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Robust surface matching as a rapid technique for terrain change detection

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Abstract

Digital elevation models (DEMs) are widely used in GIS to predict the impact of coastal flooding and Sea Level Rise in coastal areas. Furthermore, DEM change detection within a certain time period may be also used to automatically quantify the coastal landscape changes. In this sense many researchers have adopted 3D surface matching techniques without control points (GCPs) to automatically co-register multi-temporal DEMs.

In this paper a new approach based on robust surface matching for DEM 3D geo-referencing is proposed to avoid the costly and time-consuming necessity of GCPs. The algorithm starts from a coarse orientation of the historical DEM where the stereo model y-parallax is removed by means of an Automatic Relative Orientation. Additionally, it is necessary to manually mark three control points to apply a coarse Helmert 3D transformation, obtaining a preoriented stereo-pair which turned out to be helpful to improve and speed up the subsequent surface matching process. Absolute z-differences between reference and historical DEMs are calculated, allowing for the application of the widely known K-means algorithm to cluster up to four groups of homogeneous absolute differences. The two clusters showing the high values are considered as outliers or areas where terrain has significantly changed. The remaining areas are deemed as potentially matching areas where the robust surface matching can be applied using the M-estimator called Tukey's Biweight (TB). In this way the diagonal weight matrix, regarding TB function, is introduced in an iterative least square routine to compute the Helmert 3D transformation parameters.

The proposed methodology was tested for geo-referencing a historical grid format DEM, comprising a little coastal area of Almeria (South Spain), obtained by digital stereo-photogrammetry from a B&W photogrammetric flight taken in 1977 at an approximated scale of 1:18000. The reference DEM was the 10 m grid-spacing digital elevation model produced by the Andalusia Regional Government (Spain) from a 1:20000 scale B&W photogrammetric flight taken in 2001. As well, we counted on two accurate DEMs based on LiDAR technology (ground truth) taken in 2005 and 2009 respectively.

The results obtained from this work may be deemed as very promising, showing a high efficiency and accuracy for historical DEM 3D geo-referencing. After the application of the robust surface matching for non-altered or stable areas, the computed uncertainty, measured as standard deviation of DEM z-differences, turned out to be 1.08 m. That is quite similar to the estimated uncertainty for the reference model (around 1.03 m).

1 Introduction

Spatial registration of multidate data is required for many applications in remote sensing, such as change detection, the construction of image mosaics, Digital Elevation Models (DEMs) generation from stereo pairs, and orthorectification. The geometric correction must be accurate enough, because misalignments of features at the same location could render the results useless.

On the other hand, DEMs are widely used in GIS to predict the impact of coastal flooding and Sea Level Rise (SLR) in coastal areas. Furthermore, DEM change detection within a certain time period may be also used to automatically quantify the coastal landscape changes. In this sense many researchers have adopted 3D surface matching techniques without control points to automatically co-register multi-temporal DEMs, usually using the newer DEM as the reference surface to achieve the 3D registration of an older and generally less accurate DEM [1], [2], [3], [4] and [5].

In fact, nowadays DEM production is efficiently accomplished by means of LiDAR technology which is contributing, often coupled with passive optical imaging, to a wide range of coastal scientific investigations [6]. Nonetheless, as LiDAR is a relatively new technology, historical data beyond the past decade are practically unavailable [7]. This is the reason why most of the studies headed up to extract shoreline position and evolution along a certain period of time (*i.e.* monitoring studies) are mainly based on rectified aerial photographs, beach profiles from surveying techniques and topographic maps.

Despite DEMs are deemed as the best choice to extract accurate shoreline position [8], few attempts have involved stereo-photography and thus 3D information extraction to monitoring shoreline evolution. Taking into account that the accuracy of DEMs is clearly bound to the accuracy of the derived variables via error propagation [9], it is crucial to start from the best possible DEM, both for newly-made DEMs and for historical DEMs mostly compiled from historic stereo photogrammetric flights.

The same could be said about terrain change detection from multitemporal stereo-photogrammetric flights [7] where it is necessary to count on a precise and well distributed set of ground control points (GCPs) to georeference the generated DEM. However those GCPs are cumbersome to obtain in remote areas or from relatively old flights, simply because historical features are difficult to be currently localized and measured or even pointed out onto the digital images (fig. 1) depending on their scale, resolution and radiometric quality.

Furthermore, the current process of manual GCP measurement can be prohibitively labor-intensive for large projects under operational conditions, and it does not enforce subpixel level correlation between images due to the limitation of human visual interpretation.

