3D scene reconstruction and structural damage assessment with aerial video frames and drone still imagery

JOHNNY CUSICANQUI 2016

SUPERVISORS: Prof. Dr. Norman Kerle Dr. Francesco Nex



3D scene reconstruction and structural damage assessment with aerial video frames and drone still imagery

JOHNNY CUSICANQUI Enschede, The Netherlands, 2016

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation. Specialization: Applied Earth Sciences

SUPERVISORS: Prof. Dr. Norman Kerle Dr. Francesco Nex

THESIS ASSESSMENT BOARD: Prof. Dr. F.D. van der Meer (Chair) Dr. S. Zlatanova (External Examiner, Delft University of Technology)

#### DISCLAIMER

This document describes work undertaken as part of a programme of study at the Faculty of Geo-Information Science and Earth Observation of the University of Twente. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the Faculty.

### ABSTRACT

Structural damage assessment (SDA) is a crucial activity during post-disaster response and reconstruction phases. Recent advances in photogrammetry and computer vision permit to obtain very dense 3D point cloud models from overlapping aerial multi-perspective images. Both 3D point clouds and multi-perspective imagery are rich sources of information for damage mapping. Multi-perspective aerial imagery is commonly obtained by Unmanned Aerial Vehicles (UAVs); however, these data can be scarce during crisis situations. An interesting alternative are post-disaster aerial video footages, but low resolution and redundancy of video frames hinders its utility. Exploration of video frames usability for 3D modelling, particularly regarding postdisaster applications, is still lacking. In this research the quality of aerial video-generated 3D models was assessed from geometric/absolute and SDA application perspectives, and was compared with models derived from aerial still imagery for two different study areas. Particularly video blur-motion, resolution and frame redundancy influence on 3D model quality was determined. The analysis demonstrated that in general video data produce more noisy and imprecise 3D point clouds; however, the external and absolute accuracy is still comparable to the one of still imagery. Low resolution video was clearly hampered by sensor proximity to the ground, whereas frame redundancy was the main cause of noise. These quality parameters, however, were also related to higher point density and in most cases better representability of damage-related features. Consequently, it was demonstrated that video data are suitable for the generation of rich damage-related information 3D models.

### ACKNOWLEDGEMENTS

To my family in Bolivia for the constant support from the distance. To my lovely wife, Andrea and the greatly-expected baby coming in a couple of months, who are and will be the source of dedication every single day. Additionally, to all the collaborators of this thesis: Professor Norman Kerle and Doctor Francesco Nex for their guide and supervision. To Anand Vetrivel for his valuable advices and contributions. To the data providers: Dr. Filiberto Chiabrando (Politecnico di Torino, Italy) for Pescara del Tronto and MSc Jyun-Ping Jhan (Institut für Photogrammetrie Universität Stuttgart) for Tainan data. Finally, thanks to my master classmates for sharing with me their daily life experiences in the human and academic environment, thanks for their company and friendship.

## TABLE OF CONTENTS

1.	Intro	duction	1
	1.1.	Background	1
	1.2.	Problem Statement	5
	1.3.	Research objectives	5
	1.4.	Research questions	6
2.	Litera	ture review	7
	2.1.	Advances on aerial-based SDA	7
	2.2.	Semantic and cognitive SDA approaches	8
	2.3.	3D scene-based SDA	8
	2.4.	Video-based 3D IBM/SDA	9
	2.5.	3D Point cloud quality assessment	10
	2.6.	Conclusions	11
3.	Meth	odology	12
	3.1.	Study area	12
	3.2.	Data	13
	3.3.	Research approach and flowchart	15
4.	Resul	ts and discussions	24
	4.1.	3D Modelling	24
	4.2.	Quality assessment	26
	4.3.	3D model application analysis (debris volume change analysis)	42
5.	Conc	lusions and recomendations	44

## LIST OF FIGURES

Figure 1. Disaster Management Cycle and activities (based on: Kelman (2004) and Van Westen (2012))	1
Figure 2. Nadir and oblique perspectives (Geomares, 2014)	3
Figure 3. Image Based Modelling quality parameters (modified from: Nex & Remondino (2014))	5
Figure 4. First study area, Tainan (Taiwan). Left: Tainan localization, centre: Pre-disaster situation, right: disaster	
situation. Delimited in white: Weiguan Jinglong collapsed building11	2
Figure 5. Second study area, Pescara del Tronto (Italy). Left: Pescara del Tronto localization, centre: Pre-disaster situation	
and right: disaster situation	3
Figure 6. Research flowchart describing the main three stages: 3D modelling, Quality assessment and Application analysis1'	7
Figure 7. Flowchart for Wise Frame Selection approach for video frames extraction using Zephyr image quality and	
similarity indices.	9
Figure 8. Image quality index tool in 3D Zephyr user interphase. Left: Image quality calculation, right: image quality map	
2	0
Figure 9. Planar fitting analysis example. Left: subset of a plane surface, Right: distances from point clouds to a theoretical	
flat surface (fit plane)	1
Figure 10. Debris volume calculation at different time steps. Green areas represent the base of the calculation polygon, red are	e
the volumes calculated.	3
Figure 11. General visualization of some 3DPCs generated for Tainan (up) and Pescara del Tronto (down). Datasets used:	
Video Wise Frame Selection (WFS). Random Frame Selection (RFS) and Still imagery. Some noise on Video (RFS) due	2
to smoke	5
Figure 12. Dublication effects due to displacement caused by wrong model orientation using the complete still imagery dataset	
(not refined)	5
Figure 13. Unsatisfactory Wise Frame Selection (WFS) model using Zetbhyr similarity index tool, lack of frames for some	-
sections in the 3DPC. Still some similar overlation frames are selected.	6
Figure 14. WFS: Wise Frame Selection modified approach using rayCloud of the Rough 3DOC and image quality index	-
as ouide	6
Figure 15. Image quality index distribution boxplots	7
Figure 16. Image quality index series blot and maps for Tainan (TW). In maps red represent areas of low quality. Dips are	e
caused due to smoke (red areas in imager auality mats) in most cases.	8
Figure 17. Image quality index series blot and mats for Pescara del Tronto (IT). In mats red retresent areas of low quality	
Dits are caused due general image blurriness and textural homogenous areas (red areas in image quality mats)	8
Figure 18. Mean distance (m) to fit blane for Tianan. Distances represent 3DPC precision and standard deviation	-
dispersion. Different resolutions are tested for still imagery complete and video Random Frame Selection (RES) data sets2	9
Figure 19. Mean distance (m) to fit blane for Pescara del Tronto. Distances represent 3DPC precision and standard	-
deviation distortion Different resolutions are tested for still imagery complete and video Random Frame Selection (RFS)	
data sets	9
Figure 20 Mean distance (m) to fit plane for Tainan (second test). Distance to plane reduces with resolution (more precision	j
A more looical trend is presented for video models.	${0}$
Figure 21 3D Point cloud density (points/m <sup>2</sup> ) from vertical and horizontal perspective for Tainan (TW) 3	1
Figure 22. 3D point cloud density (points/ $m^2$ ) from vertical and horisontal perspectives for Tainan (1 $m$ )	1
Figure 23. 3D point cloud density mats (ut: Tainan down: Pescara del Tronto) RFS: Random Frame selection WFS:	-
Wise Frame Selection.	2
Figure 24, 3D point cloud map (Tainan, horizontal perspective) RFS·Random Frame Selection WFS·Wise Frame	_
selection	2
	-

Figure 25. Point density distribution boxplots. Maximum values are labelled for every 3DPC. Every data set is divided in	
four quartiles (Q) and the distribution of every quartile is presented by the box heights	3
Figure 26. Percentage of gaps from vertical and horizontal perspectives. From vertical perspectives oblique and video WFS	
(Wise Frame selection) models present more gaps, from the horizontal at-nadir and also WFS model	3
Figure 27. Mean distance to the reference model (external accuracy). The closer to the reference the higher the accuracy, Still	
imagery complete (oblique and at-nadir) 3D model presents high deviation and the lowest accuracy due to model orientation	
errors	5
Figure 28. Mean distance to the reference model (close up). Video 3D models achieved 7cm accuracy, not that far from still	
imagery ones, however precision is high due to noise generated from smoke and frame redundancy	5
Figure 29. Cracks recognition for Tainan. The crack can be identified in the oblique model, video (WFS Wise Frame	
Selection) model is not able to represent this feature	5
Figure 30. Cracks recognition for Pescara del Tronto. The crack can be identified up to video RFS (Random Frame	
Selection) medium resolution and video WFS (Wise Frame Selection) original resolution models	7
Figure 31. Left: Structural failure recognition (Pescara del Tronto). Right: Distance between Video Random Frame	
Selection (RFS) and at-nadir still imagery models (m)	3
Figure 32. Structural failure recognition (Tainan). RFS: Random Frame Selection. WFS: Wise Frame Selection	3
Figure 33. Left: Inclined wall representation and comparison of oblique and video model fitted planes. Right: mean distances	
to reference model plane	)
Figure 34. Left: Inclined wall analysed. Right: Differences between inclined walls using oblique and video WFS (Wise	
Frame Selection) 3DPCs	)
Figure 35. Roughness indices as an indicator for debris representatibility 40	)
Figure 36. Mesh models of debris areas from different 3DPCs for visual analysis of debris features representability. Video	
RFS (Random Frame Selection) 3DPCs are able generate clear debris areas even at low resolutions	L
Figure 37. Spalling feature mesh models for visual recognition (Tainan). RFS: Random Frame Selection. WFS: Wise	
Frame Selection	L
Figure 38. Debris volume change estimations for Tainan computed with the complete (oblique and at-nadir) still imagery-	
based models	2
Figure 39. Debris volume comparison analysis. video model volume estimation is closer to Reference volume than the other	
models	2

## LIST OF TABLES

Table 1. Data general descriptions	13
Table 2. Data acquisition details divided on study area and data type	14
Table 3. Research approach followed and the individual experiments performed	16
Table 4. Parameter under analysis for every data/ sensor type	17
Table 5. Damage-related features inventory with the main research focus for an effective visual SDA	22
Table 6. 3D Point Clouds inventory	24

### **GLOSSARY OF TERMS**

- ALS: Aerial Laser Scanning
- BIM: Building Information Models
- DMC: Disaster management Cycle
- DSM: Digital Surface Models
- GCP: Ground Control Points
- GSD: Ground Sampling Distance
- IBM: Image Based Modelling
- LiDAR: Light Detection and Ranging
- MTP: Manual Tie Points
- RADAR: Radio Detection and Ranging
- RFS: Random Frame Selection
- SAR: Search and Rescue
- SDA: Structural Damage Assessment
- SfM: Structure from Motion
- TLS: Terrestrial Laser Scanning
- UAVs: Unmanned Aerial Vehicles
- VHR: Very High Resolution
- WFS: Wise Frame Selection

# 1. INTRODUCTION

#### 1.1. Background

Long-term studies show that the number of global disasters has risen during the last decades; on average over 200 million people have been affected by different kinds of disasters each year (Van Westen, 2012). A common way to understand, conceptualize and primarily manage disasters is through the Disaster Management Cycle (DMC) (Figure 1). A DMC is a chronologically classified representation of different pre and post-disaster stages and activities. Mitigation and preparation stages are included in the pre-disaster phase. For both, an array of activities is grouped with the common purpose to avoid or mitigate disaster effects. These stages are of high significance and look to enlarge the time between individual disasters and diminish their effects. When dealing with low frequency disasters a different perspective focused on the post-disaster phase is required. This is because low frequency disasters might have a low or even null predictability. In these cases, more emphasis is given to activities within the response and recovery stages. When facing a disaster, several activities are executed by emergency public, military, private and civil institutions. First aid and relief activities within the response stage, such as Search and Rescue (SAR) depend essentially on primary, general and reliable information about damage extend (Barrington et al., 2011; Kelman, 2004). Therefore, a rapid, but still reliable spatial damage estimation is crucial for best deploying emergency resources during the response stage. After the response stage, a transition to reconstruction stage takes place. At this point healing, repairing, demolition, and reconstruction activities are more significant. The duration of this stage can vary significantly depending on the effectivity of the activities performed through it; at this point, not only reliable but also detailed data about damage is relevant (Barrington et al., 2011; J. Fernandez, Kerle, & Gerke, 2015). Henceforth first reliability and then precision of structural or physical damage estimations are essential components for the effective accomplishment of post-disaster phase activities.



