FOUR-DIMENSIONAL AUTOMATIC DETECTION OF COPPER MINERALIZATION FROM TANDEM-X

Maged Marghany and Shattri Mansor Geospatial Information Science Research Centre, Faculty of Engineering University Putra Malaysia 43400 UPM, Serdang, Selangor Email :magedupm@hotmail.com

KEY WORDS: Particle Swarm Optimization, Copper mine, Automatic detection, TerraSAR-X satellite data.

ABSTRACT: This work presents a new approach for geological copper mining. In doing so, such optimization algorithm of Particle Swarm is implemented with involving of TanDEM –X satellite data. TanDEM-X with high resolution spotlight mode of 1 m resolution and X-band with HH polarization are used. Four-dimensional view is reconstructed based on 3-D data obtained from TanDEM –X satellite data and 4-D phase unwrapping algorithm. The particle Swarm Optimization algorithm is used with 4-D phase unwrapping algorithm. The study shows that the Particle Swarm Optimization algorithm is used to optimize the 4-D reconstruction of copper mineralization after 2000 iterations with RMSE of 0.23. In conclusion, the integration of Particle Swarm is implemented with involving of TanDEM –X satellite data with 4-D phase unwrapping algorithm.

1. INTRODUCTION

The TanDEM-X operational consequence involves the coordinated operation of two satellites flying in adjacent configuration. The alteration constraints for the formation are: (i) the orbits ascending nodes, (ii) the angle between the perigees, (iii) the orbit eccentricities and (iv) the phasing between the satellites. The foremost aim of the TanDEM-X mission is to create a precise three-dimensional image (3-D) of Earth which is consistent in superiority and extraordinary in precision. Presently, the elevation models (DEMs) are accessible which are of low resolution, unreliable or imperfect. Furthermore, DEMs are generally established on diverse data bases and ground survey approaches. With these regards, TanDEM-X, and TerraSAR-X additional for DEM quantity, which is premeditated to end these disparities and provide a precise DEM which should verify vital for numerous scientific and commercial requests.

The TanDEM-X satellite has been planned for a minimal lifetime of five years and has a deliberate correspondence with TerraSAR-X of three years. TerraSAR-X grips consumables and resources for up to seven years of operation nevertheless, theoretically permitting for a perpetuation of the overlay and the period of the TanDEM-X mission. Moreover, the key objective of the TanDEM-X mission, and numerous secondary mission aims based on along-track interferometry along with novel techniques with bistatic SAR which have been well-defined and signify an imperative and advanced portion of the mission. TanDEM-X delivers the remote sensing scientific public not only with a global DEM of unique precision. Nonetheless also with a unique reconfigurable SAR system to validate innovative bistatic and multistatic radar systems for improved bio- and geophysical parameter retrievals.

The TanDEM-X applications are based on (i) across-track SAR interferometry, (ii) along-track SAR interferometry and (iii) new SAR techniques. The three radar techniques evolve from the system specification defined by the TerraSAR-X satellite and the interferometric configuration itself. Due to its manifold system configurations, TanDEM-X is a flexible and multimode mission, which delivers a wide variety of application possibilities. Across-track SAR interferometry is an recognized method to determine the terrain topography. The usage of this procedure is established for the calculation of phase variances calculated with two SAR antennas separated by an appropriate baseline. This permits approximating the radar elevation angle to the phase centre of each image resolution cell, where the height statistics is derived from the interferometric phase change (Marghany 2012c and Marghany 2014c). Along-track SAR interferometry is used to compute velocities of moving objects which is function of a phase modification measurement whereby the two SAR antennas attain complex SAR images of the same area with a short time lag. Therefore, new SAR techniques will establish the possibility of advanced SAR systems that have yet not or only incompletely been established on ground or with airplanes.

DEMs deliver a vital footing for all subjects in geological science, hence the demand for precise and trustworthy DEMs is of certain prominence. DEMs For instance are a requirement for the improvement of geological maps.

Supplementary, districts with volcanoes and predictable earthquakes events require an up to date extremely high resolution DEM to govern the deviations post occasions. Moreover, trustworthy and precise DEMs are required for the recognition of perilous developed regions being affected by disasters (Marghany 2012d and Marghany 2013). The global coverage of topographic data at adequate extraordinary three-dimensional resolution is presently not accessible and would be delivered by the TanDEM-X mission. The accurate DEMs is important for geological mining detections in spite of disadvantages of synthetic aperture radar data due to speckles and object geometry distortions Lopes et al., 1990; Touzi,2002; Yu and Scott 2002; Hondt et al., 2006; Helmy and El-Taweel, 2010; Marghany 2012b; Marghany 2014). Recently, Marghany (2015) developed a new approach for geological mining detection in TerraSAR-X based Particle Swarm Optimization (PSO). With this regard, Marghany (2015) stated that Particle Swarm Optimization has accurate performance in solving numerous single and multi-objective optimization problem in TerraSAR-X data such as despeckles which agreed with Riccardo et al., (2007) and Jin et al., (2008).