In this way, the main goal of this work is to develop, test and validate a new rapid, efficient and robust surface matching algorithm, non sensitive to true terrain changes (considered as outliers in the surface matching jargon), able to georeference coarse-oriented historical DEMs using a newer DEM as the reference surface without the need of GCPs. In this sense, the paper is structured as follows: In section 2 the skeleton and workflow corresponding to the new robust surface matching approach are presented. The study site and datasets are subjects of section 3. In section 4 the results are presented and discussed, followed by the conclusions and outlook on future studies in section 5.

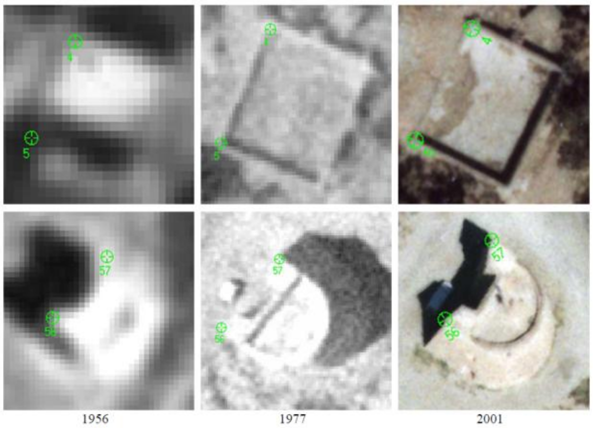

Fig. 1 Difficulty in ground control point location working on historical photogrammetric images (rough scales: 1956-1:33000, 1977-1:18000, 2001-1:5000).

2 Robust surface matching approach

The basic flow chart diagram regarding the new robust surface matching fundamentals is shown in fig. 2. Briefly, the proposed method starts from a coarse relative orientation of the historical DEM, applied onto previously digitized photographs, where the stereo model y-parallax is removed by means of an Automatic Relative Orientation (ARO).

Subsequently, suitable photogrammetric software must be utilised to carry out the interior orientation and the ARO processes. In this case ImageStation Digital Mensuration software (ISDM 4.0® from Z/I Imaging) was employed. As it is widely known, ARO is the process that determines the relationship between two overlapping images, providing the position and attitude of one image with respect to another image by automatically matching tie points. Thus it is an unattended process. Nonetheless it is worthy to manually mark three control points (two full points XYZ and one only Z point) to apply a coarse seven parameters Helmert 3D transformation, obtaining a preoriented stereo-pair which will be very helpful to improve and speed up the convergence of the subsequent robust surface matching process. It is important to notice that those ground points only have to present approximated coordinates, both horizontal and vertical, so they can be easily extracted from available orthophotos (horizontal) and supposing a common Z (e.g. an average ground height for the whole working area).

In this way, a Digital Surface Model (DSM) or, after applying a filtering process, a DTM (Digital Terrain Model), can be obtained by means of digital stereo image matching techniques [10]. ImageStation Automatic Elevations (ISAE 4.0® from Z/I Imaging) was the software utilised to automatically generate a large number of DSM points.

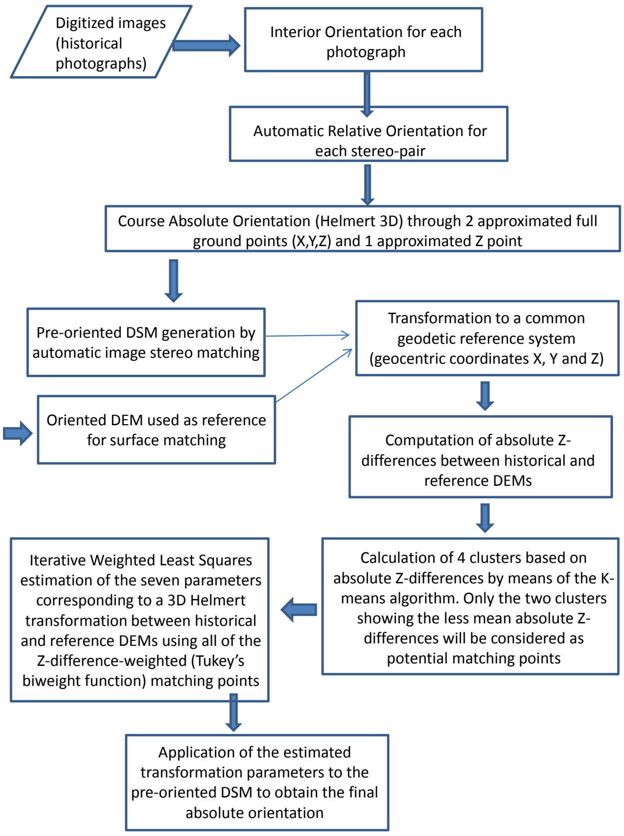

Fig. 2 Flow chart diagram showing the algorithm fundamentals.

