27178

Employing CEEMD for Improving GPR Images - A Case Study from a Neolithic Settlement in Thessaly, Greece

M. Manataki* (Institute Mediterranean Studies), A. Sarris (Institute for Mediterranean Studies) & A. Vafidis (Technical University of Crete)

SUMMARY

In this study we apply Complete Ensemble Empirical Mode Decomposition on several GPR lines derived from a survey at Magoula Almyriotiki, a Neolithic settlement in Thessaly, Greece where buried structures are identified but are obscured by noise. The workflow we followed consists of a preprocess step (time zero, dewow, gain and background removal) followed by decomposition with CEEMD. The modes that exhibit less noise and at the same time gather all the reflections from the buried houses, were the third and the fifth IMF. Their summation was then used to calculate instantaneous envelope and to extract slices. From the obtained results the images are significantly improved highlighting further details of the buried antiquities, suggesting that CEEMD is a promising tool for processing GPR data when combined with standard filters and corrections.

Introduction

Complete Ensemble Empirical Mode Decomposition (CEEMD) is a noise assisted and adaptive method introduced by (Torres et al., 2011). The functionality of CEEMD is based on Empirical Mode Decomposition (EMD) (Huang et al., 1998), and is similar to Ensemble Empirical Mode Decomposition (EEMD) (Wu and Huang, 2009) as white noise is inserted into the input data to eliminate EMD's mode mixing problem that limits the frequency resolution of the extracted components, called Intrinsic Mode Functions (IMFs). Additionally, the summation of the resulted IMFs fully reconstructs the original signal, a feature that EEMD lacks.

CEEMD appears to be a promising tool for processing GPR data and compared to EMD and EEMD performs better; Random noise is distributed into the first two IMFs and can be supressed effectively by a simple subtraction of the corresponding components from the input section (Manataki et al., 2014). Additionally, in a recent study, the instantaneous attributes from the resulted IMFs obtained by CEEMD seem to manifest higher time-frequency resolution than EMD and EEMD (Li et al., 2015).

In this study, we employ CEEMD and instantaneous envelope on several GPR lines derived from a survey conducted at a Neolithic settlement in Thessaly, Greece where buried structures are located but were obscured by noise. Depth-slices are extracted and compared with the original ones. The results are further discussed to better understand the behaviour and the capabilities of this method to separate noise from reflections derived from buried antiquities, and to contribute to the literature that, up to this point, contains very few studies related to CEEMD and GPR.

Complete Ensemble Empirical Mode Decomposition

The algorithm of CEEMD as proposed by (Torres et al., 2011), starts by making $i = 1, \dots, I$ different white noise realizations and adding them to the original GPR trace, $x[n]$, resulting in $x^i[n]$ new inputs. Then EMD is applied on every $x^i[n]$ to extract only the first IMFs of the inputs, IMF_1^i . The first IMF of CEEMD will be the ensemble mean of the resulted first IMFs, as $\overline{IMF_1}[n] = \frac{1}{I}\sum_{i=1}^{I} IMF_1^i$. The next step is to extract the second IMF; $\overline{IMF_1}[n]$ is subtracted from the original trace as, $r_1[n] = x[n] - \overline{IMF_1}[n]$, and the input to calculate the second IMF will be $R_1[n] = r_1[n] + \varepsilon_1 E_1(w^i[n])$, where $E_1(\cdot)$ denotes an operator which returns the first IMF of the input with EMD, while ε_1 is a fixed coefficient defining the white noise amplitude. The second IMF will be the ensemble mean of the resulting first IMFs when applying EMD on $R_1[n]$ i.e. $\overline{IMF_2}[n] = \frac{1}{I}\sum_{i=1}^{I} E_1(R_1[n])$. This is an iterative procedure similar to EMD's sifting (Huang et al., 1998) through which the rest of the modes are extracted; If k is the number of the last extracted mode, then for $k = 2, \dots, K$ the residues $r_k[n] = r_{(k-1)}[n] - \overline{IMF_k}[n]$ are computed to make the input $R_k[n] = r_k[n] + \varepsilon_k E_k(w^i[n])$ to obtain the next mode as $\overline{IMF_{(k+1)}}[n] = \frac{1}{I}\sum_{i=1}^{I} E_1(R_k[n])$. This procedure terminates when the residue $r_k[n]$ becomes monotonic, so it is assigned as the last IMF of the decomposition with CEEMD. The original signal can be fully reconstructed by summing the resulting IMFs. Since CEEMD is based on EMD, it also performs as a time varying bandpass filter (Flandrin et al., 2005), where the first IMF contains the highest frequencies of the input trace while the last IMF contains the lowest.