This work has hypothesized that 4-D phase unwrapping using Particle Swarm Optimization can be used to reconstruct four-dimensional of copper mineralization from the TanDEM-X data. The main novelty of this work to use across track interferometry of TanDEM-X data by establishing 4-D phase unwrapping based Particle Swarm Optimization. The foremost aim of this work is to develop 4-D phase unwrapping algorithm based of Particle Swarm Optimization for 4-D copper mineralization from TanDEM-X data.

2. 4-D Phase Unwrapping

The 4-D unwrapping is composed by using the temporal phase unwrapping method with velocity of ground motion which is encoding instead of time as the unwrapping direction. This method creates use of four dimensions: x, y, t and V. Each voxel (x, y, z, and t) is unwrapped independently of the rest of the voxels using the velocity encoding dimension. The accurate 4-D phase unwrapping is obtained by modification of phase matching algorithm proposed by Schwarz (2004). According to Schwarz (2004), phase matching algorithm is matched the phase of wrapped phase with unwrapped phase by the given equation

$$\Psi_{i,j,k,V} = \phi_{i,j,k,V} + 2\pi\rho \left[\frac{1}{2\pi} \left(\hat{\phi}_{i,j,k,V} - \phi_{i,j,k,V} \right) \right]$$
(1)

where $\Psi_{i,j,k,V}$ is the phase matched unwrapped phase, *i,j, k and V* are the pixel positions in the quality phase map,

 $\phi_{i,j,k,V}$ is the given wrapped phase, $\phi_{i,j,k,V}$ is the approximated unwrapped phase and $\rho[.]$ is a rounding function. Then the phase unwrapping based on the quality map can be modified to 4-D as (Marghany 2015),

$$Q_{m,n,l,t} = \frac{1}{m \times n \times lxt} * \left(\left(\sum (\Delta \phi_{i,j,k,V}^x - \overline{\Delta \phi_{i,j,k,V}^x})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^y - \overline{\Delta \phi_{i,j,k,V}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} + \left(\left(\sum (\Delta \phi_{i,j,k,V}^z - \overline{\Delta \phi_{i,j,k,J}^z})^2 \right)^{0.5} \right)^{0.5} \right)^{0.5} \right)^{0.5}$$

where $\Delta \phi^x, \Delta \phi^y, \Delta \phi^z$ and $\Delta \phi^t$ are the unwrapped-phase gradients in the *x*, *y*, *z*, and *t* directions, respectively. $\overline{\Delta \phi}^x, \overline{\Delta \phi}^y, \overline{\Delta \phi}^z$ and $\overline{\Delta \phi}^t$ are the mean of unwrapped-phase gradient in $m \times n \times lxt$ cube in $\Delta \phi^x, \Delta \phi^y, \Delta \phi^z$ and $\Delta \phi^t$, respectively.

3. 4-D PARTICLE SWARM OPTIMIZATION

Following Marghany (2014), Particle Swarm Optimization (PSO) is a population-based randomly searching process. It is assumed that there are *N* "particles" i.e., lineaments, faults, topographic breaks, bedding, depressions, lithologies, which are presented in SAR data. These geological features invasive contacts randomly seem in a "solution space". Thus the optimization problem can be solved for data clustering, there is always a criteria (for example, the squared error function) for every single particle at their position in the solution space. The *N* particles will keep moving and calculating the criteria in every position the remain which is named as fitness in PSO pending the criteria reaches satisfied threshold. Therefore, each geological feature (particle) maintains its coordinates in the solution space of TanDEM-X which are combined with the finest fitness that has extremely accomplished by requested geological feature i.e. particle. In fact, the pixel of each feature i.e. particle (m, n, l, t) denotes a probable solution to the optimization problem. Following Kennedy and Eberhart (1995), each agent moves the particle with a direction and

velocity $V_{m,n,l,t}$

$$p_{m,n,l,t} = p_{m,n,l,t} + v_{m,n,l,t},$$
(3)

where $p_{m,n,l,t}$ represent particle and $v_{m,n,l,t}$ is the velocity of the 4-D particle in the *i*,*j*,*k*,*t* agents, respectively.