The next step consisted of using a reference DEM (a more recently obtained and already georeferenced DEM) as a reference topographic surface to robustly register the preoriented historical DEM. The conjugate points were extracted by planimetrically overlapping both DEMs (e.g. map projection UTM ETRS89 and heights above GRS80 ellipsoid) using bilinear interpolation over the reference

DEM to obtain different and planimetrically corresponding elevations (one for each DEM). At this time, those non-overlapping points detected have to be pointed out and excluded from the matching process from here onwards (i.e. each observation is assigned a weight 0). In this way, a dense dataset of residuals or Z-differences (r_i) between historical and reference DEM for every grid point can be computed.

The widely known K-means clustering method was employed to take into account potential divergences between new and old DEM elevations due to true terrain change. Those true changes are deemed here as outliers, and thus they have to be excluded from the surface matching process. In K-means clustering we are given a large dataset of N absolute z-differences data points in a 2-dimensional space and an integer K (K=4 for our particular application), and the problem is to separate the N observations into K clusters by means of an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves points between clusters until the sum cannot be decreased further. The result is a set of K clusters that are as compact and well-separated as possible [11]. In this way, once the four clusters involving absolute z-differences are computed, the two clusters presenting higher mean absolute z-differences are to be considered as potentially altered areas and so discarded to be applied in the subsequent matching process. The remaining clusters are considered as potentially matching areas where the robust surface matching can be applied using the M-estimator called Tukey's Biweight (TB). TB function is one of the most commonly-utilised M-estimators, and as noted by [12], is difficult to surpass in terms of delivering good performance in most situations. The weight function is defined as follows:

$$w(u_i) = \begin{cases} (1-u_i)^2 & if\ |u_i| \leq 1 \\ 0 & if\ |u_i| > 1 \end{cases} \qquad (1)$$

Being u_i the standardised least-squares residuals (r_i/σ), where σ is the standard deviation of all the residuals potentially selected to intervene in the surface matching process. In this way the diagonal weight matrix regarding TB function ($w(u_i)$ in eq. 1) is introduced in an iterative and massive least square weighted solution ([2], [13]) to compute the so-called Molodensky-Badekas seven-parameters transformation:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \lambda \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} \Delta X \\ \Delta Y \\ \Delta Z \end{bmatrix} \qquad (2)$$

Where λ is a global scale non-dimensional factor and ΔX, ΔY and ΔZ (m) are the three translations along the coordinate axes. The orthonormal rotation matrix is represented by 3x3 elements which are trigonometric functions of the rotation angles Ω, Φ and K. The coordinates of both reference systems must be previously transformed to geocentric coordinates.

Afterwards estimating the seven transformation parameters, the resulting 3D transformation was applied to the historical DEM (using geocentric coordinates) to orientate it. All the processes constituting this basis framework, except for ARO and DEM generation, were programmed using MATLAB® code (fig. 3).

