Fusion of Remote Sensing and Numerical Simulations to Detect Damage in the Infrastructure

Luis Moya[1] , Erick Mas[2], Shunichi Koshimura[3]

1. Introduction

From remote sensing data, the most common procedure to identify the effects of a disaster is by the study of a pair of images recorded before (pre-event) and after (post-event) the event. If the date of both images is close enough, changes observed among them are assumed to be correlated to the effect of the disaster.
In order to identify changes, certain features are computed from both images. Discriminant functions using the features were proposed to infer whether a change occurred or not. At first, discriminant functions were set from observations of previous events and applied to subsequent events. Such approach proved to be effective in events such as the 2011 Tohoku-Oki earthquake and tsunami. However, these methods have some limitations. For instance, a discriminant function could not be applied to images recorded from a sensor different than the one used during the calibration. A re-calibration was necessary. Furthermore, the discriminant function was restricted to certain features. If the performance of a new feature wanted to be tested, a new discriminant function has to be built.

The referred issues were addressed by the application of machine learning techniques. Applications of machine learning in remote sensing became popular, including the identification of damaged buildings. Machine learning algorithms offered a robust way to treat *n*-dimensional set of features and, in some way, it could be applied independent of the kind of sensor. However, a new problem showed up when machine learning techniques were applied to identify buildings affected by a large-scale disaster. In the aftermath of a large-scale disaster, all the efforts are spent in rescue and relief distribution. An important contribution from remote sensing data is the identification of collapsed building, for people might be trapped inside and they survival depends on a prompt rescue. Therefore, in order to apply machine learning, training samples has to be gathered the soonest possible. However, it has been observed that gathering training samples right after the occurrence of the disaster is quite complicate. Reports regarding damage in the infrastructure are published several weeks later. Field surveys might take some days as well. Some researchers have adopted to set training data from visual inspection of optical images; a task that requires significant time and might introduce biases. This is an issue that few publications have addressed. A great deal of the scientific publications related to applications of machine learning in remote sensing used training data that were available several weeks, or even months, later.

2. Replacing training data with demand parameters and damage functions

In order to overcome the problem of training samples, we decided to eliminate that requirement, or at least, to avoid the ordinary process of gathering training samples. It came to our knowledge the existence of a relationship between a disaster demand parameter and an expected percentage of damaged buildings.
Here, disaster demand parameter refers to a certain metric that express the intensity produced by an arbitrary event at a specific geo-location. Inundation depth and peak ground velocity are such examples for tsunami and earthquake, respectively. It is intuitive to think that areas with large demand parameter contain greater number of affected buildings than areas with low demand parameter. In fact, researchers have been working for decades on this relationship, known as building damage functions or fragility functions, using rigorous statistical analysis and numerical models. It was also noted that because of the great progress regarding instrumentation and numerical modelling of certain disasters, such as tsunamis,

[1] Researcher, International Research Institute of Disaster Science, Tohoku University, Japan (lmoyah@irides.tohoku.ac.jp)
[2] Associate Professor, International Research Institute of Disaster Science, Tohoku University, Japan (mas@irides.tohoku.ac.jp)
[3] Professor, International Research Institute of Disaster Science, Tohoku University, Japan (koshimura@irides.tohoku.ac.jp)

earthquakes and floods, several new frameworks provide estimations of the demand parameter in almost real time.

We decided to use the demand parameters together with the building damage functions as new constrains to calibrate the discriminant function referred in the previous section. It is expected this new constrain would be enough for the calibration and training samples would not be necessary. The details of our first proposed framework can be found in Moya et al. (2018a). Although the proposed procedure proved to be effective, there was still room for improvements. For instance, the parameters of the discriminant function were computed from an exhaustive search. Such approach is indeed not practical when the dimensional space is significantly large. Thus, a second procedure was then implemented. The fundamental basis lies on modifications of the well-known method *Logistic Regression*. There, we replace training data with weight factors computed from the numerical simulations and damage functions. Details of the method are reported in Moya et al. (2018b).

3. Current research

It was pointed out that damage functions are available in restricted events, such as tsunamis and earthquakes. There are no damage functions, for instance, to floods or landslides. Therefore, we are currently implementing a new framework that uses only remote sensing data and numerical simulation of disasters. So far, we defined two potential frameworks, which will be published soon.

4. Perspectives for collaboration

It is our belief there are many points to work on this subject. We would like to test our frameworks on more events. We have tested it with tsunamis, earthquakes and floods and we are looking for other types of disasters, such as landslides. Another topic is the damage functions (fragility curves); so far we have used empirical functions. We would like to test analytical damage functions as well. We also would like to exchange ideas on new ways to combine remote sensing data with numerical simulations.

References

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