$$v_{m,n,l,t} = v_{m,n,l,t} + c_1 r_1 (lbest_{m,n,l,t} - p_{m,n,l,t}) + c_2 r_2 (gbest_{m,n,l,t} - p_{m,n,l,t})$$
(4)

where $lbest_{m,n,l,t}$ is the local best particle, $gbest_{m,n,l,t}$ is the global best particle, r_1 and r_2 are random variables and c_1 and c_2 are the swarm system variables. After each iteration the global best g_{best} particle and the agent local best l_{best} particle are evaluated based on the maximum fitness functions of all particles in the solution space. Then equations 1 and 2 can be expressed as follows

$$v_{m,n,l,t} = w \cdot v_{m,n,l,t} (t-1) + c_1 \cdot r_1 (p_{m,n,l,t} (t-1)) - Q_{m,n,l,t} (t-1)) + c_2 \cdot r_2 (p_{m,n,l,t} (t-1)) - Q_{m,n,l,t} (t-1)) Q_{m,n,l,t} = Q_{m,n,l,t} (t-1) + v_{m,n,l,t} (t)$$
(6)

where $Q_{m,n,l,t}$ is the position of the particle for phase unwrapping based on quality map, $v_{m,n,l,t}$ is the current velocity of the particles in $m \times n \times lxt$. The velocity is regulated by a set of rules that influence the dynamics of the swarm. Further, there are several parameters must be considered such as initial population, representation of position and velocity strategies, fitness function identification and the limitation. These parameters are for PSO performances. Following Ibrahim et al., (2010) the initial swarm particles proposed PSO is initialized to contain 3000 points of particles for $Q_{m,n,l,t}$ and velocity $v_{m,n,l,t}$. The points had been randomly selected in the azimuth and range directions in phase unwrapped of TanDEM-X data.

After reaching a precise number of iteration or an accurate, error threshold is performed, the optimal solution is obatined. p_i is the personal best position of the particle, w, c, are all constant factors, and r is the random numbers uniform distributed within the interval [0,1]. Thus the general swarm algorithm can be changed into binary particle (*Discrete Particle Swarm Algorithm DPSO*) which handles particle values of either 0 or 1 by a given equation (Kennedy and Eberhart 1997 and El Meserry et al., 2009).

$$P(m,n,l,t) \leftarrow \{ \begin{matrix} 1 & if \quad r_3 > p_{m,n,l,t} \\ 0 & if \quad r_3 < p_{m,n,l,t} \end{matrix} \}$$
(7)

where P(m,n,l,t) is the numerical values of the particle and r_3 is a random variable.

According to El Meseery et al., (2009) the PSO can segment the geological features in SAR data. With this regard, The input TanDEM-X data T with N points can be represented by set $T = \{x_1, x_2 \dots x_N\}$ where x_i is the location of 3-D geological feature on the point *i*. The swarm algorithms consist of M agents which are represented by the set $A = \{P_i | i = 1, 2 \dots M\}$ where P_i is a single solution particle from the solution space. Each particle decodes the problem using a binary array with the same length N as the input SAR data. Consequently, the system denotes each particle $P_{i,j,k,t}$ by $P_i = \{p_{ijk} | k = 1, 2 \dots N\}$ where p_{ijk} has only two values a)1 ($p_{ijk} = 1$); means that this point (k) is a dominate point, or b) 0($p_{ijk} = 0$)which means that means this point (k) is not a dominate point (El Meseery *et al., 2009*). The fitness is computed using the given equation

$$\max fitness(p_{i,j,k,t}) = \begin{cases} -E/\varepsilon N & ifE > \varepsilon, \\ D/\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sum_{t=1}^{N} p_{i,j,k,t} & otherwise \end{cases}$$
(8)

where N is the number of points in the TanDEM-X data, D is the number of points in the solution that was previously labeled as a possible dominant point (P_{pd}), E is the computed error and \mathcal{E} is the error threshold. As said by El Meseery *et al.*, (2009), it should be noticed that when the error is larger than the threshold \mathcal{E} the fitness is given a -ve value to lower the fitness value of the solution. Otherwise the system favors the lower number of vertices.

4. RESULTS AND DISCUSSION

The TanDEM-X data of high resolution spotlight mode of 1 m resolution and X-band with HH polarization is shown in Figure 1. In the center of the Atacama Desert near South America's west coast lies the world's largest open-cast copper mine. The mine was founded by Guggenheim Brothers at the beginning of the 20th century. Figure 1 shows the 400-metre deep mine. In addition, 3-D TanDEM-X data shows a clear infrastructures which are represented in water filtration tanks which can be observed clearly as square surfaces in the mine. According to Marghany (2015),the mine is located in the center of the Atacama desert near South America's west coast lies the world's largest open-cast copper mine. The mine was founded by Guggenheim Brothers at the beginning of the 20th century.