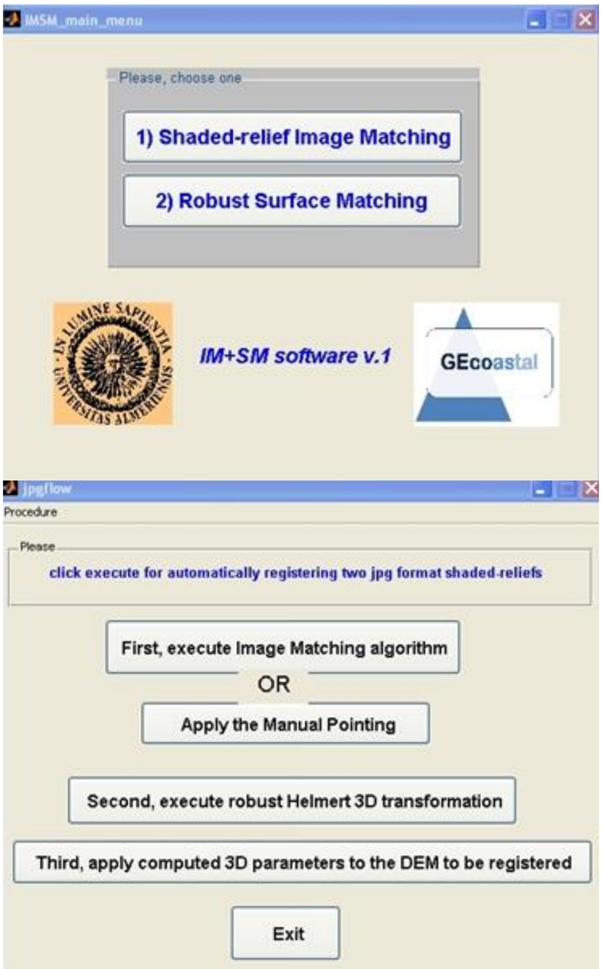

Fig. 3 Software developed to carry out the proposed methodology based on Matlab© code.

3 Study site and datasets

3.1 Study site

The previously described robust surface matching method was tested on one stereo-pair belonging to a historical photogrammetric flight which will be described in the next section. The study area comprised a heavily developed coastal area of Almería (Mediterranean Sea, Southeast Spain). It was situated between the harbor of Garrucha and Antas dry-ravine mouth (fig. 4). This is currently a high risk inundation zone joined to an urban area of high cultural density.

3.2 Datasets

3.1 Dataset corresponding to 1977 (Historical Flight)

It comes from an analogic W&B stereo-pair belonging to the so-called "Agriculture Photogrammetric Flight". This flight presented an approximated scale of 1:18000 and focal distance around 152.77 mm. It was taken in 1977. A 10 m grid-spacing DSM was carried out by means of stereo matching techniques (ISAE 4.0® from Z/I Imaging) ranking over previously digitized images (15 microns per pixel ≈ 30 cm ground sample distance) with a radiometric resolution of 8 bits. ISDM 4.0®, from Z/I Imaging, was used to carry out the preliminary coarse orientation by means of automatic relative orientation (see section 2).

To test the capability of the developed method to deal with highly deformed DEMs (i.e. not quite well preoriented), different rotations, translations and scale changes were applied to the original preoriented DEM to obtain three synthetic deformed DEMs, as it is described in tab. 1.

Parameters	Shifts, rotations and scale change applied to the preoriented DSM 1977 to produce synthetic deformations		
	Version 1	Version 2	Version 3
ΔX	10 m	50 m	100 m
ΔY	10 m	50 m	100 m
ΔZ	10 m	50 m	100 m
ΔΩ	10º	30º	45º
ΔΦ	10º	30º	45º
ΔK	10º	30º	45º
Δλ	0.9	0.7	0.5

Tab. 1 Synthetic deformations applied to the preoriented DSM 1977.

Fig. 4 Image of the study site along the Almeria coast.

3.2. Reference dataset corresponding to 2001

The reference DEM corresponding to 2001 consisted of a 10 m grid-spacing DTM produced by the Andalusia Regional Government (Spain) throughout a photogrammetric flight taken in 2001 at an approximated scale of 1:20000. This original DTM was transformed from UTM European Datum 1950 and orthometric heights to the new Spanish official geodetic system called the European Terrestrial Reference System (ETRS89) and elipsoidic heights above GRS80 ellipsoid. The corresponding DTM accuracy was estimated upon 62 DGPS check points located at open terrain, yielding a standard deviation value close to 1.03 m. The historical DEM to georeference (1977) and the reference DEM (2001) are depicted in fig. 5 as 3D surface maps.

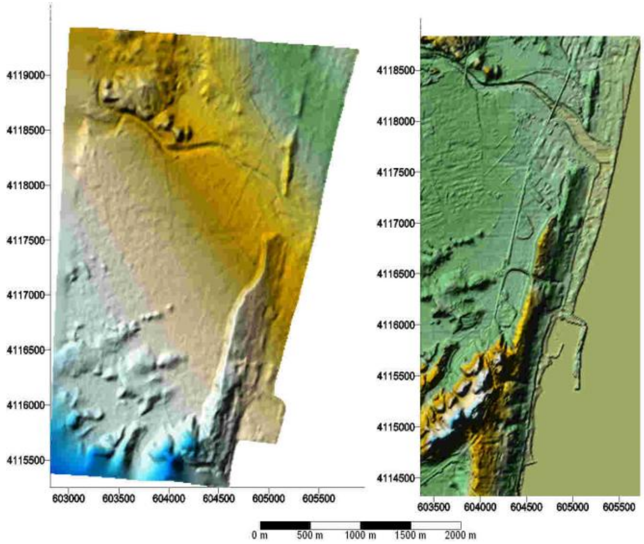

Fig. 5 Photogrammetrically-derived DEMs corresponding to 1977 (left) and 2001 (right). Reference system UTM-ETRS89.