Figure 1. Disaster Management Cycle and activities (based on: Kelman (2004) and Van Westen (2012))

#### 1.1.1. Structural Damage assessment (SDA)

Currently there are several methods to estimate structural damage; however, traditional ground surveying classification is still the preferred choice. Ground-based SDA based on the European Macroseismic Scale 1998 (EMS-98) is so far, the most common method for a detailed and accurate classification of damage stages at different scales. For a rapid SDA, the reliability and detailed criteria used in this approach is very high, but it is not as efficient as it is required (Kerle, 2010). This approach, as other ground-based damage estimation methods, is time and resource demanding; besides, it is also limited by its slow accessibility (Gerke & Kerle, 2011). Alternatively, there are other practical methods to assess structural damage in the remote sensing field. These methods deal with all the limitations of ground-based SDA, but their reliability and precision (i.e. level of detail) have become their major issues, and have limited their application. Moreover, remote sensing approaches based on image analysis for automated classification of damage stages are very unbiased and rigid due to aspects unlinked to traditional classification schemes such as the EMS-98 which are based on subjectivity and flexibility (J. Fernandez et al., 2015; Saedi, 2015; Schweier & Markus, 2006)

#### 1.1.2. Remote sensing-based SDA

During the last century, intensive researches have shown the potential of using Remote Sensing on postdisaster SDA. Many approaches were developed to extract and analyse damage patterns and perform SDA. For instance, feature change detection has been used to quantify damage when pre-existing data about a disaster is available (Dekker, 2011). Nevertheless, in most of cases pre-event data is not available and only post-disaster data can be analysed; in such a case, other approaches are implemented. Automated single image-based damage estimation methods are also focused on the identification of damage features, however they rely on semantic reasoning techniques (Fernandez Galarreta, Kerle, & Gerke, 2015; Ogawa & Yamazaki, 2000; Zhang, Wang, Liu, & Zhang, 2010). Semantic reasoning involves a deep and cognitive description of objects in a 2D environment using distinctive parameters. These parameters can be: scale, shape, compactness, spectral and textural characteristics of a certain object or segment, which is then used to define a damage related-feature. The idea behind this approach is to emulate ground surveyors' perception and knowledge on damage estimation and classification (Zhang et al., 2010).

In parallel to the approach chosen, SDA can also be differentiated according to the data source nature. Different aerial platforms and sensors were tested for assessing physical damage, such as air and spaceborne optical Very high resolution (VHR) cameras (Ehrlich, Guo, Molch, Ma, & Pesaresi, 2009; Ogawa & Yamazaki, 2000), space-borne Radio detection and ranging(RADAR) sensors (Dell'Acqua & Polli, 2011), air-borne Light detection and ranging (LiDAR) (Khoshelham, Elberink, & Xu, 2013) and combinedapproaches (e.g. air-borne VHR with LiDAR) (Hussain, Ural, Kim, Fu, & Shan, 2011). In relation to aerial optical data, resolution becomes a major parameter to consider. Commonly available satellite imagery is usually not suitable to detect building details which are in the order of centimetres, then VHR satellite imagery or aerial photographs must be used. However, these kind of VHR data is hardly available during critical post-disaster stages, due to many financial and technical reasons (Ehrlich et al., 2009). Moreover, most of these traditional platforms acquire data from vertical angles (i.e. at-nadir perspective). This represents a main limitation for the identification of damage-related feature, since an oblique perspective (i.e. opposite to at-nadir, Figure 2) allows the identification of important damage features, such as total building inclination, collapse of low stories (pancake collapse), overhanging elements and cracks at building façades, and others (Kerle & Stekelenburg, 2004; Schweier & Markus, 2006). Early researches using Pictometry oblique aerial images demonstrated a big improvement in classification using oblique data. However this approach also presented some geometrical limitations, since only few view perspectives were used and it is still performed based on a 2D space (Gerke & Kerle, 2011)



Figure 2. Nadir and oblique perspectives (Geomares, 2014)

Recent studies have been focused on Unmanned Aerial Vehicles (UAVs) as data source for detailed and reliable SDA due to multiple reasons. First, multi-rotor models present a big potential in this subject due to their multi-perspective characteristic which allows to identify damage features at building façades. Second, UAV data is highly available and accessible, besides their relative low costs and ease manoeuvrability. Third, UAVs data is of very high spatial resolution (order of centimetres), which enables detail feature-related damage identification (Adams, Friedland, & Levitan, 2010; Boccardo, Chiabrando, Dutto, Tonolo, & Lingua, 2015; J. Fernandez et al., 2015; Nex & Remondino, 2014). Finally, UAV data can be easily processed through Image Based Modelling (IBM) to obtain very dense 3D point clouds for damage scene reconstruction and detailed SDA; this kind of product is even denser than LiDAR sensors and includes valuable spectral (colour) information (Nex & Remondino, 2014; Remondino, Spera, Nocerino, Menna, & Nex, 2014). SDA through this multi-perspective and high quality data source may certainly attain the accuracy only possible for ground-surveying methods.

#### 1.1.3. 3D Image Based Modelling (IBM)

3D scene reconstruction or Image based Modelling (IMB), either by overlapping image sequences or video frames, is now feasible thanks to advances in computer vision and photogrammetry fields (Remondino et al., 2014). For instance, computer vision algorithms for feature identification, tracking and description; developments in photogrammetry for robust estimations of the relative orientation of two overlapping images; or a set of steps to generate sparse 3D point clouds from a sequence of images of a static scene called Structure from Motion (SfM) (Gerke, 2014). All these advances led to the development of accessible user-friendly automated methods for dense 3D point cloud generation, based on dense image matching or SfM algorithms (Gerke, 2014; Tian, Vosselman, & Zhu, 2011). Two main data types that can be processed by IBM, still imagery and video frames, this suggest two different modelling approaches. In the case of video frames, image matching is relatively straight forward, because the corresponding features are hardly moving between two adjacent frames (Alsadik, Vosselman, & Gerke, 2015). However, this kind of data also represents a problem in the estimation of the 3D model geometry and quality due to the relative shorter base-lines (i.e. distance between two subsequent images) and low resolution (Alsadik et al., 2015; Gerke, 2014). In the case of still cameras, they generate images with larger base-lines, and their corresponding features require other techniques based on the identification and description of invariant features among adjacent images (feature matching). Feature matching is not that affected by the previously mentioned video data-related problems (Gerke, 2014).

IBM has many applications such as mapping, mining, forensics, agriculture, construction (Building Information Models BIM and inspection) and others (Pix4d, 2016b). SDA domain could be treated separately, but it is also closely related to mapping and construction applications. First, terrain 3D models such as Digital Surface Models (DSM) are of high importance in SDA; this type of information can be complemented with spectral information to identify collapsed or severely damaged buildings for rapid damage estimation (Gerke & Kerle, 2011). Second, construction application such as BIMs and inspection are based on very dense 3D point clouds with radiometric information suitable for a detail scene reconstructions of buildings, which are rich and precise in damage-related semantic information and therefore very relevant for SDA (Pix4d, 2016b; Xiong, Adan, Akinci, & Huber, 2013).

3D model quality can be assessed from two different perspectives. The first is an absolute or geometric validation, where the obtained 3D point cloud is compared in different ways against another model of the same area with a known high accuracy. This high accuracy model is ideally a ground-based collection of measurements or Terrestrial Laser Scanning (TLS) (Khoshelham, 2012). The second is associated to the model representability of damage-related features and how cognitive and semantic methods can identify and extract these features from this model (Dekker, 2011; Kerle & Stekelenburg, 2004; Zhang et al., 2010). The latter is considered a more complex approach since there is not a standard method to assess this aspect, and there are many inconsistencies when comparing damaged scores at building level with field scores (See also 1.1.1)(Saedi, 2015).

Different kinds of parameters can affect 3D model quality and its application accuracy. Parameters can broadly be grouped in data acquisition and pre-processing stages (*Figure 3*). Data acquisition parameters (e.g. Ground Sampling Distance, Area of interest, etc.) are related to mission planning and data acquisition process. Thus, they must be wisely defined since there is no way to modify them farther. Data pre- and post-processing parameters (e.g. Image selection, Ground Control Points, etc.) are more flexible and can be used to solve errors caused during the data acquisition process (e.g. The use of accurate GCPs in IBM would lead to a better stabilization of the 3D model geometry) (Nex & Remondino, 2014; Remondino et al., 2014). IBM errors in image matching processes are mainly related to data quality (e.g. resolution, blurriness, etc.) and scene characteristics (e.g. smooth textural objects, transparent objects, etc.). In the case of SfM models, IBM errors are considered more as a black box, since they can be related to bundle adjustment divergences or geometric deformations in the process (Remondino et al., 2012). Data acquisition parameters are relevant, since although some data quality pre- and processing parameters can be modified, some of them such as resolution cannot. Hence, the priority must be given to an appropriate selection of data acquisition parameters to impede error propagations on pre- and processing steps.



Figure 3. Image Based Modelling quality parameters (modified from: Nex & Remondino (2014))

#### 1.2. Problem Statement

Image-based SDA has been carried out using a diverse array of data sources mainly air and space borne VHR sensors. Recent studies have been focused on VHR multi-perspective oblique cameras, improving quality on aerial-based damage assessment. However, practically all of them have been based on still imagery which is often unavailable or highly expensive. Video data, on the contrary, present a big advantage related to these aspects especially during post-disaster situations, since it is the first type of data produced and uploaded on the web. First aid providers, such as fire fighters, police, red cross and local media usually collect this information from aerial vehicles such as helicopters, and currently by Unmanned Aerial Vehicles, and make it public even hours after the disaster occurred (Kerle & Stekelenburg, 2004). Additionally, video data quality has improved substantially in the last decades due to technological efforts to increase resolution and reduce common data artifacts. It has been stated that this kind of data are in general less adequate for IBM due to low resolution, redundancy, blur-motion effects, and lack of geolocation information. Nonetheless, questions regarding how these quality parameters can influence 3D model absolute quality and how suitable they are for SDA, have not been addressed.

This research aims at analysing the influence of data quality parameters on 3D model absolute quality and suitability for SDA. This is complemented with the study of one main activity during post-disaster stages, debris volume estimation. The results then will allow to determine what is the usability of video data on SDA.

#### 1.3. Research objectives

#### 1.3.1. General Objective

To determine video data usability for 3D scene-based SDA in comparison to still imagery.

#### 1.3.2. Specific objectives

- To determine how video data artifacts and quality parameters (resolution and frame rate selection) influence absolute 3D model accuracy
- To determine how suitable video-based 3D models are for extracting damage-related features for posterior Structural Damage Assessment.
- To determine how scene distinctive conditions and characteristics of two different study areas can influence on 3D model quality and SDA.
- To evaluate how feasible is it to perform relevant activities such as debris volume estimations with video-based 3D models in comparison with still imagery ones.

#### 1.4. Research questions

- 1. How do video data artifacts (e.g. motion-blur) and inherent characteristics (e.g. resolution and image redundancy) influence absolute accuracy of video-based 3D models?
- 2. How do video data artifacts (e.g. motion-blur) and inherent characteristics (e.g. resolution and image redundancy) influence damage-related features identification and extraction from 3D scene models for SDA?
- 3. How useful are video data in comparison to at-nadir and/or oblique still imagery for SDA, based on the identification and extraction of damage-related features from 3D models?
- 4. How distinctive characteristics of the area under study can affect video-based generated 3D models?
- 5. How suitable are video and still imagery-based 3D models for other relevant post-disaster activities, apart from SDA?

# 2. LITERATURE REVIEW

#### 2.1. Advances on aerial-based SDA

Remote sensing from aerial and space platforms has been considered a potential tool for damage assessment since it provides a more general sight of the scene in a relative shorter time (J. Fernandez et al., 2015). George Lawrence was one of the pioneers in using aerial data to study fire and earthquake damage extend in the city of San Francisco, in 1906; since then, many other advances in this field have been achieved (Baumann, 2014). A traditional approach is visual inspection of aerial or space imagery, which allows a broad perspective of the area. Ogawa & Yamazaki (2000) for example applied photo interpretation of aerial photographs taken after Kobe earthquake stroke in Japan (1995), and classified buildings under different categories according to their damage state. Likewise, when pre- and post-disaster VHR imagery is available, a semi-automatic approach for the identification of damage features based on change detection can be performed for SDA as demonstrated by Zhang et al. (2010). A main limitation of this approach however is that pre-disaster VHR data is scarce. Furthermore, Ogawa & Yamazaki (2000) also stated that due to the camera angle for VHR imagery acquisition, mainly vertical to the ground, there is an important limitation on the identification of minor damage-related features at building walls and columns. A possible alternative is Pictometry data, which is obtained from five different perspectives, and could solve this lack of obliqueness of traditional platforms. However, it is still not enough to have a complete scene representation and recognize damage at façade level (Gerke & Kerle, 2011). Additionally VHR data can be also considerably expensive, specially imagery obtained from air-borne sensors (Adams et al., 2010).

Radar and LiDAR sensors demonstrated to be better alternatives compared to VHR optical data for several reasons. In the case of Radar, because of its particular double bouncing response reduction from damaged buildings, the rough-surface scattering form debris, and also because of its cloud cover independence (Dekker, 2011; Dell'Acqua & Polli, 2011; Ehrlich et al., 2009). In LiDAR in turn, mainly for detecting relevant damage geometric features with a great precision and allowing a more oblique perspective analysis (Khoshelham, 2012; Schweier & Markus, 2006). However, processing and analysis of the data derived from these sensors is resource demanding; and availability is highly limited, in particular for LiDAR data (Arciniegas, Bijker, Kerle, & Tolpekin, 2007).

In recent years, some sensor-fusion approaches have been tested using space and air platforms. For example, Hussain et al. (2011) used Lidar and Geoeye-1 data for detecting earthquake damages in Port-au-Prince, Haiti. Likewise Ehrlich et al. (2009) used VHR aerial and satellite imagery in combination to SAR data for damage classification, indicating the effective recognition of damage features at building level using VHR airborne data and also the advantage of using SAR, where cloud cover hinders satellite or airborne based damage feature recognition.

The use of these aforementioned aerial hybrid approaches, highlight the limitations and advantages of different data sources. At the present, UAVs represent the most accessible and complete platform which combines obliqueness of ground-based imagery, resolution of VHR imagery and breath of satellite imagery (Adams et al., 2010). Furthermore, especially on damage scenarios, UAVs present high manoeuvrability and can fly through very limited-access zones (Jorge Fernandez, 2014).

