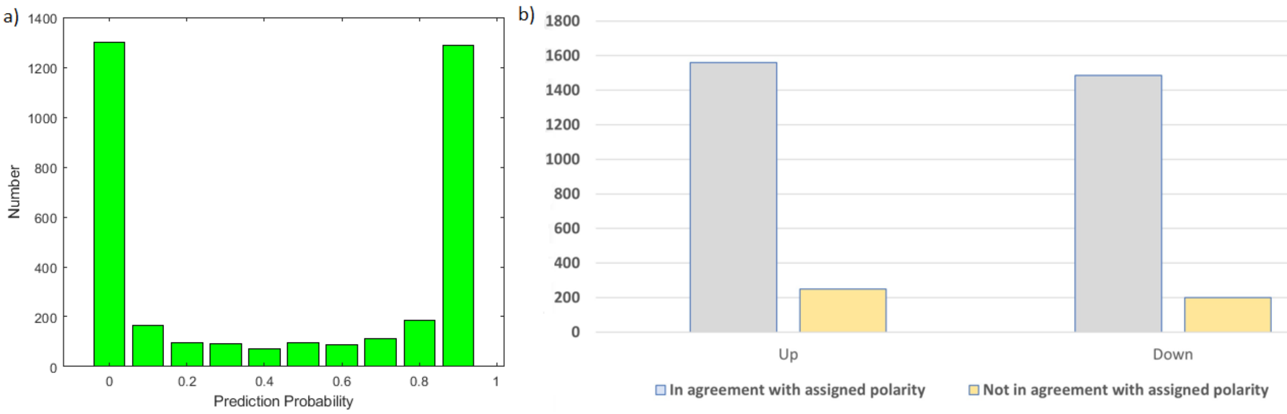

Fig. 2 - Validation results of the CFM neural network for first-motion polarity classification. (a) Histogram of prediction probabilities, showing the confidence of the model in assigning polarities. High confidence is reflected in the peaks near probabilities of 0 and 1. (b) Agreement between the model-assigned polarities and the manually assigned polarities from Magrin et al. (2024), demonstrating 87% consistency. These polarities were subsequently used for focal mechanism computation, highlighting the reliability of the CFM model for application in the study area.

The new focal mechanisms computed with our approach showed strong consistency with the FPFIT solutions from the Magrin et al. (2024) catalogue, demonstrating agreement in strike, dip, and rake values. Fig. 3 illustrates a comparison for the event on 2014-07-07 06:46:35 (Md 3.0). Slight differences were observed in the station distribution on the beachball diagrams. These discrepancies were attributed to differences in takeoff angle computation between the two methods.

Building on this validation, we updated the existing focal mechanism catalogue (Saraò et al., 2021; Sugan et al., 2024) with 26 new events (magnitude ≥ 2.5) that occurred in 2024 in northeastern Italy. The focal mechanisms for these events were computed automatically using the CFM-SKHASH workflow, demonstrating the feasibility of rapid focal mechanism determination for small-to-moderate magnitude earthquakes.