3.3 Validation datasets

Two validation datasets were used in this work to test the accuracy of the Robust Surface Matching (RSM) oriented historical DEM.

The first one consisted of a LiDAR dataset taken during August and September 2004 in the framework of a project led by the Water Andalusian Agency (Andalusia Regional Government) to carry out a flood risk mapping study in Andalusia, Spain. The LiDAR data capture was handled by the Cartographic Institute of Calalunya (Spain) by means of an Optech ALTM 3025 LiDAR sensor. Among its main operational parameters, we highlighted the following ones: flight height 2300 m, point density 1 point/m^2 and computed vertical accuracy between 6 cm and 15 cm depending on the land cover. The accurate and high resolution (1 m grid spacing) raw DSM was filtered and decimated using TerraScan© software to produce a 3 m grid spacing DTM comprising a non urbanized zone along the Antas dry-ravine bed and within the working area (vid. fig. 8).

The second one constituted a very recent DEM taken in 2009 in the context of a research project funded by the Andalusia Regional Government comprising the whole working area (vid. fig. 9). This second DEM was a high accuracy and resolution LiDAR-derived DEM. The flight height above ground was about 1000 m, using a Leica ALS60 airborne laser scanner with 35º FOV, 1.61 points/m^2 average point density. The estimated vertical accuracy computed from 62 DGPS high accuracy check points distributed over the whole working area offered a vertical accuracy (measured as standard deviation) of 8.9 cm. All the processes to filter the laser point cloud, adjusting the four flight-lines strips and managing LiDAR data were carried out by means of TerraMatch® and TerraScan® software. The initial very high resolution DEM was resampled to an easier to handle 5x5 m grid DEM.

4 Results and discussion

4.1 Coarse preoriented DEM using ARO

The initial preoriented historical DEM presented a clearly diagonal-rotated (N-W to S-E direction) leaning as compared with the 2001 reference DEM. It originated a sparse histogram of signed vertical residuals, as can be observed in fig. 6.

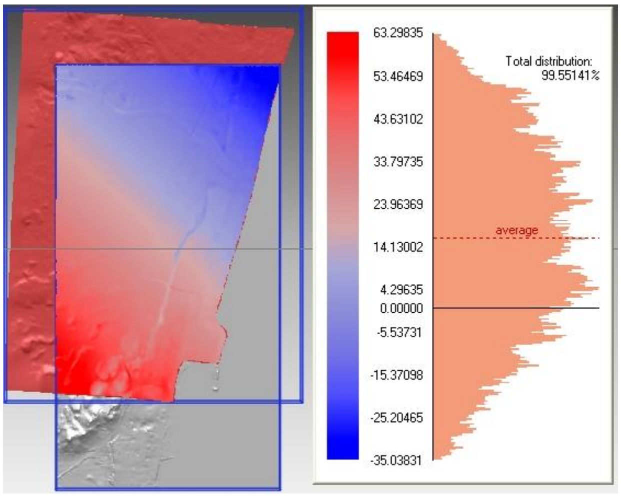

Fig. 6 Distribution of signed vertical residuals (initial preoriented DSM 1977 – DTM 2001 within the overlap area) and the corresponding histogram.

The mean error took a value of 16.12 m (tab. 3), indicating a notable overall bias or systematic error in the pre-orientation process as could be expected given the approximated coordinates of the ground points utilised to compute the absolute orientation. At the same time, random errors also were very large as can be deduced from the high standard deviation of the whole Z-differences (tab. 3). Thus the starting pre-orientation should be improved a lot to allow an acceptable terrain change detection analysis. In this case it is necessary to cope with these high local deformations by treating them as outliers, and the designed algorithm, as a robust estimator technique, should be less sensitive to the existence of outliers. It is a non easy to resolve problem because there will be coexisting matching points, gross errors (significant surface differences due to the passage of time) and boundary outliers (i.e. points within the transition area). In the remaining sections the proposed algorithm will be tested to check its ability to afford that intriguing challenge.

4.2 Iterative least-squares weighted solution

According to the results depicted in tab. 2, and incorporating the weight matrix aforementioned in section 2, the seven parameters for the 3D Helmert transformation can be computed by means of an iterative least-squares weighted estimation. The shifts and rotations can be considered as relatively small, which it was expected owing to a not excessively bad pre-orientation. The accuracy for the estimated parameters, calculated through the dispersion matrix, is very high. It was due to the huge number of matching points what confers to the process an important soundness. Despite the matching area, once excluded the potentially outliers from the K-means algorithm, was quite reduced (around 42% of the whole points were employed to carry out the RSM; vid. fig. 6), the number of steps till reaching the final convergence through the iterative algorithm was always lower than 10 and normally lower than five.