#### 2.2. Semantic and cognitive SDA approaches

Due to the scarcity of pre-disaster information SDA was mainly done by visual interpretation, which is not the most practical approach due to its high demand of time and effort. In recent years different semantic and cognitive methods for the automatic identification of damage-related features were tested. Zhang et al. (2010) tested a semantic process based on object recognition and identification, complemented with segment-based image characterization for the classification of a rural damaged area, showing accurate results and a possible general cognitive model of knowledge and rules which may be reused in other cases. Similarly Hussain et al. (2011) used an object-oriented analysis for land cover classification, which then was used to extract buildings and rubble from VHR aerial imagery and LiDAR data for damage mapping. While land cover classification accuracy was acceptable, the author stated the difficulties of characterizing densely structured neighbourhoods and rubble, and detection of some damage types such as "pancake" damaged buildings.

In recent studies this kind of analysis was done using UAV imagery. Fernandez et al (2015) developed a SDA method using semantic reasoning for the identification and extraction of damage-related features using object-oriented analysis. Nevertheless, due to problems in the aggregation of the damage information at building level, not clear damage classes were accurately classified. In a similar approach, (Vetrivel, Gerke, Kerle, & Vosselman, 2015) building gap identification and classification was performed using UAV VHR imagery and radiometric descriptors as damage indicators; these were able to discriminate damage-related gaps due to the distinctive textural patterns of surrounding features such as debris and spalling. However, the author stated that in case this evidence is missing, damage-related gaps will not be discriminated in a proper way, therefore, semantic information (e.g. gap predictable position) together with geometrical uniformity descriptors would be needed. This kind of framework then can be applied to analyse other damage-related features, such as inclined walls, cracks, etc.

Interest on using semantic features for SDA is evident, since most of traditional SDA classification approaches (e.g. EMS-98) are based on cognitive interpretation of damage-related features on affected buildings. Nonetheless, there is not yet a broad automated approach which allows the conceptualization and aggregation of all the domain specific semantics for building level SDA. Traditionally SDA approaches holds subjectivity which cannot be transformed to a consistent set of rules for an automated SDA methodology. Additionally, some aerial based radiometric and geometric information is unused since it cannot be aggregated to the these traditional SDA schemes (Saedi, 2015).

#### 2.3. 3D scene-based SDA

The combination of multiple 3D measurements, referred as 3D point cloud, makes a 3D scene reconstruction. A conventional measurement of these points is through laser scanning or LiDAR. Based on the reflection properties of a laser beam, distance measurements to different surfaces are taken. Depending on the sensor, an individual point can be accurate to a few centimetres. Airborne Laser Scanning (ALS) was the main source used in SDA due to the fast collection of data. The advantage of using ALS in SDA is the identification of geometrical surfaces with high precision. In the field of SDA, Schweier & Markus (2006) proposed a new catalogue based on geometrical damage features which can be derived with change detection techniques, however, as mentioned before, the main limitation is pre-disaster data. Later Hussain et al. (2011) processed 3D point cloud data for buildings delimitation and rubble mapping together with object-oriented classification of VHR imagery. The author found LiDAR elevation information valuable for determining damage in the building geometry, although, he also states limitations on the detection of other subtle damage features and "pancake type" damage. In a similar approach Khoshelham et al. (2013) performed a basic

classification of building roof damage from extracted features of planar surfaces. In this case the author used uniquely 3D geometry for damage estimation based on a large range of features to detect. This range was too large in comparison to the training samples taken, affecting classification accuracy. Moreover, only two categories (i.e. damaged and undamaged) were analysed which might not be enough in rehabilitation and reconstruction phases, where more detailed damage estimations are needed. At present ALS limitations are related to the relative limited density of 3D points, big occlusion zones (i.e. areas not reach by the laser beams), and lack of spectral information. Therefore, derivation of a semantic rich 3D models such as BIMs for reliable and detailed SDA is still not feasible with this kind of data.

Another approach to obtain 3D point clouds can be done through IBM. IBM is a technique based on the definition of the fundamental matrix (F-matrix), which defines the model coplanarity constrain and the relative orientation of two subsequent images. The F-matrix can be estimated with SfM algorithms and/or robust dense feature matching techniques (see also 1.1.3 3D Image Based Modelling (IBM)). 3D point clouds derivation by IBM represents many advantages for SDA. First, point clouds generated are very dense; while LiDAR sensors can acquire on average 1 to 25 points per square-meter, IBM techniques can in theory measure 100 points per m<sup>2</sup> using conventional aerial imagery (10 cm GSD), and even 10,000 points per m<sup>2</sup> with higher spatial resolution imagery (1 cm GSD), considering every pixel will result in a new 3D point. Moreover, every point also stores spectral information, relevant for semantic reasoning approaches for SDA. Considering these advantages, some studies were done to test IBM in SDA. A semantic reasoning approach was applied by Fernandez et al. (2015) to classify damage states of buildings using UAV multi-perspective imagery. The method was focused on the identification of geometric damage-related features for high damage categories, and an object-oriented scheme applied to the oblique images to detect features corresponding to lower ones. Although the method rested mainly on 2D space analysis, it could successfully classify highly damaged buildings. A main limitation is the difficulty to aggregate information at building level, but this can be managed by working directly on the 3D information. Besides, Vetrivel et al. (2015) developed a method to accurately delineate buildings using IBM 3D models generated from UAV still imagery. The main outcome of this research however was to identify damage-related gaps using image radiometric damage indicators and aggregate this information for at building level SDA. The latter did not reach the expected accuracy and even this accuracy decreased when applied to another geographic location and when using other training sample. The author recommends the use of additional information coming from semantic-rich image-based 3D models (e.g. BIM), which can be analysed by ontological (e.g. rule set) approaches to characterize additional damage features and classify SDA at-building level.

#### 2.4. Video-based 3D IBM/SDA

Oblique aerial images can also be obtained with video footages. The main advantage of this kind of data is their fast production and availability (Kerle & Stekelenburg, 2004); their main disadvantages are their low resolution, blur-motion effect, and image redundancy. Recently the efficiency of using this kind of data on cultural heritage modelling was studied by Alsadik et al. (2015), who additionally presented a methodology to process these in order to avoid problems caused by their inherent characteristics. The author demonstrated that in spite of losing the level of details, this kind of data is still valid for mid-range applications using the framework proposed, at least in cultural heritage domain. In disaster management studies, video-data was mainly used for change detection and motion tracking applications, where mounted video cameras can be used for disaster surveillance in order to determine interior and exterior damage (Kanda, Miyamoto, Kondo, & Oshio, 2005; Sahin, Kabar, Saglam, & Tek, 2011). These studies determined how a cheap alternative can be implemented for real-time damage estimations, but also revealed some problems using these systems, such as sun light and weather dependency, and more important, its local nature.

Therefore, some primary researches showed the possibility of using these data for roughly determine damage zones in a widespread range. For example, Mitomi, Saita, Matsuoka, & Yamazaki (2001) analysed thought multi-level slice method, distinctive spectral damage features on video-extracted fames, and used maximum likelihood classifier for damage classification. Later Ozisik & Kerle (2004) tested how video data are able to improve structural damage estimations once integrated to moderate satellite imagery. Hence it was demonstrated that even though video data requires substantial work to be processed, orientated, and integrated, it can be a relevant source of damage-related information, mainly from horizontal perspectives for analysing building façade characteristics. A similar, but more elaborated approach was presented by Kerle & Stekelenburg (2004), by creating 3D environment from orientated improved video frames. In this research the automated classification results were poor, revealing main limitations of using video data, such as low image quality and lack of geographical position. By that time however, video data was collected in low resolution and there were limited resources for image based modelling. Nowadays, technological advances allow obtaining very high resolution videos and create very precise 3D scenes from video scenes (Alsadik et al., 2015).

#### 2.5. 3D Point cloud quality assessment

Errors in 3DPCs can have their origin from many sources. In general, two categories of errors can be differentiated, systematic and random errors. Systematic errors are related to data collection or processing deficiencies, which for image-based modelling can be due to flawed camera calibration or orientation, inconsistencies in image matching, or registration using imprecise 3D GCPs. Random errors are linked to the characteristics of the objects under observation, and the medium between them and the sensor. In the case of IBM, there is long list of possible random errors, the most common are: object texture and surface homogeneity, reflectivity, light conditions (e.g. shadows), dust or smoke, humidity, among others. Common error tracking is a difficult task for the robustness of algorithms used in IBM, such as bundle block adjustment, where divergence and geometric deformations can be experimented. However, error budget estimations and nature can be identified using accuracy assessment of generated 3DPCs (Nex, 2016; Remondino et al., 2014).

Even though 3DPC accuracy was used in principle to determine absolute quality of models generated by range sensors, the same approaches are applied to Image-based models. Model accuracy can be measured theoretically and empirically (Nex, 2016). The former implies the estimation of expected model errors based on the mathematical relations of model parameters, which as a result indicate sources of systematic error. Some examples are Khoshelham (2012) and Soudarissanane, Lindenbergh, Menenti, & Teunissen (2009). However, this accuracy estimation needs to be confirmed later by an empirical accuracy assessment, which is focused on the model geometric or absolute truthfulness. Empirical accuracy is composed by internal and external assessments (Jarzabek-Rychard & Karpina, 2016; Nex, 2016). Internal accuracy assessment infers model precision by the use of error metrics. This can give some indication of discrepancy on object registration coordinates or point cloud density and noise. Examples of internal accuracy can be found in Jarzabek-Rychard & Karpina (2016); S Soudarissanane et al. (2009) and Sylvie Soudarissanane, Lindenbergh, & Gorte (2005). External accuracy uses a reference model (e.g. calibration field, accurate 3DPCs or 3D object model), and by a comparison to the generated one, it determines what is the overall 3DPC or model geometric correctness. This approach is the one with larger application, and there are a variety of examples where close-range photogrammetry, ALS, TLS data and calibration fields, were used as benchmark models (Abbas et al., 2017; Alsadik et al., 2015; Kersten & Lindstaedt, 2012; Lichti, 2007).

#### 2.6. Conclusions

Post-disaster SDA is an important activity for response and recovery disaster phases. Remote sensing technologies have been exploited on the SDA field as a source of fast and reliable information. However, the lack of obliqueness of most traditional platforms have hindered their coverage advantages, indicated by lower damage estimation accuracies. On the contrary, multi-perspective (i.e. also oblique) imagery demonstrated to be a rich source of direct and semantic damage-related information based on radiometric characterization. In the same way, 3DPCs application was tested on SDA field, especially for the extraction of geometric damage-related features. 3D IBM is in both aspects (i.e. radiometric and geometric) a promising approach for the extraction of all kinds of damage-related information. However, information extraction has not been yet achieved; one of the main reasons for that are the several inconsistencies between traditional ground-based SDA schemes, which are subjective and detail-less. Moreover, a potential source of imagebased 3DPCs are video frames. According to literature there are main video quality parameters to consider when using this kind of data on IBM, these parameters are: resolution, redundancy and blurriness. However, in practice it is still not well studied, and even less on the field of SDA. The present research aims (1) to empirically determine video-based 3D modelling quality and compare it with IBM one, analysing in parallel the influence of the previously mentioned quality parameters, (2) to test the representability of the different damage-related features on the 3DPC. Finally, (3) an application on relevant post-disaster activities will be studied.

# 3. METHODOLOGY

#### 3.1. Study area

Two study areas were selected based on the data availability of recent earthquake events occurred in these areas. Additional criteria used were the particular damage settings of each area, which allows a more comprehensive and general understanding.

#### a) Tainan - Taiwan

On February 6th, 2016, a 6.4M earthquake struck Taiwan causing a widespread damage and 117 deaths. This was the second deadliest event in Taiwan and the main reason of this high amount of deaths was the collapse of a 17-storey building located in the city of Tainan. This concrete-based building known as Weiguan Jinglong was the centre of discussion basically because presumably the weak architecture design and materials were the cause of its collapse (University of California, 2016). A clear sign of this was the general damage setting, since it was the unique collapsed building in the area showing that even some old structures could stand despite the earthquake magnitude (*Figure 4*). An important point to mention about the present study area is its scene complexity that could affect Image-based 3D point cloud extraction, such as smoke, people and moving elements.



Figure 4. First study area, Tainan (Taiwan). Left: Tainan localization, centre: Pre-disaster situation, right: disaster situation. Delimited in white: Weiguan Jinglong collapsed building

#### b) Pescara del Tronto – Italy

A more recent earthquake event occurred on August 24th, 2016 when a 6.1M earthquake struck in Italy, affecting severely towns located around the central Apennines in the north-eastern part of Italy where many faults are active, and some other earthquakes occurred in the past (e.g. L'Aquila or Norcia). The earthquakes which occur in this zone are structurally complex and shallow, and are relatively not that large in the global context, but due to the presence of many historical and vulnerable buildings can cause severe damages. One of the affected towns located in this region is the town of Pescara del Tronto, which is a historical town in the hill top of a mountain range (*Figure 5*). This town is mainly characterized by steep slopes and very ancient stone houses built in the Middle Ages. During the August 24th earthquake, many of these buildings were totally and partially collapsed, showing a different damage setting than Tainan.



Figure 5. Second study area, Pescara del Tronto (Italy). Left: Pescara del Tronto localization, centre: Pre-disaster situation and right: disaster situation.

#### 3.2. Data

The data used in this research is presented in *Table 1* and explained in the following subsections, more detailed information about acquisition is presented in *Table 2*.

