# Effective Residual and Regional Gravity Anomaly Separation
## *Using 1-D & 2-D Stationary Wavelet Transform*

Naeim Mousavi[1], Vahid E. Ardestani[2] and Hassan Moosavi[3]
[1]*Young Researchers Club & Elites, Hamedan Branch, Islamic Azad University, Hamedan, Iran*
[2]*Institute of Geophysics, University of Tehran, Tehran, Iran*
[3]*Rah Avard Danesh Institute Affiliated with Ministry of Training and Education of Iran, Hamedan, Iran*

Keywords: Separation, Stationary Wavelet Transform, Gravity Data, Correlation Coefficient.

Abstract: Numerous studies on capabilities of de-noising and separation by wavelet were performed, and their all aims more and less was elimination of possible largest nongeological factors, noise, and to achieve pure regional effects free from residuals. De-noising could be used for removal of non-desired effects like latitude, terrain, tides, drift etc., from our desired portion of data as target. Separations of anomalies that are not of interest conclude shallow structure is suitable to be optimal. Hence detection and removal of ever larger surface anomalies to obtain optimal separation is of interest. At up to now studies, large deviation of primarily original signal has been prevented. In this paper controlling factors which limit the overall deviation of transformed signal from the original one have been replaced with two new parameters that simultaneously cause extracting the maximum surplus signals, residuals, and also preserving the original form ever possible. Results of artificial models along with application of separation to real data indicate the usefulness of discrete stationary wavelet transform in order to optimal separation of anomalies with various wavelengths.

## 1 INTRODUCTION

The traditional Fourier-based low or high pass filters, such as Butterworth and Wiener, attenuate the effect of noise in the data, but these have a severe effect on smoothing out high frequency signals and do not always work well because globally remove high frequencies. General smoothing substantially broadens features of interest while gravity data is globally smooth. Moreover many geophysical signals are non-stationary in nature, therefore analyzing either in uniquely time or only frequency domain is not appropriate since the main draw back of Fourier domain processing is edge effect and global denoising (Fedi et al, 2004).

The other conventional approach to high frequency separation is to apply a Naudy style and nonlinear statistical filter. Success of these methods, is due to some prior knowledge of nature of the high frequency components. The shortcomings of Fourier and Nonlinear filtering are apparent and pose limitations on the detail and accuracy of information accessible (Leblanc and Morris, 2001). As an innovative technology developing from the 1980's, wavelet transform has been widely used in geophysics for its characteristics such as time frequency analysis, multi-resolution and decorrelation (Yan and Wu, 2011).

Since wavelets can successfully decompose and separate the signal into discrete levels, the application of separation procedures can be discriminately applied to these wavelet levels (Leblanc and Morris, 2001). The result is to effectively removal the contribution of the high frequency component to the whole of the data, while keeping the geologically significant data as free as possible from the effects of the thresholding process.

The procedure to manipulate the coefficients to force some parts to remain at or converge to a specified value is known as thresholding. Separation and denoising can be viewed as a very practical and advanced form of thresholding. Denoising of data sets using wavelet transform has been performed by a number of researchers (Donoho, 1993); (Donoho and Johnstone, 1994); (Saito, 1994); (Coifman and Donoho, 1995); (Moreau et al., 1999); (Ridsdill-mith and Dentith,

Mousavi N., E. Ardestani V. and Moosavi H..
Effective Residual and Regional Gravity Anomaly Separation - Using 1-D & 2-D Stationary Wavelet Transform.
DOI: 10.5220/0004219806590668
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods* (PRG-2013), pages 659-668
ISBN: 978-989-8565-41-9

1999). Soft thresholding has been applied to all the data of this study. We consider the issue of high-frequency components created by shallow micro-anomalies and separation of them within the wavelet transform domain. The minimum-risk method simply minimizes a least-squares estimate of the error involved in the difference between the true reading and the best estimate of that reading. The best estimate for the ideal threshold estimator using soft thresholding is based on the standard deviation of the high frequency components and the number of sample points (Leblanc and Morris, 2001). The investigation by Neumann and von Sachs (1995) has furthered the basis for the risk estimator to include non-Gaussian distributions. However, the micro-anomalies (high frequency components) were comprised of features that are of considerably shorter wavelength than the portions of interest of the signal.

The wavelet approach has minimized the presence of the spikes without introducing the effects of splining the signal that is seperated by the wavelet process. In Lebelance study in 2001, the nongeological components at times, are similar in amplitude and wavelength to the signal of interest therefore are considerably more difficult to eliminate.