Parameters	Estimated parameters	
	value	accuracy
ΔX	-3.319 m	0.0031 m
ΔY	0.177 m	0.0031 m
ΔZ	-2.439 m	0.0057 m
$\Delta\Omega$	0.630º	3.64E-04º
$\Delta\Phi$	0.974º	3.75E-06º
ΔK	-0.744º	3.18E-06º
λ	0.9998	4.79E-06

Tab. 2 Estimated parameters and corresponding accuracy for the 3D Helmert iterative least-squares adjustment

4.3 Robust surface matching validation

Afterwards using the RSM algorithm, the initial 1977 historical DEM position respect to the 2001 reference DEM has been notably corrected and the matching results have been clearly improved (fig.7). In fact, signed vertical error distribution showed a non-disperse histogram without systematic error and low uncertainty (mean error around -0.14 m and standard deviation of 2.17 m; vid. tab. 3). Furthermore the spatial error distribution turned out to be quite stable and homogeneous over the whole working area, what indicated a good performance of the matching algorithm able to correct the poor pre-orientation of the original historical DEM (cf. fig. 7 and 8).

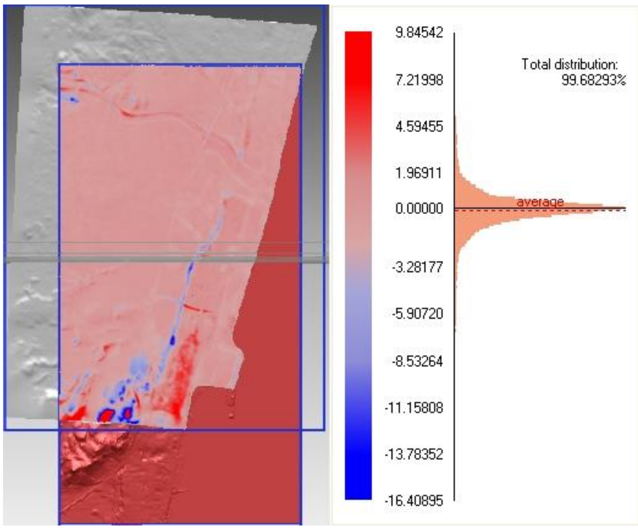

Fig. 7 Distribution of signed vertical residuals (RSM oriented DSM 1977 – DTM 2001 within the overlap area) and the corresponding histogram.

The same could be said about the validation results regarding the LiDAR DTM corresponding to the Antas dry-ravine (fig. 8). This area can be supposed as non-altered during the last decades and so reasonably free of change.

In this sense the maximum and minimum errors were the lowest, while the matching accuracy worked the best (standard deviation of 1.08 m; tab. 3), even being lower than the estimated uncertainty for the reference model of around 1.34 m. That was a good new, demonstrating the great capacity of this method to obtain excellent multidate surface registrations without costly and time-consuming ground points.

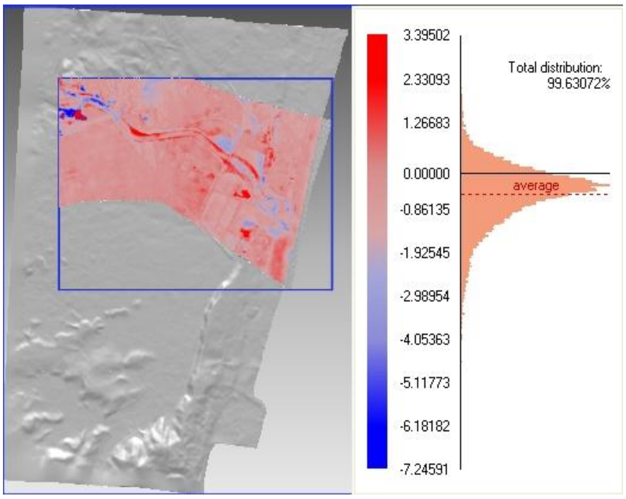

Fig. 8 Distribution of signed vertical residuals (RSM oriented DSM 1977 – Antas dry-ravine DTM 2004 within the overlap area) and the corresponding histogram.