Data Sensor and Source		Relevant parameters	Description
	Tainan, Taiv	wan (Weiguan Jinglong buildin	g)
High Quality aerial still imagery	Multirotor UAV Camera: Phantom DJI FC300S (MSc. Jyun-Ping Jhan, Institute of Photogrammetry- University of Stuttgart)	4000x3000p (12MP) Oblique and at-nadir perspective Includes EXIF file (geolocalization) shutter speed = 1/1099 sec	Daily basis (Feb. 07, 10, 11, 12, 13, 14 and 15, 2016), multi- perspective imagery of the entire area around Weiguan Jinlong building
High Quality Aerial Video footage	Probably Multirotor UAV Phantom (Youtube)	1080p (1920x1080pix FHD, 2.1 MP) Frame rate = 29 fps Duration = 234 sec = 6786 frames	Aerial video footage from the top and surroundings of the Weiguan Jinglong building moments after the earthquake (Feb. 06, 2016)
GCPs	MSc. Jyun-Ping Jhan, Institute of Photogrammetry- University of Stuttgart	Well distributed (horizontally) TWD97 / TM2 zone 121	25 well distributed GCPs in the area surrounding Weiguan Building. All of them are taken at the same elevation.
	Pe	escara del Tronto, Italy	
	Probably Fixed-wing UAV Camera: Canon	4000x3000p (12MP)	Aerial at-nadir imagery acquired
aerial still imagery	PowerShot S110 (Dr. Filiberto Chiabrando Politecnico di Torino,	Includes EXIF file (geolocalization)	the town. Some images are blurry.
High Quality Aerial Video footage	Italy) Probably Multirotor UAV Phantom (Youtube)	shutter speed = 1/60sec 1080p (1920x1080pix FHD, 2.1 MP) Frame rate = 25fps	Video shot from different angles but not in an specific order,

Table 1. Data general descriptions

		Duration = 118 sec = 3422 frames	shows also the old part of the town.
	Dr. Filiberto Chiabrando,	Well distributed	22 GCPs distributed in different
GCPs	Politecnico di Torino, Italy	WGS84 zone33	points of the town.

Table 2. 1	Data ac	quisition	details	divided	on	study	area	and	data	type
		1				. /				

Study area		Tainan	Pescara del Tronto		
Data type	Still imagery at-nadir	Still imagery oblique	Video frames	Still imagery at-nadir	Video frames
Area covered (km <sup>2</sup> )	0.4	0.1673	0.1712	0.2	0.02
Approximate flight height (m)	87	42	50	166	18
Average GSD (cm)	11.64	3.56	7.66	5.91	3.8
GSD: Ground sampling distance					

#### 3.2.1. Aerial still camera imagery

In case on Tainan UAV still images were collected on a daily basis frequency after the earthquake. Two perspectives and flight paths were used for UAV data collection. The first kind of data was obtained atnadir perspective, using a regular grid or corridor pattern over a large area at high elevation (*Table 2*). The second type of data was obtained by using an oblique perspective camera, at lower flight height and focused on the Weiguan Jinglong building. The same data collection procedure was done for following days after the earthquake, the first acquisition date is February 7th, then data was collected from February the 10<sup>th</sup> until the 15<sup>th</sup>.

Data from Pescara del Tronto was obtained only at-nadir perspective in a grid or corridor pattern from a higher altitude (*Table 2*). Date of acquisition in this case is unknown but presumably is on the fourth week after the earthquake. Related to quality, it is important to mention that the shutter speed is quite low here, which implies more light and blur effects in images from Pescara.

#### 3.2.2. Aerial video footages

This kind of data was downloaded straight from Youtube and presumably was recorded the same day of the earthquake for both study areas. To avoid problems with watermarks and irrelevant footage parts, both videos were pre-processed (e.i. edited), but their quality and resolution remained the same. Video footages were made from lower elevations and covering smaller areas (*Table 2*).

#### 3.2.3. 3D Ground Control Points

Precise 3D GCPs were obtained from both study areas, although in the case of Tainan they were mainly measured using street marks at the same plane, while in Pescara del Tronto different reference points at different elevations were chosen as control marks.

#### 3.3. Research approach and flowchart

This research is focused on two recent earthquake events that struck two different areas. The first one was a 6.4M earthquake in Taiwan on February 6<sup>th</sup>, 2016, and it was the second deadliest event in the country's history. The second is a lower magnitude 6.1M earthquake occurring in Italy on August 24<sup>th</sup>, 2016, which also caused severe damage in towns located around the central Apennines in the north-eastern part of Italy. These cases were chosen based on data availability and especially on the distinctive damage spatial patterns they present. In case of Taiwan a very localized damage pattern can be evidenced from aerial imagery; particularly a big complex-17-storey collapsed building known as Weiguan Jinglong situated in the centre of Tainan city. In the case of Italy, the damage pattern is more spread, and images from Pescara del Tronto city show only few standing buildings. This intensity differences are mainly due to the building characteristics of each area. In Tainan, buildings are reinforced, tall and made of concrete. In Pescara del Tronto buildings are one or two stories-masonry buildings. Having different data types, video footages and still imagery from these two study areas together with the described contrasting settings, will give a broader understanding on how accurate video-produced 3D models are and what is these models usability for SDA in comparison with still imagery.

The analysis of video and still camera datasets from Pescara and Tainan areas, and the 3D models obtained from them, can be divided in two different aspects (*Table 3*). The first one encompasses different activities to assess data quality influence on model quality and SDA. This includes a direct estimation of data quality for all datasets used on this research, complemented by an absolute accuracy assessment, which refers to the model geometry accuracy itself, and supported by a damage-related feature representability analysis, based on the identification of these features on every model generated. Finally, a more practical activity aims to assess video data application on debris volume estimation as a relevant post-disaster application.

Aspect to analyze			Tainan (TW)		Pescara del Tronto (IT)				
Experiment		Activity	Measurement parameter	Still imagery	Video	Still imagery	Video	Approach	Scale
	Direct image quality assessment		Blurriness assessment	Vertical imagery Oblique imagery	Video dataset	Vertical imagery	Video dataset	Blur metric algorithm application	
		racy	Planar fitting	Oblique 3DPC Oblique and vertical 3DPC	Video 3DPCs			Difference to an theoretical flat surface (plane)	Flat surface subset
Image quality influence	data parameters	metric/absolute accu	External accuracy	Oblique 3DPC Oblique and vertical 3DPC Oblique and vertical 3DPC (refined)	Video 3DPCs			Comparison with a highly accurate model (refined 3DPC)	A large subset of the model
	Effect of	Effect of Geo	Completeness	Oblique 3DPC Oblique and vertical 3DPC	Video 3DPCs	Vertical 3DPC	Video 3DPCs	Calculation of 3D point density and gap percentages	A large subset of the model
			Damage features representability assessment	Recognition of direct and semantic damage-related features	Oblique 3DPC Oblique and vertical 3DPC	Video 3DPCs	Vertical 3DPC	Video 3DPCs	Recognition and characterization of identified damage-related features
3D model application post disaster activities		Debris Change analysis	Multi- temporal Volume estimation	Oblique and vertical 3DPC (daily x5 and refined)				Obtain differences in volume estimations from video and still imagery- generated models	Weiguan Jinglong buildiing, Tainan (TW)

Table 3.	Research	approach	followed	and the	individual	' experiments	performed
		11 .	/			/	1 ./

The flowchart implemented for this research is shown in *Figure 6*. In broad, the research can be divided in three main stages: 3D modelling, quality assessment and 3D model application analysis. As a first step however video data was processed to generate multi-perspective imagery for 3D modelling. Then these data processing is grouped inside the 3D modelling stage; here both data types are processed using different quality parameters. From this procedure, many 3D point clouds will be generated, their quality characteristic will depend on the data type (i.e. video or still images), study area, and the quality parameter used. Also during this stage a benchmark 3DPC will be generated using a refining procedure with the Tainan still imagery and default parameters. Hereafter all the 3DPCs generated will pass through a quality assessment phase, in which all of them will be tested by different means in relation to their geometric or absolute quality, their capability to represent damage features for SDA and a direct image quality index using blur and texture metrics. Once finished this process the usability of Video data for 3D modelling and SDA can be determined during a general objective results interpretation procedure.



Figure 6. Research flowchart describing the main three stages: 3D modelling, Quality assessment and Application analysis

#### 3.3.1. 3D modelling

This research is focused on the analysis of the influence of four data parameters: Sensor or data type, sensor perspective, resolution, and frame selection method. Sensor type will be simply analysed by comparing video and still imagery-generated 3DPCs. While the other parameters will be analysed based on the applying different data preparation and processing settings during the 3DPCs generation (Table 4). Processing 3DPCs is detailed in the next subsection according to the data type.

Sensor type	Sensor perspective	Resolution	Frame selection			
	Oblique	Original <sup>1</sup>				
C (*11	At-nadir	Medium				
Still camera		Low				
	Oblique and at-hadir <sup>1</sup>	Coarse				
		Original <sup>1</sup>	Radom <sup>1</sup>			
X7: 1		Medium	Wise selection			
video camera		Low				
		Coarse				
1. Used as default parameter when it is not under analysis						

Table 4. Parameter under analysis for every data/ sensor type

#### a) Still Imagery

Numerous post-disaster data were generated for both study areas, but mainly for Tainan case. This allowed processing still imagery in different ways and get diverse 3DPCs for the posterior analysis. Still imagery from both study areas were processed in a similar way, however more alternatives and the generation of an accurate model (i.e. benchmark) was only possible using Tainan data.

In case of Tainan still imagery was first processed using Pix4d (2016) workflow. The first 3DPC generated was the one used as benchmark. In this case, all data were used, oblique and at-nadir images were considered for a first relative orientation step. Then, despite the relative orientation was able to give a good approximation of the scene orientation, 3D GCPs were used to adjust the model and obtain a precise geographical position and scale. Only three 3D GCPs were discarded because they were either out of the study area or were invisible in the image. Once the model was accurately orientated, a refining step was applied to improve precision of matching points. In this step, some Manual Tie Points (MTPs) were identified in the images. MTPs are user-determined corresponding points in two or more images which are used to adjust the initial matching results. Finally, a dense 3D point cloud was created with this MTPs, the original images size, and all 3D GCPS (see *Appendix 2*).

A similar procedure was follow to generate other 3DPCs, parameters and datasets were altered in order to test their effect on the final products. In a first test, only oblique images were selected for the matching and 3DPC generation. In a second test, image size and resolution were degraded to three levels (i.e. medium, low and coarse resolution), obtaining three different 3DPCs. Besides, since post-disaster multi-date data was available, a single 3DPC for each day was generated from the study area.

For Pescara de Tronto the generation of 3DPCs was more limited due to the reduced amount of data. Only at-nadir perspective was tested, and no benchmark was produced. Nevertheless, image size and resolution were degraded in order to analyse the influence of these quality parameters. Since 3DPCs are available in this area, a precise geo-localization of the generated 3DPCs was possible. Because of the different damage settings of this study area, in comparison to Tainan, an interesting analysis on internal accuracy and completeness was applied.

In general, every time a new parameter was tested a default setting was applied to the remaining ones (i.e. oblique and at-nadir images and original image size, *Table 1*). Thus, several 3DPCs were generated using different settings and aerial still imagery from both study areas, one was refined to be used as benchmark, and six were produced using daily-base post-disaster images to be used in the 3D model application analysis.

#### a) Video frames

Since video was directly obtained from YouTube, a preliminary editing task was needed to erase irrelevant parts, such as video introductions and credits. Once video data was clean, processing for both data sets was performed.

Current versions of Pix4D have video input tools which allow frame extraction following a certain userdefined range (e.g. 1 image every frame, default value). For Tainan, a random value of 45 was chosen (i.e. extract 1 frames every 45, 176 frames), extracting 176 frames from the video data. This random selection certainly does not consider blur-motion effects or image redundancy. Hence, another dataset was selected using Zephyr 3D (3D Flow, 2016) software (*Figure 7*). An image quality index, related to image textural richness and sharpness, together with similarity indices were computed by the software. By this low quality and redundant video frames are filtered out from the previous random selection, and a wise selection of frames can be obtained. Henceforth, two 3DPCs were obtained, one using the random frame selection (i.e. RFS) and the other using 3D Zephyr tools for a more logical selection of frames (i.e. Wise frame selection, WFS. *Figure 7*). In case of Pescara the same procedure was performed, however since the video duration is shorter, a value of 25 was chosen for the RFS (i.e. 1 frame every 25, 118 frames).



Figure 7. Flowchart for Wise Frame Selection approach for video frames extraction using Zephyr image quality and similarity indices.

Additionally, image resolution of video frames was also degraded in the three levels of still imagery. Since video resolution is already low, the idea is to analyse how even coarser resolutions will affect 3DPC quality.

Geolocalization of all the video-based generated 3DPCs was based on the use of correspondent 3D points from the still-based generated benchmark 3DPC. Additionally, one video-based 3DPC was generated using all default parameters for the 3D model application phase.

#### 3.3.2. Quality analysis

#### a) Direct image quality assessment

For this analysis, unprocessed data (i.e. still images and extracted video frames) were analysed using a quality index developed by 3D Flow (2017). This index allows to measure blurriness and texture homogeneity of every single image, and also displays a map to check what parts of the image may present problems in 3D IBM (*Figure 8*). Still images were directly used; whereas for video data, a subset was generated using RFS, explained in the previous section. This analysis is very practical and by statistical means describes roughly data quality for 3D modelling of all the datasets used. Quality index is a unit-less value, with no maximum or minimum boundaries. When images below a quality index value of 0.5 should be filtered out, since usually they are too blurred and do not have texture information. This index represents still images and video frames characteristics by a single image-based examination, based on a multiscale approach with frequency analysis. This index is also able to generate a graphical representation of low and good quality maps (3D Flow, 2017).