Figure 1.3-D copper mine from TanDEM-X data of high resolution spotlight mode.

Figure 2 shows the coherence results of TanDEM-X data. It is clear that the coherence map is ranged from 0 to 1. It is interesting to find that the copper mineralization has highest coherence value of 1 than the surrounding infrastructures. The infrastructures has coherence value of 0.8 which can be seen along the road and building. The high coherence perhaps because of the strongest backscatter events a companied with steeper incident angle and short baseline. This finding does not agree with Marghany (2015). In fact, Marghany (2015) examined the backscatter of single Terra-SAR-X data in the same area.



Figure 2. Estimated coherence map of TanDEM-X data.

Figure 3 shows the result of 4-D Phase unwrapping using PSO algorithm. It is obvious the clear appearance of fringe cycles. In fact, the PSO circumvents a decreasing resolution by making a weighted combination of running average with the neighbor surrounding pixels of the 4-D phase unwrapping. This reduced the noise in the feature s' edge areas without losing edge sharpness. Clearly PSO within approximately 7 hour within 2000 iterations is able to reconstruct

4-D phase unwrapping with RMSE of 0.23.



Figure 3. Particle Swarm Optimization for 4-D phase unwrapping with different iterations (a) 0,(b) 10, (c) 44 and (d) 2000 iterations

Figure 4 shows the 4-D copper mineralization reconstruction from 3-D TanDEM-X data. It is obvious that from different angle of view clear 4-D morphological feature detections. This includes deep of copper mine within 400 m depth and surrounding mountains. Besides deep descriptions of the edge of the infrastructures. The geomorphology of copper mineralization being to be more obvious with rotation angle of 180° (Figure 4b). The involving of 4th dimension increase from deep visualization of the scene as different features are observed with different view angles from 0° to 360°. This agrees with the work of Ibrahim et al., (2010).



Figure 4. 4-D copper mineralization from different view angles (a) 0°, (b) 180° and (c) 360°.

The implementation of PSO with 4-D phase unwrapping assisted to determine optimal grows regions across the continuing unwrapping of edges. With this regard, PSO synchronized the voxels on both sides of the edge (Figure 4. In addition, 4-D phase unwrapped algorithms constructed the discontinuity in quality order. This is appropriate in the high intensity line or curve of fixed length and locally low curvature boundary is known to exist between edge elements and high noise levels in TanDEM-X data. On the words, PSO optimized the gaps remains between discontinuity edges. With this regard, 4-D phase unwrapping based PSO is optimal search to real edge pixels which are existed on the boundary of copper mineralization and the optimization of 4-D phase unwrapping in hypercube can reconstruct the 3-D object displacement with additional 4th dimension. Finally, 4-D phase unwrapping based PSO permits for reliable unwrapping of low signal to noise ratio (SNR). This study could improve of 3-D phase unwrapping proposed by Hussien et al., (2005) and Karout (2007).

4. CONCLUSIONS

The work demonstrated a new approach for geological copper mining detection. With this regard, optimization algorithm of Particle Swarm is used with 4-D phase unwrapping of TanDEM –X satellite data. The study shows that

the Particle Swarm Optimization algorithm is used to optimize the 4-D reconstruction of copper mineralization within 7 hours and post 2000 iterations with RMSE of 0.23. The results shows that the 4-D of copper mineralization improved morphological feature detection such as the depth of copper mine and surrounding infrastructures. It can be said that the integration of Particle Swarm with 4-D phase unwrapping of TanDEM –X satellite data is promise approach for 4-D reconstruction of copper mining.

References

El Meseery, M. El Din, M.F. ; Mashali, S. ; Fayek, M. ; Darwish, N 2009. Sketch recognition using particle swarm algorithm, 16th IEEE International Conference on Image Processing. 7-10 Nov. 2009, Cairo,Egypt. 2017 – 2020.

Ibrahim, S., Abdul Khalid, N.E., Manaf, M. 2010. Computer aided system for brain abnormalities segmentation. Malaysian Journal of Computing (MJOC) 1(1): 22-39.

Jin Yisu, Joshua Knowles, Lu Hongmei, Liang Yizeng and Douglas B. Kell 2008.," The landscape adaptive particle swarm optimizer", Applied Soft Computing, Vol.8, pp. 295–304.