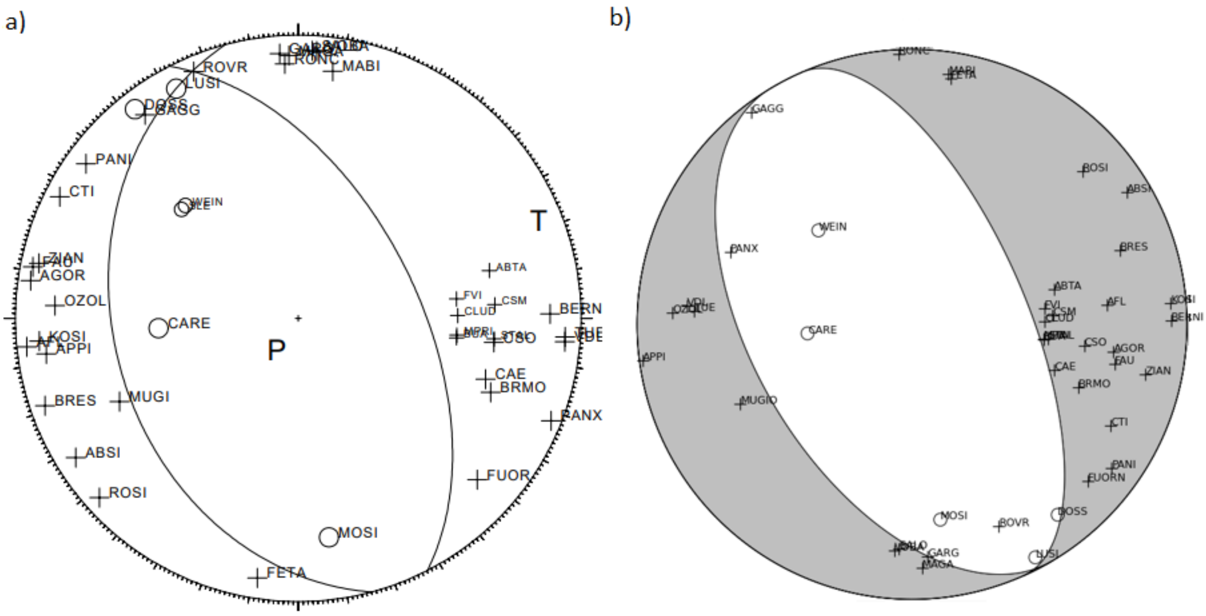

Fig. 3 - Comparison of focal mechanism solutions for the event on 2014-07-07 06:46:35 Md 3.0. (a) displays the FPFIT solution from the Magrin et al. (2024) catalogue, while (b) shows the focal mechanism computed using the SKHASH method in our study.

4. Conclusions

In this study, we focused on tuning and validating an automated workflow for focal mechanism computation in northeastern Italy. By calibrating the CFM neural network and SKHASH algorithm for the region, we achieved robust validation against existing solutions. The workflow was then used to compute focal mechanisms for 26 new events, demonstrating its potential for improving regional seismic analysis and cataloging efforts. The results highlight the potential of combining machine learning with advanced computational tools for seismological applications. The updated catalogue provides a valuable resource for understanding the stress distribution and fault dynamics in northeastern Italy. Furthermore, the rapid processing capabilities of the workflow improve the speed and reliability of focal mechanism computations, particularly in seismically active regions with dense seismic monitoring networks.

References

Hardebeck J.L.; 2002: A new method for determining first-motion focal mechanisms. Bull. Seismol. Soc. Am., 92, no. 6, 2264–2276, doi: 10.1785/0120010200.

Hardebeck J.L., Shearer P.M.; 2003: Using S/P amplitude ratios to constrain the focal mechanisms of small earthquakes. Bull. Seismol. Soc. Am., 93, no. 6, 2434–2444, doi: 10.1785/0120020236.

Magrin A., Sugan M., Snidarcig A., Romano M.A., Guidarelli M., Santulin M., Di Bartolomeo P., Saraò A.; 2024: Focal mechanism solutions of 162 earthquakes occurred between 2014 and 2023 in the Southeastern Alps. Zenodo. doi: 10.5281/zenodo.10851786.

Messuti G., Scarpetta S., Amoroso O., Napolitano F., Falanga M., Capuano P.; 2023: CFM: a convolutional neural network for first-motion polarity classification of seismic records in volcanic and tectonic areas. *Front. Earth Sci.*, 11:1223686. doi: 10.3389/feart.2023.1223686.

Reasenberg P., Oppenheimer D.; 1985: FPFIT, FPPLOT and FPPAGE: Fortran computer programs for calculating and displaying earthquake fault-plane solutions. Open-File Rep., 85-739, USGS, Menlo Park, 109 pp.

Saraò A., Sugan M., Bressan G., Renner G., Restivo A.; 2021: A focal mechanism catalogue of earthquakes that occurred in the southeastern Alps and surrounding areas from 1928–2019. Earth System Science Data, 13, 2245–2258, https://doi.org/10.5194/essd-13-2245-2021.

Skoumal R. J., Hardebeck J. L., Shearer P. M.; 2024: SKHASH: A Python Package for Computing Earthquake Focal Mechanisms. *Seismol. Res. Lett.*, 95, 2519–2526.

Sugan M., Saraò A., Magrin A., Snidarcig A., Bressan G., Renner G., Romano M.A., Guidarelli M., Santulin M., Di Bartolomeo P., Restivo A.; 2024: Focal mechanisms of the Southeastern Alps and surroundings (2.0). Zenodo. https://doi.org/10.5281/zenodo.10853582.

Williams, M. C., 2014: HASHpy, doi: 10.5281/zenodo.9808

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