Figure 8. Image quality index tool in 3D Zephyr user interphase. Left: Image quality calculation, right: image quality map

In total five datasets were analysed. Three from Tainan: 176 randomly selected video frames, the complete still camera dataset and the still camera oblique imagery. And two from Pescara del Tronto: the randomly selected video frames and the at-nadir still images.

#### b) Geometric or absolute quality assessment

At this stage, all 3DPC obtained passed through a first quality assessment branch. Geometric or absolute quality assessment was based on different geometric measurements of each generated model. These are: planar fitting, completeness, and external model fitting. The former two indicate the model internal accuracy, while the last one is related to the external accuracy. Internal accuracy is an empirical indication of the model precision, which can be described by the model consistency and completeness; it can give indications of feature matching errors mainly. External accuracy instead is in fact related to the model accuracy, so how the model fits a high accuracy model or geometric object (i.e. benchmark). Therefore, to determine absolute or geometrical accuracy of every 3DPC a combination of both is necessary. In case of Tianan, the large amount of data allows to process, in theory, a high accuracy 3DPC, applying eventually a refining procedure. However, the limited data of Pescara del Tronto does not allow this kind of product, and only internal accuracy will be analysed for this dataset.

First planar fitting was applied to the different generated 3DPCs models. This measurement reflects 3DPCs distribution and noise, it is based on the analysis of objects that should be flat, therefore by fitting a plane from the 3DPC, the distribution of every single 3D point along this plane can be analysed (*Figure 9*). Plane objects were first identified for every study area. In this research house roofs were used as reference plane surfaces, since also at-nadir imagery precision will be tested at this analysis, subsets from every 3DPCs were extracted based on this planar objects. A plane section was created using Cloud Compare software (CC)(Girardeau-Montaut, 2017) along the extracted 3DPC subset. In theory, the 3D points will fit this plane in case the model is precise, but in reality, a refined model should have some deviated points (i.e. model noise). Therefore, some statistical indicators (e.g. mean distance to the plane and standard deviation) of how each generated 3DPC fits this theoretical plan will be computed and analysed to determine model precision.



Figure 9. Planar fitting analysis example. Left: subset of a plane surface, Right: distances from point clouds to a theoretical flat surface (fit plane).

An additional test to determine 3DPC internal accuracy is a model completeness analysis. This was done using also CC software, and similarly a subset of every 3DPC was clipped and then projected in a raster grid of 1 m<sup>2</sup> cell size. The projection was made from vertical and horizontal perspective; therefore, two raster maps were created for each 3DPC. Every cell value in these raster maps represents the total number of 3D points they content, correspondent to the 3DPC density per cell or square-meter. The mean of 3DPC density of every 3DPC was then computed to indicate it as first completeness indicator. Complementary to this, these raster maps cell value (i.e. 3DPC density) distribution was also analysed using box plots and visually on classified maps. Finally, also the proportions of empty cells were used as a last indicator of completeness, or in this case incompleteness.

As a complement for the absolute or geometric quality analysis, an external quality test was performed for Tainan generated 3DPCs. CC software was used to clip the same area from all generated 3DPCs, then a point to point distance was computed using the subset of the refined model and the one of the 3DPC under analysis.

#### c) Damage features representability analysis

A second perspective to analyse model quality and posterior usability, is evaluating the 3DPC capability to retrieve damage related features. For this quality assessment branch, a procedure based on the visual inspection and geometrical analysis of damage-related features was performed in the produced 3DPC models. Owning indications of the absolute quality of every 3DPC, and in order to optimize the workload, only the most relevant models from both datasets and datatypes were analysed at this phase.

This analysis started with the inventory of possible recognizable damage related features (*Table 5*). These features were divided into the direct detectable ones and those that can be retrieved by semantic methods. The latter belong to a more complex field in which damage can be identified and estimated based on the scene context indicators of damage analysed mainly in a 2D environment; in general, they are of high importance for automated SDA approaches. For every study area, the inspection was made in a specific 3DPC subset clipped using CC software.

Indicator type	Damage feature	Focus	
Directly related	Cracks	Mainly thin ones (hair-line)	
	Structural failures	Detached building elements (structural gaps)	
		Inclined walls	
Semantic	Debris	Mainly small pieces (plaster and stones)	
	Spalling	Building Façades	

Table 5. Damage-related features inventory with the main research focus for an effective visual SDA

Damage-related features defined mainly by radiometric characteristic (i.e. cracks and spalling), were analysed by visual inspection on mesh models created from the different 3DPCs. For the geometrically defined ones (i.e. structural failures and debris) also a mesh was created, but additionally metrics on object geometry were analysed. Mesh models were created using Delaunay 2.5D (best fit plane) triangulation for regular shapes and Poisson Surface Reconstruction (plugin) for the irregular ones (Cloud Compare, 2015a; Kazhdan, 2015).

Starting with the directly damage-related features, cracks were analysed using base a model mesh of the identified Façade. Every mesh then was visually inspected to verify in weather the crack feature was still recognizable or not. Additionally, a measurement of the crack width was made using the original 3DPC for reference. Besides, for structural features the analysis were more case-specific. In Pescara a 3DPC comparison was made between the generated models to analyse damage-related building gaps recognition; whereas In Tainan the mesh model of a building block was used to visually inspect unusual damage-related features (e.g. pancake effects and deformed structures). Additionally, an inclined wall was also analysed in Tainan by a similar approach of the planar fitting analysis, but using instead a meshed model of the reference 3DPC as a reference plane. Complementary to this, the inclination degree of all models was computed and compared with one obtained using the reference model.

Within the semantic damage-related features, spalling representability analysis approach was similar to cracks one. Visual inspection was applied in other to determine this damage feature recognition on every mesh model generated. For debris features, a representative area was first subset and the roughness index was estimated using CC software (Cloud Compare, 2015b). Thus, first a comparison roughness means of every debris area was made, and it was complemented by visual inspection of the correspondent mesh model to determine this feature representability.

#### 3.3.3. 3D model application analysis (debris volume change analysis)

With the availability of post-disaster daily-based still imagery data, several 3DPCs were generated during the 3D modelling stage (*Figure 10*). These then were used to perform a temporal analysis of change on debris volumes for Tainan study area. 3D models along with their respective STMs and one polygon to delimit computational area, were used to estimate debris volume for every model and every day (e.i. February 7, 10, 11, 12, 13 and 14<sup>th</sup>, 2016) in Pix4d software (Pix4d, 2016a). In parallel an additional 3D model was generated from video RFS frames to make a valid comparison of results. The exact date when the aerial footage was executed is unknown, but most likely it was recorded the same day of the earthquake (February 6<sup>th</sup>, 2016); the scene present a lot of smoke, and there is a lot of movement of SAR teams working on the buildings searching for victims. Therefore, the estimations obtained with these data should be correspondent with the still imagery ones of the first collecting date (February 7<sup>th</sup>, 2016). It is also important to mention that with the aim making a consistent analysis, the same 3D vector was at the ground level used in all calculations. Finally, these estimations were plotted and analysed.



Figure 10. Debris volume calculation at different time steps. Green areas represent the base of the calculation polygon, red are the volumes calculated.

# 4. RESULTS AND DISCUSSIONS

#### 4.1. 3D Modelling

Twenty-one 3DPCs were generated in total in this research, twelve for Tainan and nine for Pescara del Tronto data set (*Table 6*). Already at this stage by visual comparison it is possible to identify some quality and completeness differences between video frames-generated models and still imagery ones. In case of Tainan clearly the reference model (i.e. still imagery-based, refined) presents high density and clarity compared to a blurred 3DPC generated using video frames (RFS). On the other hand, for Pescara del Tronto still imagery models are similar to the video frames (RFS) generated ones; both present many gaps at specific area, although in general still imagery 3DPC seems more complete (*Figure 11*).

No	Tainan (TW) still imagery	Details	No	Pescara del Tronto (IT) still imagery	Details
1	Normal resolution (original Size)	Using oblique and at-nadir still imagery, not refined, 3D GCPs for geolocalization	13	Normal resolution (original Size)	At-nadir still imagery, not refined, 3D GCPs for geolocalization
2	Medium resolution (half image size)	Using oblique and at-nadir still imagery, medium resolution, not refined, 3D GCPs for geolocalization	14	Medium resolution (half image size)	At-nadir still imagery, medium resolution, not refined, 3D GCPs for geolocalization
3	Low resolution (quarter image size)	Using oblique and at-nadir still imagery, low resolution, not refined, 3D GCPs for geolocalization	15	Low resolution (quarter image size)	At-nadir still imagery, low resolution, not refined, 3D GCPs for geolocalization
4	Coarse resolution (eight image size)	Using oblique and at-nadir still imagery, coarse resolution, not refined, 3D GCPs for geolocalization	16	Coarse resolution (eight image size)	At-nadir still imagery, coarse resolution, not refined, 3D GCPs for geolocalization
5	Oblique	Using oblique imagery, not refined, 3D GCPs for geolocalization			
6	At-nadir	Using at-nadir still imagery, not refined, 3D GCPs for geolocalization			
7	Reference model	Using oblique and at-nadir still imagery, refined with MTP, 3D GCPs for geolocalization			
No	Tainan (TW) video data	Details	No	Pescara del Tronto (IT) video data	Details
8	Random frame selection	Random frame selection, reference model 3D points for geolocalization	17	Random Frame selection	Random frame selection, Normal resolution still imagery model for geolocalization
9	Medium	Random frame selection, medium resolution, reference model 3D	18	Medium	Random frame selection, medium resolution. Normal resolution still
	Resolution	points for geolocalization		Kesolution	imagery model for geolocalization
10	Low resolution (Quarter image size)	points for geolocalization Random frame selection, low resolution, reference model 3D points for geolocalization	19	Low resolution (Quarter image size)	imagery model for geolocalization Random frame selection, low resolution, Normal resolution still imagery model for geolocalization
10 11	Low resolution (Quarter image size) Coarse resolution (eight image size)	points for geolocalization Random frame selection, low resolution, reference model 3D points for geolocalization Random frame selection, coarse resolution, reference model 3D points for geolocalization	19 20	Low resolution (Quarter image size) Coarse resolution (Quarter image size)	imagery model for geolocalization Random frame selection, low resolution, Normal resolution still imagery model for geolocalization Random frame selection, medium resolution, Normal resolution still imagery model for geolocalization

#### Table 6. 3D Point Clouds inventory



Figure 11. General visualization of some 3DPCs generated for Tainan (up) and Pescara del Tronto (down). Datasets used: Video Wise Frame Selection (WFS), Random Frame Selection (RFS) and Still imagery. Some noise on Video (RFS) due to smoke.

There are three remarks related to quality to denote from this process already. First, a lot of noise is produce for the video RFS model; this is clearly sign of smoke perturbation, which is instead removed in video WFS one (see also Appendix 1). Second, without refining 3DPCs of Tainan still imagery presented a clear displacement of features, or a sort of duplication (Figure 12). Second, for WFS approach proposed using Zephyr3D software tools did not give appropriate results; too many frames were filtered out and initial identification of key points was not satisfactory or even not possible (Figure 13). In the first case, it may be that the absolute orientation of the model was not accurate, since all 3D GCPs used were uniquely identified on the at-nadir images and they were almost at the same plane; there are only 2 m of elevation difference between all Tainan 3D GCPs. This is supported by the fact that also the 3DPC generated with oblique imagery presented a similar displacement, which was then corrected using 3DCPs form the reference model. Besides, in case of WFS approach, the proposed procedure using Zephyr did not succeed. Many thresholds were tested for image quality and similarity index, however most of relevant sections were lost and initial image matching was not possible to make or resulted in a very poor 3D key point structure. Therefore this approached was modified and only image quality index was used as a guide to manually select video frames from the rayCloud of a rough 3DPC created using a random selection of video frames (Figure 14); the same values of RFS approach were used here (45 for Tainan and 25 for Pescara del Tronto). RayCloud was analysed by sections and frames were manually selected considering two aspects: Not having to many overlapping images per section and keeping the minimal number of overlapping images to cover a section.



Figure 12. Duplication effects due to displacement caused by wrong model orientation using the complete still imagery dataset (not refined)



Figure 13. Unsatisfactory Wise Frame Selection (WFS) model using Zephyr similarity index tool, lack of frames for some sections in the 3DPC. Still some similar overlapping frames are selected.



Figure 14. WFS: Wise Frame Selection modified approach using rayCloud of the Rough 3DOC and image quality index as guide.

#### 4.2. Quality assessment

#### 4.2.1. Direct image quality assessment

Results showed some logical aspects about image quality in all the studied datasets. In case of Tainan datasets, all kinds of still imagery present high quality scores above the maximum obtained by RFS video frames; the latter in turn presents highly variable quality (*Figure 15*). Besides, it is observable that the subtraction of low quality and redundant frames using the WFS approach did not increase quality of frames, but instead reduced variability, clearly removing inadequate frames of the first quartile and rising the min value to 1.5. For Pescara del Tronto datasets, the difference between data type qualities is less evident. Still at-nadir imagery presents a very high variability, but the median value is still high. Video imagery in this case

is more stable than the other data type, and WFS approach instead here did increased image quality rising the 75% of the dataset to values above 2.3.