Kennedy, James, and Russell C. Eberhart, 1997. "A discrete binary version of the particle swarm algorithm." *Systems, Man, and Cybernetics, 1997. Computational Cybernetics and Simulation., 1997 IEEE International Conference on.* Vol. 5. IEEE, 1997.

Kennedy, J. and Eberhart, R. 1995. Particle Swarm Optimization. (14): 1942--1948.

Karout S., 2007. Two-Dimensional Phase Unwrapping, Ph.D. Theses, Liverpool John Moores University, 2007.

Helmy, A.K., and G.S., El-Taweel 2010. Speckle Suppression of Radar Images Using Normalized Convolution. Journal of Computer Science. 6 (10): 1125-1129.

Hondt, O.D', L. Ferro-Famil, and E. Pottier, 2006. *Nonstationary spatial texture estimation applied t adaptive speckle reduction of SAR data*. IEEE Transactions on Geosciences and Remote Sensing Letter, 3 (4), pp. 476–480.

Hussein S A, Gdeist M, Burton D, Lalor M., 2005 fast three-dimensional phase unwrapping algorithm based on sorting by reliability following a *non-continuous path Proc. SPIE*, 5856 40.

Lee, J.S., D. Schuler, T. L. Ainsworth, E. Krogager, D. Kasilingam, M.A. and W.M. Boerner, 2002. *On the estimation of radar polarization orientation shifts induced by terrain slopes*. IEEE Transactions on Geosciences and Remote Sensing, 40, 30–41.

Lopes, A. Touzi, R. and E. Nezry, 1990. *Adaptive speckle filters and scene Heterogeneity*. IEEE Transactions on Geosciences and Remote Sensing, 28(6): 765-778.

Marghany 2015. Copper mine automatic detection from TerraSAR-X using particle swarm optimization. CD of 36th Asian Conference on Remote Sensing (ACRS 2015), Manila, Philippines, 24-28 October 2015,a-a-r-s.org/acrs/administrator/components/com.../files/.../TH3-2-1.pdf.

Marghany 2014a. Particle Swarm Optimization for Geological Feature Detection from PALSAR Data. 35th Asian Conference of remote sensing, at Nay Pyi Taw, Myanmar, 27-31 October 2014. a-a-r-s.org/acrs/administrator/components/com.../OS-140%20.pdf. [Acess August 29 2015].

Marghany M., 2014b. Multi-Objective Evolutionary Algorithm for Oil Spill Detection from COSMO-SkeyMed Satellite. In Beniamino M., Sanjay Misra, Maurizio Carlini, Carmelo M. Torre, Hong-Quang Nguyen, David Taniar, Bernady O. Apduhan, and Osvaldo Gervasi(Eds.,) ICCSA 2014. Part VI, pp 355-371.

Marghany, M., 2014c, August. Hybrid Genetic Algorithm of Interferometric Synthetic Aperture Radar For Three-Dimensional Coastal Deformation. In *SoMeT* (pp. 116-131).

Marghany, M., 2013. DInSAR technique for three-dimensional coastal spit simulation from radarsat-1 fine mode data. *Acta Geophysica*, 61(2), pp.478-493.

Marghany, M. 2012a. Three-Dimensional Lineament Visualization Using Fuzzy B-Spline Algorithm from Multispectral Satellite Data. In Escalante-Ramirez B. (ed.) "Remote Sensing - Advanced Techniques and Platforms". InTech - Open Access Publisher, Croatia. pp.213-232.

Marghany, M. 2012b. 3-D coastal bathymetry simulation from airborne TOPSAR polarized data. *Bathymetry and Its Applications*, 57-76.

Marghany, M., 2012c. Three-Dimensional Coastal Geomorphology Deformation Modelling Using Differential Synthetic Aperture Interferometry. *Zeitschrift fur Naturforschung A-Journal of Physical Sciences*, 67(6), p.419.

Marghany, M., 2012d. DEM reconstruction of coastal geomorphology from DINSAR. In *International Conference* on Computational Science and Its Applications (pp. 435-446). Springer Berlin Heidelberg.

Schwarz, O. 2004. Hybrid phase unwrapping in laser speckle interferometry with overlapping windows, Shaker Verlag.

Riccardo, P., J., Kennedy and T., Blackwell, 2007." Particle swarm optimization - An overview", Swarm Intell, Vol.1, pp.33–57.

Touzi, R., 2002. A review of speckle filtering in the context of estimation theory. IEEE Transactions on Geosciences and Remote Sensing. p. 2392–2404.

Yu, Y., and T. A., Scott, 2002. *Speckle reducing anisotropic diffusion*. IEEE Transactions on Geoscience and Remote Sensing. pp.1260-1270.