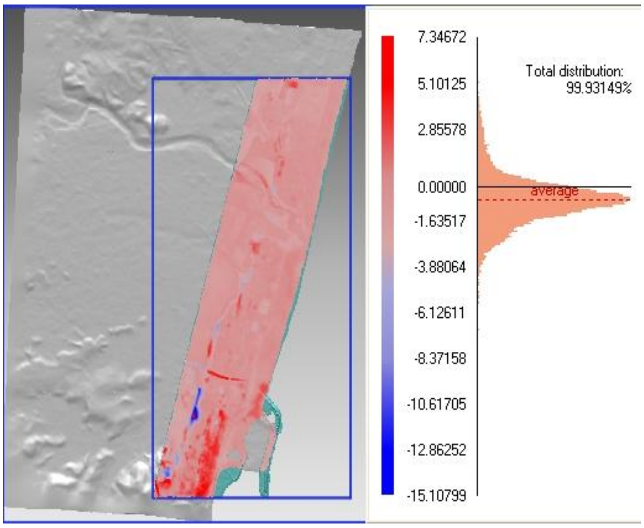

Fig. 9 Distribution of signed vertical residuals (RSM oriented DSM 1977 – Lidar dataset DTM 2009 within the overlap area) and the corresponding histogram.

Notice that the validation matching results coming from the 2009 LiDAR dataset were slightly poorer than those achieved in the case of Antas dry-ravine. It was likely due to the larger number of years passed since 1977 and, above all, the presence of new urbanizations in this heavily developed coastal area which, somehow, means a lesser correspondence between 1977 and 2009 DEMs. Shortly, this area can be deemed as more contaminated and altered and so the number of potentially matching points has decreased (fig. 9 and tab. 3). In other words, the height changes between multidate DEMs contain three main parts: random errors, terrain deformations and matching errors. Random errors come from DEM generation while terrain deformations are mainly caused by anthropogenic activities (constructions, land use changes, etc.). Obviously the area embraced by the 2009 LiDAR DEM is more tending to suffer terrain deformations than the 2004 LiDAR DEM.

	Signed residual statistics			
	Mean (m)	Standard deviation (m)	Maximum (m)	Minimum (m)
Preoriented DSM 1977 - DTM 2001	16.12	22.15	63.29	-35.03
RSM oriented DSM 1977 – DTM 2001	-0.14	2.17	9.84	-16.40
RSM oriented DSM 1977 – Antas dry-ravine DTM 2004	-0.50	1.08	3.39	-7.24
RSM oriented DSM 1977 – Lidar dataset DTM 2009	-0.59	1.57	7.34	-15.10

Tab. 3 Signed residuals statistics for the overlap area corresponding to the comparison between DSM 1977 (preoriented and RSM oriented) and multidate reference DTMs.

4.4 Terrain change detection

Detecting regions of change in DEM for the same area taken at different times is of widespread interest due to a large number of applications in land cover or land use studies [14]. Furthermore, terrain changes could be relevant to studies such as shoreline evolution, soil sealing, flooding analysis and so on. Anyway the goal is to identify the set of points (pixels in a raster context) that are significantly different between the last DEM of the sequence and the previous DEMs; these pixels comprise the "change mask". The methods usually used in this discipline can be very sophisticated when they are applied to images, but are notably simplified working on DEMs because there is no need to apply pre-processing methods (radiometric/intensity adjustments, sudden changes in illumination, shadows, etc.) except for geometric adjustments (just matching as best as possible all the compared DEMs as it has be already done via RSM algorithm).

Several methodologies have been developed for change detection, from the simplest one (simple differencing), to the more sophisticated such as those based on significance and hypothesis tests, predictive models, shading models, background modelling, etc [15]. In this case, and just as an approximation attempt, a mixed approach has been used involving simple differencing and significance tests supposing that the z-differences follow a normal distribution. In fact, a 95% confidence interval has been computed from the reference DEM estimated uncertainty (Sd ≈ 1.03 m; vid. section 3.2). Thus the symmetric upper and lower limits would adopt the values ±1.96.Sd = ±2.02 m (supposing as

0 the mean of z-differences). This methodology has been applied to the working area highlighting a few and defined areas where there have likely been changes between 1997 and 2001 (fig. 10). Those areas were concentrated in high relief zones and, in some cases, may be partially due to the different quality of the compared DEMs (fig. 5), being the 1977 DEM smother and worse defined than the 2001 DEM. Actually the results can be visually tested turning out to be relatively reliable. Additionally most of the working area presented z-differences within the computed confidence interval (vid. the corresponding histogram in fig. 10 on the right).