Figure 15. Image quality index distribution boxplots

Besides, trying to determine whether Tainan or Pescara del Tronto data set present more quality is a more complex issue. Although Tainan still imagery have a higher score than Pescara del Tronto data set, video frames are of low quality. There are some considerations to take into account and clarify these results. First, acquisition flight path of still imagery in Pescara del Tronto presents a very irregular pattern and higher elevation above ground (i.e. higher GSD) compared to Tainan; these aspects are related to the higher variability and lower quality index scores respectively. An additional element to take into account here is that shutter speed is higher for Tainan; even not having information about flight speed this parameter represents a higher probability of having motion-blur effects on the obtained images. On the other hand in relation to video frames, Pescara del Tronto footage was on the contrary achieved closer to the ground than the one of Tainan, which increases the level of details and also GSD. Additionally, Tainan video is largely affected by smoke, while Pescara del Tronto one has no perturbation at all and frames present high texture-rich parts.

To analyse more all these aspects and image quality distribution, datasets were plotted in a series by video frame and still image (*Figure 16* and *Figure 17*). Tainan series clearly show the features described above, descending dips precisely indicate frames and images with some kind of perturbation, in this study area specially smoke. For Pescara del Tronto instead, these dips represent blurred frames and images with texture less zones; however this is less evident than in Tainan, since low quality zones (i.e. red areas) do not indicate if they are related to texture less and blurriness causes (3D Flow, 2017). However, observing at the image closely a generalized motion-blur pattern can be recognised.

Image quality index is a very useful tool, especially for treating video frames and use them later for 3D modelling. However, this index is simply a reference value that shows how suitable a certain image is for 3D IBM proposes. According to 3D Flow (2017) this index, and mainly the range of values is sensitive to resolution, therefore comparing datasets of different resolutions might give some biased indications. What is certain instead is the comparison of equal resolution datasets (e.g. video-video datasets from every study area). Therefore, the results obtained on this first stage of analysis were used as reference and judged on the following assessments.



Figure 16. Image quality index series plot and maps for Tainan (TW). In maps red represent areas of low quality. Dips are caused due to smoke (red areas in imager quality maps) in most cases.



Figure 17. Image quality index series plot and maps for Pescara del Tronto (IT). In maps red represent areas of low quality. Dips are caused due general image blurriness and textural homogenous areas (red areas in image quality maps).

#### 4.2.2. Geometric or absolute quality assessment

#### a) Planar fitting assessment (internal accuracy)

Some arguable results were obtained by this assessment in relation to the study area under analysis. In case of Tainan, a high mean distance to the plane was calculated for still imagery models, with exception of atnadir and oblique datasets, which were also analysed individually (*Figure 18*). Moreover, in relation to resolution an inverse direct relation between resolution and mean distance to the plane can be observed; so more precision when having a lower resolution. On the other hand, opposite and more evident results were observed for Pescara del Tronto data sets (*Figure 19*). First, in this case still imagery present lower mean distance to the plane than video data. Second, resolution more reasonably decreases abreast of mean distance to the plane.



Figure 18. Mean distance (m) to fit plane for Tianan. Distances represent 3DPC precision and standard deviation dispersion. Different resolutions are tested for still imagery complete and video Random Frame Selection (RFS) data sets.



Figure 19. Mean distance (m) to fit plane for Pescara del Tronto. Distances represent 3DPC precision and standard deviation dispersion. Different resolutions are tested for still imagery complete and video Random Frame Selection (RFS) data sets

Two observations on Tainan results deserve more analysis at this stage: The high mean distances of the models generated using Tainan still imagery (i.e. unrefined) and the unexpected inverse relation between resolution and mean distance to the plane. Regarding the first observation, the low precision of still imagery was caused by the displacement or duplication effect, also discussed in the above subchapter (4.1 3D Modelling, Figure 13). Tainan still imagery-generated 3DPCs are characterized by noise due to several duplicated objects; this was negatively influencing during the planar fitting assessment and varies according to the image resolution. In relation to the resolution issue, this trend may require a deeper analysis and even some extra tests to confirm this particular behaviour; by testing other areas the same characteristic were found, confirming this relation between resolution and 3DPC noise. A probable explanation for this is that at lower resolutions, less 3D points key points are generated, and most of the noise is removed. In case of video data this trend is less significant, although the same could be expected in areas where noise is produced by smoke. An additional test performed shows that precision could tent to increase with resolution as Pescara del Tronto case for video-generated model, however still imagery keeps the same unexpected pattern (Figure 20). Another remark is the low standard deviation of still imagery when is acquired form one perspective (i.e. at-nadir or oblique), which reflects its precision in comparison to video data. Within these single-perspective data sets, however oblique still imagery generates noisier 3DPCs compared at-nadir images, expressed by their standard deviation.



Figure 20. Mean distance (m) to fit plane for Tainan (second test). Distance to plane reduces with resolution (more precision). A more logical trend is presented for video models

This analysis demonstrated that in general still imagery data is more precise than video one, except when the two perspectives are used simultaneously without any refining procedure. Additionally, it also showed that resolution degradation can decrease model precision, excepting parts where noise exists; at this parts the relation is instead opposite (see *Appendix 4* and plane surface used in *Appendix 3*).

#### b) Completeness analysis

Two perspectives, vertical and horizontal, display point cloud density for both study areas and dataset types. Tainan results show that oblique still imagery generated denser 3DPCs in comparison to video and at-nadir data sets, even from the vertical perspective observation (*Figure 21*). However, it is largely lower that the one generated using the reference model. Higher resolution compared to video data and higher GSD in comparison to at-nadir dataset are the main causes of higher point cloud density in this case. This is confirmed with Pescara del Tronto observations, that also show denser 3DPCs produced with video data

sets compared to at-nadir still imagery considering both perspectives (*Figure 22*). This is related to the same aspects of Tainan and especially has to do with the limitation of at-nadir still imagery: high elevation above the ground and lack of vertical information. The same patterns can be seen for both study areas, excluding Tainan video WFS, which instead was not able to generate highly dense 3DPCs as the other data sets.



Figure 21. 3D Point cloud density (points/m<sup>2</sup>) from vertical and horizontal perspective for Tainan (TW)



Figure 22. 3D point cloud density (points/m<sup>2</sup>) from vertical and horizontal perspectives for Tainan

For a broader analysis of model completeness, vertical and horizontal perspective 3D points density maps were created and analysed for the principal generated models (*Figure 23* and *Figure 24*, more detail from *Appendix 5* to *Appendix 8*). Likewise, box plots for point cloud density distribution were plotted from both perspectives and study areas (*Figure 25*). Lastly proportions of empty cells were also analysed. The latter two analysis were done in base of a vertical and horizontal mask polygons in order to filter out some not representative pixel information (e.i. Not Available values) which were wrongly associated to zero values (see *Appendix 9*); otherwise these values may represent an overestimation of empty cells or change mean point density calculations.



Figure 23. 3D point cloud density maps (up: Tainan, down: Pescara del Tronto). RFS: Random Frame selection, WFS: Wise Frame Selection.



Figure 24. 3D point cloud map (Tainan, horizontal perspective). RFS: Random Frame Selection. WFS: Wise Frame selection.

From the generated maps, some 3D point clusters and gaps can be identified. In case of Tainan, most highly dense pixels were found at similar building edges for all data sets. RFS video model is less dense than oblique and reference one, but points were generated where oblique imagery does not; this model point distribution is also comparable with at-nadir still imagery models, that practically produces a similar density distribution than the reference model but with lower 3DPC density. For Pescara del Tronto these clusters are also located mainly at building edges, however are less dense. Also for this study area apparently at-nadir still imagery generates less but better distributed 3D point clouds.



Figure 25. Point density distribution boxplots. Maximum values are labelled for every 3DPC. Every data set is divided in four quartiles (Q) and the distribution of every quartile is presented by the box heights.

In case of point cloud distributions, they show the same patterns than analysed 3DPC density maps from either perspective. These distributions are generally skewed and the top twenty-five percent of the top data (forth quartile) is generally at very high ranges; this is associated to point cloud clusters in the raster (e.g. building edges). In case of Tainan, median values show the same pattern observed with the mean 3DPC density analysed above; higher medians are for the Reference and Oblique still imagery models. Likewise, boxes show a more uniform distribution for video-produced 3DPCs than oblique still camera ones. Video WFS-based 3DPCs, present in general less point cloud density, but density is uniformly distributed over the whole area, especially from the horizontal perspective; video RFS ones are more uniformly distributed on the vertical perspective than on the horizontal one. On the contrary for Pescara del Tronto video-based 3DPCs present more uneven distributions, mainly form the vertical perspective; from the horizontal one video WFS model resembles at-nadir still imagery uniform distribution. To complement this, 3DPC incompleteness was measured by the percentage of empty cells in every model (*Figure 26*).



Figure 26. Percentage of gaps from vertical and horizontal perspectives. From vertical perspectives oblique and video WFS (Wise Frame selection) models present more gaps, from the horizontal at-nadir and also WFS model

From this analysis Tainan video 3DPCs show high proportion of empty pixels specially for the horizontal perspective; while from the vertical video RFS model shows almost no gaps even compared to the reference model. Besides, for Pescara del Tronto reasonably lower proportion of empty cells were found from the vertical perspective for at-nadir still imagery model; whereas by the horizontal perspective video-generated models presented less proportion of gaps, in particular the model generated using RFS video frames. For the last study area results are correspondent to the type of data, on the contrary Tainan results are more complex to interpret. From the vertical perspective, it has been seen in the generated maps and also by boxplots, how video RFS model presents a more uniform and more complete (i.e. less empty cells) distribution than oblique imagery one from the vertical perspective, which is alike Reference and at-nadir still imagery. On the other perspective however, video RFS model distribution is uneven and presents a large proportion of empty cells. WFS approach reduces the density distribution showing a more uniform patter from both perspectives, but has negative effects on empty cells proportion in the vertical perspective; RFS approach has no gaps on this perspective by applying WFS some gaps were created.

Completeness was analysed in relation of 3D point density, distribution and gap percentage at this stage. It was observed that completeness is related to resolution, elevation and sensor perspective. For example, due to high elevation and only vertical perspective of at-nadir still imagery, 3D point density was low, even when resolution was considerably high. In general, it can be determined that the most complete 3DPCs are the ones generated from still oblique and video RFS data sets, for Tainan and Pescara del Tronto respectively. Video RFS in Tainan produced lower point density but better distributed 3DPCs than oblique imagery, at least from the vertical perspective; this can be also denoted in the density maps due to some occlusion zones that were not recognized with oblique imagery. Pescara de Tronto videos produced denser 3DPCs than in Tainan, and are also more complete from the horizontal perspective, however they present more gaps from the vertical one. This has to do with elevation and GSD on one hand, since Pescara del Tronto ones are closer to the ground (*Table 2*); on the other terrain surface is the cause of more gaps from the vertical perspective, since video platform only flew in front of the hill and could not make a footage of occluded parts between houses and hill side, especially in upper parts (see also point clouds density map, *Figure 23*).

#### c) External accuracy analysis

The analysis of external accuracy was done only using Tainan data and it shows consistent results regarding the previous assessments. In overall, oblique still imagery models show higher accuracy based on the mean distance to the reference model (*Figure 27*); which also matches with planar fitting and completeness accuracy. The combination of oblique and at-nadir still images are on the opposite the less accurate dataset, since this 3D model score shows a high distance to the reference, which additionally is largely deviated. As it was mentioned recurrently, this is caused due to displacement and duplication effects on the resulting 3DPCs using this data set (*Figure 12*). Video distances are cause by occlusion zone in most cases, however also some large differences on point cloud accuracies were not related to the model quality itself, but to changes or perturbations on the area settings (e.g. presence of cranes or smoke respectively. Mainly related to video RFS model) (see *Appendix 10*, *Appendix 11* and *Appendix 12*).



Figure 27. Mean distance to the reference model (external accuracy). The closer to the reference the higher the accuracy, Still imagery complete (oblique and at-nadir) 3D model presents high deviation and the lowest accuracy due to model orientation errors



Figure 28. Mean distance to the reference model (close up). Video 3D models achieved 7cm accuracy, not that far from still imagery ones, however precision is high due to noise generated from smoke and frame redundancy.

Accuracy of video frames derived 3DPCs is also consistent with observations of previous assessments. Both video models show larger mean distances with respect to the reference model and the same with their deviation, compared to those values obtained by still at-nadir and oblique imagery (*Figure 28*). This shows lower accuracy and precision for video data as it was also demonstrated using planar fitting assessment. A difference with planar fitting is the 3DPC standard deviation between WFS and RFS generated models. Since by planar fitting RFS indicated more precision, and instead in this assessment WFS shows less deviation; a possible cause of it is again smoke effects on RFS models, filtered out using WFS approach. Another reason for dispersion is frame redundancy, which was not corrected using WFS approach.

Despite results here are evident, there are some aspects that should be also argued. First, applying this analysis to Pescara del Tronto, opposite results may arise due to the low point density of at-nadir imagery.

Also referring to completeness, it was also presented in that the 3DPC generated using oblique still imagery presented some gaps which were less evident in the 3DPC obtained using RFS or WFS video frames. Finally, although there is a difference it is of approximately three centimetres, the fact of considering quality of video data adequate or not will depend on the final propose of the 3D model reconstruction. The following sections analyse 3DPC usability and applicability on SDA activities in more detail.