Methodology and Results

The algorithm of CEEMD was implemented in the MATLAB environment using parallel computing to improve the decomposition execution time (Manataki et al., 2014). The input data were collected within a grid using a 250 MHz antenna and derived from a GPR survey at Magoula Almyriotiki, a Neolithic settlement in Thessaly, Greece. This data set consists of 41 scans with 0.5m spacing and exhibits reflections from buried houses that are overshadowed by noise. First, CEEMD was applied on a representative section, located at 10m of the survey grid, to examine how the noise and the wall reflections are distributed into the IMFs. According to our tests, a pre-process step is required, particularly the application of gain and background removal, because this significantly improves the decomposition results. The input section is presented in Figure 1a where time zero correction, dewow, inverse amplitude decay gain (Tzanis, 2006) and background removal have been applied. Reflections from buried walls appear at 7m, 15m, 22m, 30m and 35m.

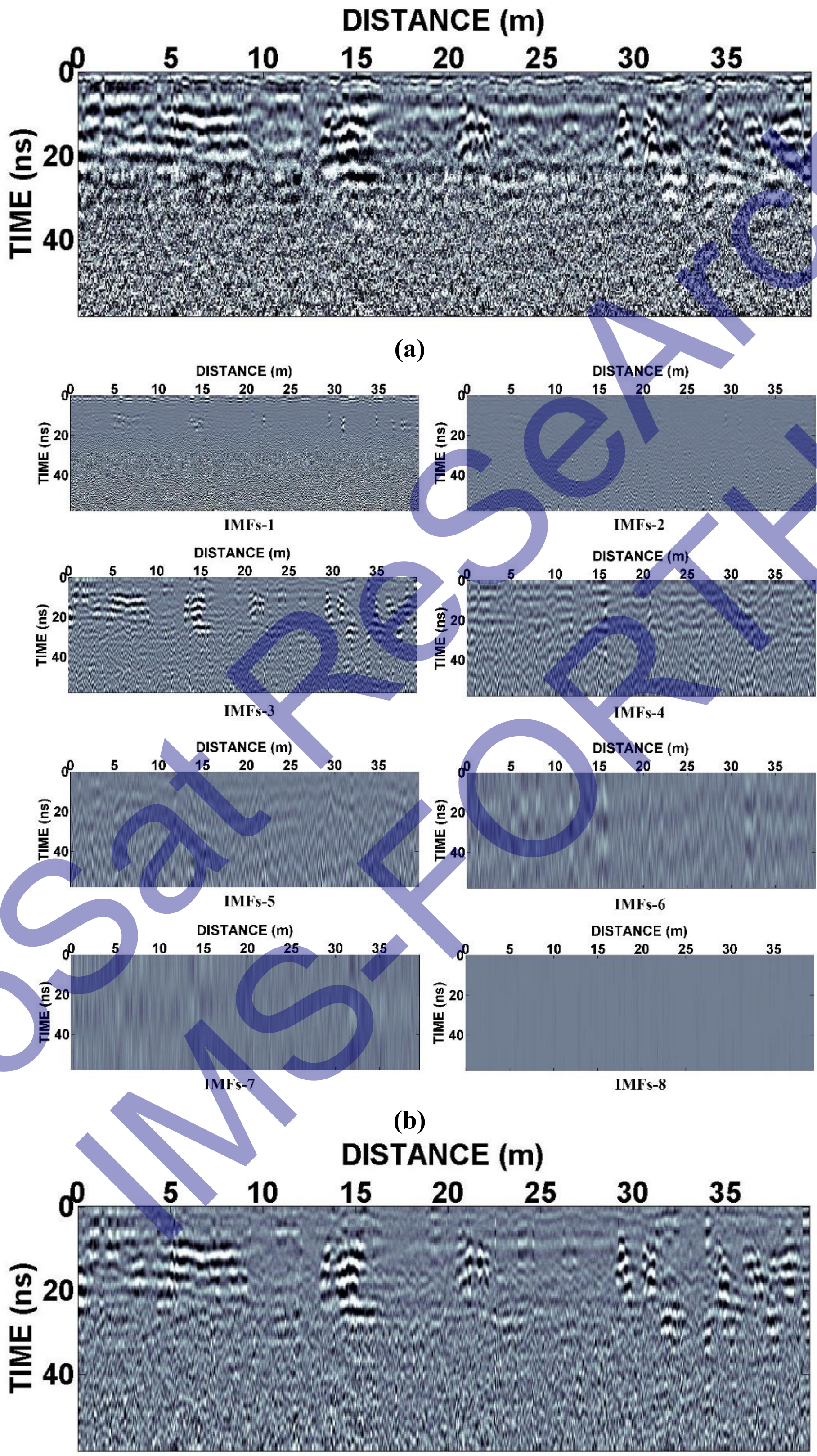

Figure 1 *CEEMD results for the GPR section, where (a) is the input, (b) are the resulted IMFs and (c) is the summation of IMFs-3 and IMsF-5 which improves the section the most. The colormap is the same for all images.*

The parameters for CEEMD are 100 noise realizations and 50% noise level of the input traces' standard deviation. The latter yielded better decomposition results in respect to the IMFs resolution and is in contradiction with our findings on a previous study where the best noise level was 20-25% for data collected by a 400 MHz antenna. The resulting IMFs are presented in Figure 1b. Random noise is extracted into the first two IMFs, while IMF-3 gathers most of the information related to the walls. IMF-4 seems to exhibit remaining noise that was not removed with background noise removal correction. The rest of the IMFs contain features of lower amplitudes that are difficult to interpret. On the effort to retain the most of the wanted information while keeping the noise level low, the summation of IMF-3 and IMF-5 appeared to be the best and the outcome is presented in Figure 1c, where the improvement over the input section is noticeable.

The procedure described above was applied to the rest of the GPR lines and instantaneous envelope (Spanoudakis and Vafidis, 2010) was calculated on the summation of IMFs 3 and 5 to extract slices. The results for selective slices where the Neolithic houses are visible, are presented in Figure 2. The images are significantly improved for all the depths highlighting further details related to the houses.The foundation boundaries are more clear for the slices at 10ns, 12 and 20ns while the slices at 14ns and 16ns shows better three individual houses (from 15 to 35m) located very close together while the one at 30-35m has two rooms. Another linear feature is identified at 7m indicating a remaining wall from another, most likely, destroyed house.