Summarising, the percentage of significant terrain change within the tested area from 1977 to 2001 (24 years) could be estimated as 11.51% as much while the fill earthworks (63.7%) clearly prevailed over cut earthworks (36.3%).

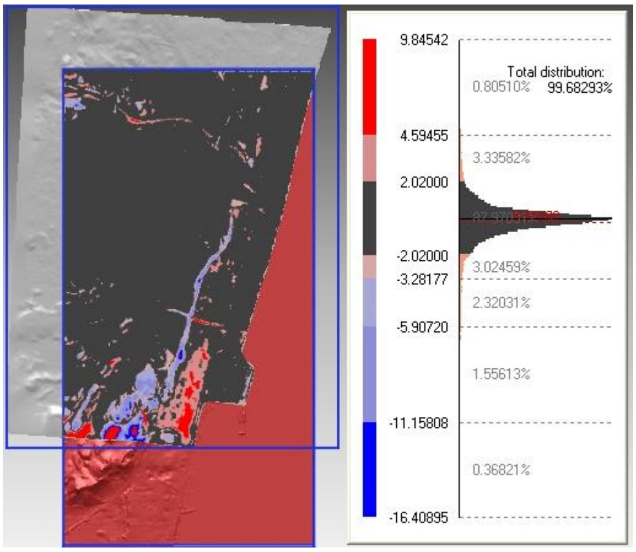

Fig. 10 Discrete distribution of signed vertical residuals (RSM oriented DSM 1977 – DTM 2001 within the overlap area) showing dark grey colour for areas within the tolerance of ±2.02 m (95% confidence interval)

4.4 Highly deformed DEMs

The most important problems when registering multi-temporal DEMs are i) the intensity of temporal deformation or change occurred between the period of the study and ii) the quality of the previous preorientation because, somehow, accentuates the problems related to local deformations. In most surface matching algorithms the deformation area is restricted to not much more than 50% by introducing the so-called differential model and improving the classic least z-difference or LZD algorithm, but it is rather complex and needs a previous rough co-registration or knowing about the approximated transformation to carry out [4]. Our RSM approach was not able to fully correct any type of the synthetic deformations applied to the original preoriented 1977 DEM, as it can be observed in tab. 4, though it is worth noting that those deformations are not usual under operational conditions.

Summing up, it is needed a relatively well preoriented historical DEM to obtain accurate results. In this way our research group has investigated to apply one previous procedure consisting of the so-called shaded relief image matching [16], which could be used making up an integrated method comprising a two steps robust surface matching. The first step should render a well coarse oriented historical DEM by means of the aforementioned shaded relief image matching (an automatic and unattended process). The second step would refine the initial coarse orientation using the RSM algorithm presented and evaluated along this paper. In this way, it would be possible to deal even with highly bad preoriented DEMs also presenting a high rate of change regarding the reference DEM.

	Signed residual statistics			
	Mean (m)	Standard deviation (m)	Maximum (m)	Minimum (m)
Raw version 1DSM 1977 - DTM 2001	-0.80	47.03	80.84	-81.48
RSM- oriented version 1DSM 1977 - DTM 2001	-1.40	8.31	25.46	-36.88
Raw version 2DSM 1977 – DTM 2001	0.89	45.93	78.91	-79.51
RSM-oriented version 2DSM 1977 – DTM 2001	-2.78	23.25	48.56	-49.68
Raw version 3 DSM 1977 – DTM 2001	-0.10	30.10	51.59	-52.00
RSM-oriented version 3 DSM 1977 – DTM 2001	5.94	15.73	38.13	-28.30

Tab. 4 Signed residuals statistics for the overlap area corresponding to the comparison between different versions of deformed DSM 1977 and reference DEM.

5 Conclusions

The results obtained from this work may be deemed as very promising, showing a good co-registration between reference and historical DEMs in heavily developed coastal areas. The last demonstrated to be true when the needed preoriented historical DEM was not excessively deformed respect to the reference DEM. In the case of highly deformed DEMs, it is necessary to count on a previous step headed up to correct such deformations, which can be afforded by shaded-relief image matching (vid. reference [16]). In such situations, the RSM method proposed along this work could be applied as a refining method to polish subtle deficiencies coming from the first step.

The point is the high efficiency and robustness demonstrated by our Robust Surface Matching approach for historical DEM 3D georeferencing, especially when it is compared to costly and time-consuming traditional methods such as photogrammetric absolute orientation based on surveyed ground control points and, very often, self-calibrating bundle adjustment techniques.

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