#### 4.2.3. Damage features representability analysis

#### a) Crack features analysis

Based on the mesh models generated using the different 3DPCs derived from imagery and video data from both study areas, a preliminary visual inspection of the cracks was done. In the case of Tainan, the width of the crack was around four centimetres. The reference oblique model allowed to visualize a more defined crack compared to the video RFS mesh model (*Figure 29*). In the case of Pescara, the width of the crack was around five centimetres, and only video data was used to generate the mesh models due to the lack of façade information on the still imagery-generated model. The crack was easily detectable in the RFS video model compared with the WFS video model. Nevertheless, for RFS video model, only normal, and maybe medium resolutions could be used to identify cracks (*Figure 30*).



Figure 29. Cracks recognition for Tainan. The crack can be identified in the oblique model, video (WFS Wise Frame Selection) model is not able to represent this feature



Figure 30. Cracks recognition for Pescara del Tronto. The crack can be identified up to video RFS (Random Frame Selection) medium resolution and video WFS (Wise Frame Selection) original resolution models.

It is interesting to see that for Tainan, RFS video data is not useful to identify the cracks, but in the case of Pescara, RFS video data is the most useful source for crack identification, even for medium resolutions. This could be due to the higher resolution RFS video data has in Pescara compared to RFS video data in Tainan. For instance in Pescara the number of pixels per cell in the horizontal setting is around 16500 points per cell, while in Tainan, the density is lower, 12500 points per cell. The lack of oblique imagery does not allow a complete comparison between both study areas with respect to this kind of data. Further work is suggested in order to make a more complete quantitative analysis. For instance, it is suggested to digitalize the cracks based on the 3DPCs, and then to perform an accuracy assessment analysis between the identified crack and the different mesh models obtained from the image and video data settings.

#### b) Structural failures analysis

As part of structural failures, an analysis of gaps was performed. This analysis was done only for Pescara del Tronto since no gaps were found in Tainan. For Pescara, meshed models of a big building block were used for visual comparison. The results suggest that RFS video data allows a better identification of gaps compared with the at-nadir still imagery. As we can see in *Figure 30*, unlike RFS video data, 3DPCs from at-nadir images capture less number of points. *Figure 30* also shows the differences in distance between RFS video data and at-nadir images. As it can be seen, red and orange areas are points that are present in the video data but not in the at-nadir images. These points represent the potential depth that allows RFS video data to identify the gaps. This could be due to the fact that the density of points per cell is higher in the RFS video data (8781) than in at-nadir still imagery (516), but also the quality of the at-nadir still imagery has a less quality index than the RFS video data due to the emotion blur effect.



Figure 31. Left: Structural failure recognition (Pescara del Tronto). Right: Distance between Video Random Frame Selection (RFS) and at-nadir still imagery models (m).

For the deformations analysis as part of structural failures, visual analysis was performed and was applied only in Tainan due to the different damage settings on both study areas. For instance in Tainan the debris after the earthquake event kept their original geometry (e.g. debris: blocks of walls) since the material of the building was pure concrete. In Pescara the debris was mainly composed of completely fragmented or shredded stone, so deformation was not possible to be analysed. As can be seen in *Figure 32*, when comparing the mesh models from the oblique still imagery and the WFS video data, it can be noticed that WFS video data allows a better representation of more detailed elements and deformations present in the building.



Figure 32. Structural failure recognition (Tainan). RFS: Random Frame Selection. WFS: Wise Frame Selection

This is contrasted with the quantitative results obtained, where it is shown that oblique still imagery have higher density of points than WFS video data, and also the number of empty cells in WFS video data is higher than oblique still imagery. It is also important to notice that this visual inspection based on the mesh models are highly dependent on how these models were generated. This suggest that oblique still imagery could be a more complete type of data than WFS video data to see deformations, but this needs a further analysis. This analysis could be for instance, an accuracy assessment of the two types of data (i.e. oblique still imagery and WFS video data) based on a geometric shape (e.g. rectangular prism) could give a better idea of how far the points have moved from their original shape (before the earthquake).

Also as part of structural failures, debris feature representation was analysed. This analysis was done only in Tainan, for the same reasons as in the deformation analysis. Based on the external accuracy assessment performed between the reference plane (i.e. reference tiled wall), and the video and imagery data it was observed that the distances of the oblique imagery data points to the reference plane were lower compared to the distance of the video data points to the reference plane (*Figure 33*). Also, based on the different planes generated from the video and imagery data, it was observed that imagery data had the same inclination angle than the reference plane (*Figure 34*). Unlike video data, which their inclination angle was one degree higher than the reference plane. The results for video and imagery data are very similar with respect to this analysis.



Figure 33. Left: Inclined wall representation and comparison of oblique and video model fitted planes. Right: mean distances to reference model plane



Figure 34. Left: Inclined wall analysed. Right: Differences between inclined walls using oblique and video WFS (Wise Frame Selection) 3DPCs

#### c) Debris features analysis

Debris was analysed in two parts. The first is the analysis of roughness, and the second, the analysis by visual interpretation. For the analysis of roughness, the CC roughness index was used (*Figure 35*). This index compares changes in elevation in a point surroundings. This allows to determine whether the level of detail of every generated 3DPC is able to identify the particular irregularity of the features. In the case of Tainan, oblique still imagery generated 3DPCs with a higher roughness index in the debris areas compared to the other data types. In Pescara del Tronto, video data (RFS) presented a higher roughness index in the debris areas than the other type of data. These results suggest that roughness could be related to the density of points for imagery and video data. In Tainan, a higher density of points is observed (around 1970 points per cell) for still oblique imagery compared to video data and at nadir imagery. For Pescara, the density of points is also high for RFS video data (1670 points per cell) compared to the other data types.



Figure 35. Roughness indices as an indicator for debris representatibility

Visual inspection was only done in Pescara del Tronto because in Tainan the irregularity of the terrain did not allowed the generation of mesh models (*Figure 36*). For Pescara, video frames and still imagery were used to produce mesh models at normal and low resolutions. Video data is still preferred also for visual inspection.



Figure 36. Mesh models of debris areas from different 3DPCs for visual analysis of debris features representability. Video RFS (Random Frame Selection) 3DPCs are able generate clear debris areas even at low resolutions.

#### d) Spalling features analysis

Finally, spalling zones were analysed. For Tainan, one spalled wall was identified in every 3DPC (*Figure 37*) and different mesh models were created from these 3DPCs. This analysis was not performed for Pescara del Tronto, since no representative objects were identified due to the highly-fragmented structure of the debris. In most of the models it was difficult to recognize all spalling characteristics, with exception of the reference model. The noise present in Tainan data such as present of people, smoke, and other elements (e.g. cars) could influence in the definition of spalling zones. It could be worthy to select different scenarios of spalling walls and try to compare the models again, maybe better mesh models are obtained, which can allow a better comparison of video and imagery data.



Figure 37. Spalling feature mesh models for visual recognition (Tainan). RFS: Random Frame Selection. WFS: Wise Frame Selection

#### 4.3. 3D model application analysis (debris volume change analysis)

For all debris volume estimations, still at-nadir and oblique imagery was used (without refining). The results show a coherent downwards trend on debris volumes which goes from 38,000 to 2 m<sup>2</sup> for still imagery 3D reconstructions (*Figure 38*).



Figure 38. Debris volume change estimations for Tainan computed with the complete (oblique and at-nadir) still imagery-based models.

In order to analyse if the same approach can be followed for video data set, debris volume was calculated for one date using the 3DPC generated from video RFS data set and included in this time series. Additionally, two other relevant 3DPCs were included in this analysis, oblique still imagery and the reference models (*Figure 39*).



Figure 39. Debris volume comparison analysis. video model volume estimation is closer to Reference volume than the other models.

Comparing volume estimations with the ones calculated using video 3DPCs there is a large difference of around 8,315 m<sup>2</sup>. This difference should not be that large, since video data presumably collected the same day of the earthquake, where Search and Rescue (SAR) activities were taken place, therefore no debris was removed. It was observed in previous analysis, that the complete still imagery data set of Tainan (oblique and at-nadir) tends to generate displacement and duplication effects on 3DPCs. This denotes an overestimation of volumes. Besides, comparing video model estimations and the ones form the reference model shows only 136 m<sup>3</sup> of difference; this is also less than the difference between the reference and the oblique still imagery model, 486 m<sup>3</sup>.

Some more detailed remarks are important for this analysis. First that during the volume assessments, trend was not matching with the downwards trending at the beginning; this trend indicated where the problem was, and it was related to a mistake on the collection date information. This shows this application potential even for solving this kind of systemically mistakes. Second, some overestimations were made due to the presence of trucks and cranes, which were inside the computational area (see *Appendix 13*). However, the primary propose of this analysis was to compare the applicability of fast processing models using either still imagery and extracted video frames, for also fast debris estimations. Correction of this overestimations or model refinement comprises resource demanding activities, such as digitalization and MTP identification.

It was demonstrated that in general the realization of this activity is more effective using video data frames. Even considering video low resolution and noise due to smoke, volumes computed with the video framesgenerated model ware fairly close to the reference.

## 5. CONCLUSIONS AND RECOMENDATIONS

In this research the influence of video data artifacts and other quality characteristics on the generation of image-based 3D models has been determined (RQ1); the same was done regarding the application of these 3D models on post-disaster SDA (RQ2). For both analysis, also still imagery was tested for a valid comparison of data quality influences on IBM (RQ3). Two study areas were used for most of the analysis, therefore also the influence of distinctive characteristics of the study areas was examined (RQ4). Additionally, the feasibility of 3D model application on a relevant post-disaster activity, such as debris volume estimation, using still and video data sets was determined (RQ5).

Results demonstrated that all 3DPCs generated from video frames are characterized by high dispersion and less precision, but accuracy was close to still imagery ones. From video quality parameters, resolution did not represent a relevant limitation, since highly dense 3DPCs were generated due to proximity to the ground (GSD). Besides, frame redundancy effects were not well determined, since even when video frames were appropriately selected by WFS approach, dispersion did not decrease. It can be that this quality element had not much relevance on the 3DPC absolute quality, because in most cases WFS video frames produced imprecise and incomplete models. Nevertheless, this is arguable due to the application of a unplanned methodology due to the unsatisfactory results obtained from the original WFS approach. Video artifacts, such as motion-blur effects instead were clearly identified during the direct quality assessment; unexpectedly in this case low quality indices were associated mainly to at-nadir still data set. In relation to external accuracy, video-based generated models were in average alike the ones obtained by oblique imagery; oblique imagery accuracy was 1 cm, and video frames (RFS) 7 cm, the relevance of these 6 cm of difference will depend on the application. Analysis on SDA application on one hand demonstrated favourable results for the analysis of debris, structural failures and cracks, with exception of Taiwan video, which has higher flight elevation and GSD (Table 2). On the other hand, features like spalling and wall inclination were not properly characterized by video frames in the 3DPCs. In comparison to still camera more advantages were found in comparison to at-nadir imagery, oblique imagery performed better for inclined walls characterization, but neither could not distinguish spalling features.

Quality of video and oblique video by the distinctive characteristics of study areas was influenced in two aspects. First, influence of smoke in Tainan did influence on image quality index values for video data, and consequently on video-generated 3Dmodel accuracy and precision. Second, topography also influenced on the gap percentage and model orientation. In Pescara, more gaps were produced even considering video frames lower elevation and GSD; this is due occlusion effects on the areas between hill sides and houses which where larger upwards. On the opposite, a better orientation of 3D models was obtained due to the variate localization of 3D GCPs on the Z axis (i.e. height); In Tainan this was more difficult due to the terrain flatness and effects were mainly reflected on displacement and duplication effects on the oblique and complete still imagery 3D models, respectively.

Debris volume change estimations were done uniquely using still imagery complete dataset. The results were found logical due to the downwards trend of debris change, however when compared to video based estimations a difference of almost 8,000 m<sup>3</sup> was determined. Due to the know geometrical errors of the still imagery 3DPC, the reference and oblique 3D models were used for an additional analysis. It was thus determined a higher accuracy in this application for Video data which is 136 m<sup>3</sup> below the estimated by the reference model; less even than the oblique imagery model which in turn overestimated 486 m<sup>3</sup>.

Likewise, some recommendation for further research were defined based on the main gaps and the conclusions reached in this research:

- A deeper analysis on the usability for SDA could be done using more elaborated feature-specific techniques for damage feature representations. The results found here can be used as guide to focus on the ones can be at least visually detected on 3D models.
- A synthetic experiment where even higher video resolutions (4K) and other data acquisition parameters are specifically tested could support conclusions arrived in this research. Thus also more data such as TLS or ground-based SDA classifications can be used as benchmark.
- Another interesting parameter to analyse is geolocalization or 3DPC registration using 3D GCPs from open sources. Nonetheless, spatial limitations of current open geo-information sources for 3DPC identification have to be considered.
- Image quality index showed worthy results for frames selection, a more elaborated WFS approach using as complement efficient similarity filters could be tested developed.