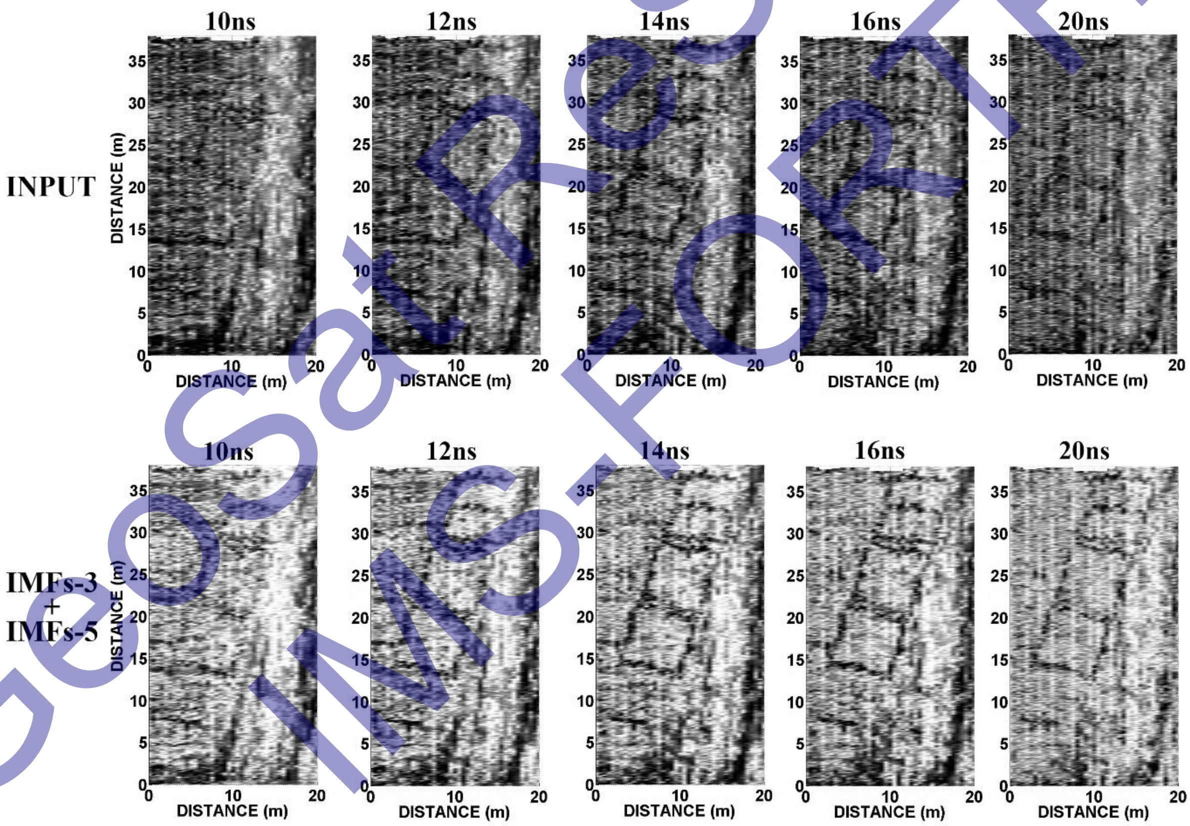

***Figure 2** Resulting slices for CEEMD at Magoula Almyriotiki. The first row are the slices of the preprocess step while on the second row are the corresponding slices for the summation of IMF-3 and IMF-5. The colormap is the same for all images.*

Conclusions

According to our results, CEEMD appears to be suitable tool for improving GPR images but not as a standalone procedure. A pre-process step of gain and background removal yields better results as CEEMD comes to further improve the image by removing noise that was highlighted with gain and which background noise removal failed to suppress. The random noise is concentrated into the first two

IMFs while the remaining background noise is located at IMF-4. IMF-3 gathers information related to the buried walls. The summation of IMFs 3 and 5 appeared to retain most of the reflections with less noise. Further, the slices obtained from the instantaneous envelope on this summation exhibited better resolution highlighting further details of the buried houses, making the interpretation easier.

The capability of CEEMD to distinguish noise from reflections is associated with the inserted noise level while the optimum value seems to be related with the system's central frequency. Thus, further research is required to determine the optimum noise level and its relationship with the central frequency as well as the improvement of IMFs' frequency resolution.

Acknowledgments

This work was performed in the framework of the IGEAN (Innovative Geophysical Approaches for the Study of Early Agricultural Villages of the Neolithic Thessaly) project which was implemented under the "ARISTEIA" action of the "OPERATIONAL PROGRAMME EDUCATIONAL AND LIFELONG LEARNING" and is co-funded by the European Social Fund (ESF) and National Resources.

