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**Next Generation Damage and Post-Crisis Needs Assessment Tool for  
Reconstruction and Recovery Planning  
Capability Project**

**Multisensor system for synoptic construction assessment of different disaster,  
incident types param**

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## Abbreviations and Acronyms

ABBREVIATION	DESCRIPTION
CNN	Convolutional Neural Network
EMS-98	European Macroseismic Scale 1998
GLCM	Grey Level Co-occurrence Matrix
BoW	Visual Bag of Words
GSD	Ground Sampling Distance
SVM	Support Vector Machines
UAV	Unmanned Aerial Vehicle
VHR	Very High Resolution
WP4	Work Package 4
SURF	Speeded Up Robust Features
HoG	Histogram of Gradient Orientation

## Glossary of Terms

Nadir	Point on the ground directly in line with the remote sensing system and the centre of the earth.
Oblique image	Image acquired with the camera intentionally directed at some angle between horizontal and vertical orientations.
Overlap	Extent to which adjacent images or photographs cover the same terrain, expressed as a percentage.
Pattern	Regular repetition of tonal variations on an image or photograph.
Resolution	Ability to separate closely spaced objects on an image or photograph. Resolution is commonly expressed as the most closely spaced line-pairs per unit distance that can be distinguished. Also called spatial resolution.
Scale	Ratio of distance on an image to the equivalent distance on the ground.
Scene	Area on the ground that is covered by an image or photograph.
Supervised learning	Techniques used to learn the relationship between independent attributes and a designated dependent attribute (the label). Most induction algorithms fall into the supervised learning category.
Texture	Frequency of change and arrangement of tones in an image.

## Executive Summary

In RECONASS, remote sensing is one of the technologies used for assessing the damage state of the buildings after a disaster event. Pertaining to that, in WP4 of RECONASS, a remote sensing based exterior building damage assessment subsystem was developed solely by ITC and delivered in D4.1. The developed sub-system is fully automatic, requiring only the UAV-captured images as input. From those images, the sub-system automatically generates a so-called 3D point cloud of the scene. Using the images and 3D point cloud, the sub-system automatically identifies and differentiates between completely collapsed and still erected buildings in the scene. The latter are further analysed for the presence of damage evidences, such as spalling and openings in building caused by the damage along every exterior element of the building. Also, the debris and rubble piles around the buildings are detected and quantified..

One of the other objectives of RECONASS is to determine how to synergistically use the above remote sensing-based assessments with sensor-based assessments from other partners in RECONASS, for: 1) validation of the outcome of one technology with another; 2) image-based assessment as a proxy in case of any sensor information loss; 3) improving the sensor based assessment if any inconsistency is observed. To achieve this, the assessments from these two technologies need to be spatially correlated. The major challenge with this task is the creation of a meaningful interface for relating the image-based external damage to the sensor based damage information of the building. A common CAD model framework has been proposed in agreement with other partners in which both the internal and external damage indicators can be referenced. Towards this, an automated method has been developed to achieve the spatial correlation of assessments from both the technologies and also a procedure has been developed to share this information to other partners in RECONASS through the so-called PCCDN tool. These are evaluated using the data from the pilot experiment and reported in this deliverable.

Additionally, automated damage detection methods have been developed particularly suitable for RECONASS monitored buildings where the CAD model of the building will be available as pre-event reference data. The developed methods are demonstrated as more reliable than methods developed as part of Task 4.1 which are based on post-event data alone.

Also in this deliverable, some of the tasks belong to Task 4.1 are presented as separate chapters for reasons that are described where appropriate.

All developed methods are evaluated using datasets from both real world and the pilot experiments conducted in Sweden. The results are reliable and accurate enough for deploying it as independent operational sub-system as part of RECONASS system to monitor the real world functioning buildings.