### LIST OF REFERENCES

- 3D Flow. (2016). 3D Zephyr overview. Retrieved February 9, 2017, from http://www.3dflow.net/3df-zephyr-pro-3d-models-from-photos/
- 3D Flow. (2017). Image quality index details. Retrieved February 1, 2017, from http://www.3dflow.net/it/forums/topic/image-quality-index-details/#post-7546
- Abbas, M. A., Lichti, D. D., Chong, A. K., Setan, H., Majid, Z., Lau, C. L., ... Ariff, M. F. M. (2017). Improvements to the accuracy of prototype ship models measurement method using terrestrial laser scanner. *Measurement*, 100, 301–310. https://doi.org/10.1016/j.measurement.2016.12.053
- Adams, S., Friedland, C., & Levitan, M. (2010). Unmanned Aerial Vehicle Data Acquisition for Damage Assessment in Hurricane Events. 8th International Workshop on Remote Sensing for Disaster Management, (August 2016), 1–7. Retrieved from

http://www.enveng.titech.ac.jp/midorikawa/rsdm2010\_pdf/13\_adams\_paper.pdf

- Alsadik, B., Vosselman, G., & Gerke, M. (2015). Efficient Use of Video for 3D Modelling of Cultural Heritage Objects. Munich, Germany: ResearchGate. https://doi.org/10.5194/isprsannals-II-3-W4-1-2015
- Arciniegas, G. A., Bijker, W., Kerle, N., & Tolpekin, V. A. (2007). Coherence- and amplitude-based analysis of seismogenic damage in Bam, Iran, using ENVISAT ASAR data. *IEEE Transactions on Geoscience and Remote Sensing*, 45(6), 1571–1581. https://doi.org/10.1109/TGRS.2006.883149
- Barrington, L., Ghosh, S., Greene, M., Har-Noy, S., Berger, J., Gill, S., ... Huyck, C. (2011). Crowdsourcing earthquake damage assessment using remote sensing imagery. *Annals of Geophysics*, 54(6), 680–687. https://doi.org/10.4401/ag-5324
- Baumann, P. (2014). History of remote Sensing, aerial photography. Retrieved July 26, 2016, from http://www.oneonta.edu/faculty/baumanpr/geosat2/RS History I/RS-History-Part-1.htm
- Boccardo, P., Chiabrando, F., Dutto, F., Tonolo, F. G., & Lingua, A. (2015). UAV deployment exercise for mapping purposes: Evaluation of emergency response applications. *Sensors (Switzerland)*, *15*(7), 15717–15737. https://doi.org/10.3390/s150715717
- Cloud Compare. (2015a). Mesh\Delaunay 2.5D (best fit plane). Retrieved July 2, 2017, from http://www.cloudcompare.org/doc/wiki/index.php?title=Mesh%5CDelaunay\_2.5D\_(best\_fit\_plan e)
- Cloud Compare. (2015b). Roughness. Retrieved February 10, 2017, from http://www.cloudcompare.org/doc/wiki/index.php?title=Roughness
- Dekker, R. J. (2011). High-resolution radar damage assessment after the earthquake in Haiti on 12 january 2010. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 4(4), 960–970. https://doi.org/10.1109/JSTARS.2011.2164516
- Dell'Acqua, F., & Polli, D. A. (2011). Post-event Only VHR Radar Satellite Data for Automated Damage Assessment. *Photogrammetric Engineering & Remote Sensing*, 77(10), 1037–1043. https://doi.org/10.14358/PERS.77.10.1037
- Ehrlich, D., Guo, H. D., Molch, K., Ma, J. W., & Pesaresi, M. (2009). Identifying damage caused by the 2008 Wenchuan earthquake from VHR remote sensing data. *International Journal of Digital Earth*, 2(4), 309–326. https://doi.org/10.1080/17538940902767401
- Fernandez, J. (2014). Urban structural damage assessment using object-oriented analysis and semantic reasoning. https://doi.org/10.5194/nhessd-2-5603-2014
- Fernandez, J., Kerle, N., & Gerke, M. (2015). UAV-based urban structural damage assessment using object-based image analysis and semantic reasoning. *Natural Hazards and Earth System Science*, 15(6), 1087–1101. https://doi.org/10.5194/nhess-15-1087-2015
- Fernandez Galarreta, J., Kerle, N., & Gerke, M. (2015). UAV-based urban structural damage assessment using object-based image analysis and semantic reasoning. *Natural Hazards and Earth System Science*, 15(6), 1087–1101. https://doi.org/10.5194/nhess-15-1087-2015
- Geomares. (2014). Digital Oblique Aerial Cameras. Retrieved December 10, 2016, from https://www.gim-international.com/content/article/digital-oblique-aerial-cameras-1
- Gerke, M. (2014). Modern Image Calibration , Orientation and matching (Notes). Enschede, The Netherlands.
- Gerke, M., & Kerle, N. (2011). Automatic Structural Seismic Damage Assessment with Airborne Oblique Pictometry© Imagery. *Photogrammetric Engineering & Remote Sensing*, 77(9), 885–898.

https://doi.org/10.14358/PERS.77.9.885

- Girardeau-Montaut, D. (2017). CloudCompare 3D point cloud and mesh processing software Open Source Project. Retrieved February 9, 2017, from http://www.cloudcompare.org/
- Hussain, E., Ural, S., Kim, K., Fu, C. S., & Shan, J. (2011). Building Extraction and Rubble Mapping for City Port-au-Prince Post-2010 Earthquake with GeoEye-1 Imagery and Lidar Data. *Photogrammetric Engineering and Remote Sensing*, 77(10), 1011–1023. https://doi.org/Export Date 6 May 2013
- Jarzabek-Rychard, M., & Karpina, M. (2016). Quality analysis on 3d building models reconstructed from uav imagery. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences -ISPRS Archives, 2016–Janua(July), 1121–1126. https://doi.org/10.5194/isprsarchives-XLI-B1-1121-2016
- Kanda, K., Miyamoto, Y., Kondo, A., & Oshio, M. (2005). Monitoring of earthquake induced motions and damage with optical motion tracking. *Smart Materials and Structures*, 14(3), S32–S38. https://doi.org/10.1088/0964-1726/14/3/005
- Kazhdan, M. (2015). Poisson Surface Reconstruction (plugin). Retrieved February 10, 2017, from http://www.cloudcompare.org/doc/wiki/index.php?title=Poisson\_Surface\_Reconstruction\_(plugin )
- Kelman, I. and S. P. (2004). Disaster Definitions, 2006(May), 17. Retrieved from http://www.ilankelman.org/miscellany/DisasterDefinitions.rtf
- Kerle, N. (2010). Satellite-based damage mapping following the 2006 Indonesia earthquake-How accurate was it? International Journal of Applied Earth Observation and Geoinformation, 12(6), 466–476. https://doi.org/10.1016/j.jag.2010.07.004
- Kerle, N., & Stekelenburg, R. (2004). Advanced Structural Disaster Damage Assessment based on aerial oblique video imagery and integrated auxiliary data sources. In XXth ISPRS Congress (p. 6). Istambul, Turkey.
- Kersten, T. P., & Lindstaedt, M. (2012). Automatic 3D Object Reconstruction from Multiple Images for Architectural, Cultural Heritage and Archaeological Applications Using Open-Source Software and Web Services. *Photogrammetrie - Fernerkundung - Geoinformation*, 2012(6), 727–740. https://doi.org/10.1127/1432-8364/2012/0152
- Khoshelham, K. (2012). Accuracy Analysis of Kinect Depth Data. ISPRS International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVIII-5/, 133–138. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W12-133-2011
- Khoshelham, K., Elberink, S. O., & Xu, S. (2013). Segment-Based Classification of Damaged Building Roofs in Aerial Laser Scanning Data. *IEEE Geoscience and Remote Sensing Letters*. https://doi.org/10.1109/LGRS.2013.2257676
- Lichti, D. D. (2007). Error modelling, calibration and analysis of an AM-CW terrestrial laser scanner system. *ISPRS Journal of Photogrammetry and Remote Sensing*, 61(5), 307–324. https://doi.org/10.1016/j.isprsjprs.2006.10.004
- Mitomi, H., Saita, J., Matsuoka, M., & Yamazaki, F. (2001). Automated damage detection of buildings from aerial television images of the 2001 Gujarat, India earthquake. *IGARSS 2001. Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No.01CH37217)*, 1(C), 147–149. https://doi.org/10.1109/IGARSS.2001.976085
- Nex, F. (2016). Quality Assessment of Point Clouds [Slides]. Enschede, The Netherlands: Lecture notes of Mod. 13 3D modelling. ITC-Faculty.
- Nex, F., & Remondino, F. (2014). UAV for 3D mapping applications: A review. *Applied Geomatics*, 6(1), 1–15. https://doi.org/10.1007/s12518-013-0120-x
- Ogawa, N., & Yamazaki, F. (2000). Photo-interpretation of building damage due to earthquakes using aerial photographs. *12Th World Conference on Earthquake*, 1–8. Retrieved from http://ares.tu.chiba-u.jp/~papers/paper/WCEE/1906Ogawa.pdf
- Ozisik, D., & Kerle, N. (2004). Post-earthquake damage assessment using satellite and airborne data in the case of the 1999 Kocaeli earthquake, Turkey. *Proc. of the XXth ISPRS Congress: Geo-Imagery Bridging Continents*, (21), 686–691.
- Pix4d. (2016a). How Pix4Dmapper calculates the Volume? Retrieved February 10, 2017, from https://support.pix4d.com/hc/en-us/articles/202559239-How-Pix4Dmapper-calculates-the-Volume-#gsc.tab=0
- Pix4d. (2016b). Pix4d Industry Surveying and construction. Retrieved December 10, 2016, from https://pix4d.com/industry/
- Remondino, F., Pizzo, S. Del, Kersten, T. P., Troisi, S., Metrology, O., Kessler, B., & Fbk, F. (2012). for

Automated Image Orientation – A Critical Overview, 40–54.

- Remondino, F., Spera, M. G., Nocerino, E., Menna, F., & Nex, F. (2014). State of the art in high density image matching. *The Photogrammetric Record*, 29(146), 144–166. https://doi.org/10.1111/phor.12063
- Saedi, Y. (2015). COMPREHENSIVE REMOTE SENSING BASED BUILDING DAMAGE CLASSIFICATION. Faculty of Geo-Information Science and Earth Observation of the University of Twente.
- Sahin, Y. G., Kabar, A. O., Saglam, B., & Tek, E. (2011). Real-time monitoring environment to detect damaged buildings in case of earthquakes. *Communications in Computer and Information Science*, 188 CCIS(PART 1), 419–425. https://doi.org/10.1007/978-3-642-22389-1\_37
- Schweier, C., & Markus, M. (2006). Classification of collapsed buildings for fast damage and loss assessment. Bulletin of Earthquake Engineering, 4(2), 177–192. https://doi.org/10.1007/s10518-006-9005-2
- Soudarissanane, S., Lindenbergh, R., & Gorte, B. (2005). Reducing the Error in Terrestrial Laser Scanning By Optimizing the Measurement Set-Up, 615–620.
- Soudarissanane, S., Lindenbergh, R., Menenti, M., & Teunissen, P. (2009). Incidence angle influence on the quality of Terrestrial Laser Scanning points, (February 2017), 183–188. Retrieved from http://www.tlsdatabase.ucalgary.ca/node/284
- Tian, Y., Vosselman, G., & Zhu, Q. (2011). Building Reconstruction From Terrestrial Video Image Sequences.
- University of California. (2016). Suspicious Collapse of Twin Towers. Retrieved September 27, 2016, from http://seismo.berkeley.edu/blog/seismoblog.php/2016/02/07/suspicious-collapse-of-twin-towers
- Van Westen, C. (2012). Application of Space Technology for Disaster Risk Reduction (p. 40). Dehradun, India: Indian Institute of Remote Sensing (IIRS), Centre for Space Science and Technology Education in Asia and the Pacific (CSSTEAP).
- Vetrivel, A., Gerke, M., Kerle, N., & Vosselman, G. (2015). Identification of damage in buildings based on gaps in 3D point clouds from very high resolution oblique airborne images. *ISPRS Journal of Photogrammetry and Remote Sensing*, 105, 61–78. https://doi.org/10.1016/j.isprsjprs.2015.03.016
- Xiong, X., Adan, A., Akinci, B., & Huber, D. (2013). Automatic creation of semantically rich 3D building models from laser scanner data. *Automation in Construction*, 31, 325–337. https://doi.org/10.1016/j.autcon.2012.10.006
- Zhang, C., Wang, T., Liu, X., & Zhang, S. (2010). Cognitive model based method for earthquake damage assessment from high-resolution satellite images : A study following the WenChuan earthquake. *Analysis*, (2006), 2079–2083.

## APPENDIXES



Appendix 1. Noise due to smoke in video-generated 3DPC



Appendix 2. MTP selection for refining procedure (Befor and after refining)



Appendix 3. Plane surfaces used for planar fitting analysis



Appendix 4. Noise reduction with resolution degradation (medium resolution) for still imagery model. Low resolution instead loses also essential information



Appendix 5. Horizontal point cloud density maps for Tianan datasets



Appendix 6. Horizontal point cloud density maps for Pescara del Tronto datasets



Appendix 7. Vertical point cloud density map for Tainan datasets



Appendix 8. Vertical point cloud density map for Pescara del Tronto dataset



Appendix 9. Dots used as mask for point density distribution and empty cells proportion estimations



Appendix 10. Video main differences with reference model. Up: noise due to smoke perturbation. Down: Occlusion zones



Appendix 11. Differences due to changes in scenario settings. A crane was mistakenly modelled only for one data set.



Appendix 12. Point cloud distance to the reference model for most video and still imagery generated models. Problems such as occlusion, changes in scenario settings and smoke perturbations, causes the main differences for video data.



Appendix 13. Volume calculation overestimation example, made by blue crane.