References

Cuenca-García, C., Sarris, A., Kalayci, T., Simon, F.-X., Cantoro, G., Donati, J.C., Manataki, M., Vouzaxakis, K., Rondiri, V., Arachoviti, P., et al. (2014). Walking over Magoulas: Mapping Neolithic Tell Settlements in Thessaly (Greece) using Integrated Archaeo-geophysical Techniques. (Burgos).

Flandrin, P., Gonçalves, P., and Rilling, G. (2005). EMD equivalent filter banks, from interpretation to applications. In Hilbert-Huang Transform and Its Applications, (Singapore: World Scientific), pp. 67–87.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.-C., Tung, C.C., and Liu, H.H. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc. R. Soc. Lond. Ser. Math. Phys. Eng. Sci. *454*, 903–995.

Li, J., Liu, C., Zeng, Z., and Chen, L. (2015). GPR Signal Denoising and Target Extraction With the CEEMD Method. IEEE Geosci. Remote Sens. Lett. *PP*, 1–5.

Manataki, M., Vafidis, A., and Sarris, A. (2014). Application of empirical mode decomposition methods to ground penetrating radar data. First Break *32*, 67–71.

Spanoudakis, S.N., and Vafidis, A. (2010). GPR-PRO: A MATLAB module for GPR data processing. In 2010 13th International Conference on Ground Penetrating Radar (GPR), pp. 1–5.

Torres, M.E., Colominas, M.A., Schlotthauer, G., and Flandrin, P. (2011). A complete ensemble empirical mode decomposition with adaptive noise. In 2011 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 4144–4147.

Tzanis, A. (2006). Matgpr: A freeware matlab package for the analysis of common-offset GPR data. In Geophysical Research Abstracts Vol. 8. No. 09448.

Wu, Z., and Huang, N.E. (2009). Ensemble empirical mode decomposition: a noise-assisted data analysis method. Adv. Adapt. Data Anal. *01*, 1–41.