The intent of this work is to show the effects of wavelet method on the removal of the largest spikelike or high frequency features led to the optimal (maximall) separation. Various of such features, high frequency one, are including measurement resulting from the imperfect instruments, persoal error and superimposing by the surface micro-anomalies which produce useless high-frequency signals. Separation is denoted often for residual distincting from regional that is established in this study. Such as these methods are independent and have recognizable process for separation.

# 2 WAVELET ANALYSIS

One of the most important characteristics of wavelet transform is that continuous wavelet transforms have an adaptive window in time-frequency space (Yan and Wu, 2011), which is sharpened automatically with high center frequency while broadened with low center frequency. Thus, wavelet transforms can offer high resolution for high frequency signals and give information for low frequency signals completely.

Wavelet coefficients are separated into different scales corresponding to different degrees of approximation to the original data. The lower frequencies are represented by a small number of large coefficients, mainly located at the coarse scales, while high-frequencies are represented by a large number of small coefficients at the finer scales. Wavelet threshold separation is simply to keep coefficients whose amplitudes are greater than a specified threshold and discard the coefficients smaller than the threshold (Yan and Wu, 2011).

Wavelet transform is applied as continuous and discrete form. The overall effect of applying the CWT is that it takes the wavelet function and continuously dilates and translates it over the series.

## 2.1 Continous Wavelet

Continuous wavelet transform function $f(t)$ can be expressed as follows:

$$CWT(a,b) = < f, W_{a,b} > = \int_{-\infty}^{\infty} f(x)\, W_{a,b}\, dx \qquad (1)$$

The basis functions are defined as:

$$W_{a,b} = \frac{1}{\sqrt{a}}\psi^*\left(\frac{x-b}{a}\right), a, b \in R, a > 0 \qquad (2)$$

where a is the dilation parameter, b is the translation parameter, and R is the set of all real numbers. Multiplier $\frac{1}{\sqrt{a}}$ is used to normalize energy function in different scales. Transform in wavelet domain is a function of time and frequency simultaneously.

## 2.2 Discrete Wavelet

The CWT allows a fine decomposition of the space-scale plane, but the dilated and translated versions of the mother wavelet do not have orthogonal properties. This property may be important, as in the case of filtering with respect to position and scale parameters, it can be useful to resort to orthogonal bases discrete families of orthonormal wavelets. Discrete families of orthonormal wavelets are introduced as follows:

$$\psi_{l,k}(x) = \frac{1}{\sqrt{2^l}}\psi\left(\frac{x-k2^l}{2^l}\right) = \frac{1}{\sqrt{2^l}}\psi(2^l x - k) \qquad (3)$$

which are obtained by dilating or contracting and translating $\psi_{0,0}$ , with the choice a = 2l and b = ka with l, k $\in$ Z (Z is the set of integers). In this case, the discrete wavelet transform (DWT) is:

$$DWT_{l,k} = \int_{-\infty}^{\infty} f(x)\psi_{l,k}(x)dx \qquad (4)$$

and the inverse discrete wavelet transform (IDWT) is:

$$f(x) = \sum_{l=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} DWT_{l,k}\, \psi_{l,k}(x) \tag{5}$$

The discrete wavelet transform (DWT), using the property of localization of wavelet bases has been used as a powerful tool in filtering and separation problems. The continuous wavelet transform (CWT) exploits the upward continuation properties of the field horizontal derivative and allows the location of potential field singularities in a simple geometrical manner (Fedi et al., 2004).

## 2.3 Thresholding

Separation is how to manipulate the wavelet correlation coefficients produced by the DWT in order to obtain the best residual-free data set, known as smoothed out regional. Residuals in real data are often seen as high-frequency or spike-like components and predefined feature corresponds to i.e. shallow micro-anomalies. With real data, there are only two practical choices of thresholding: hard or soft. With hard thresholding, all values of the wavelet correlation coefficients below (or above, depending on the application) the threshold value λ are set to zero. In soft thresholding, the values approach zero at a linear rate (Fedi et al., 2004).

The explicit difference between hard and soft thresholding is when $|x(t)| > \lambda$. In the case $|x(t)| \leq \lambda$, λ for both hard and soft thresholding is zero. For hard thresholding, λ is equal to x(t) but for soft thresholding is determined by this equation: $\mathrm{sign}(x(t))(|x(t)| - \lambda)$. Where x(t) is the value of the wavelet correlation coefficient at some level dependent observation points (Strang and Nguyen, 1996). Soft thresholding of these same data was found to reconstruct the signal in a more continuous form that did not induce obvious artefacts. This same conclusion has been reached by other studies (Donoho and Johnstone, 1994); (Moreau et al., 1999) therefore, soft thresholding has been applied to all the data of this study

# 3 GRAVITY DATA SEPARATION TECHNIQUE

High frequency events are a drastic deviation from the general trend of the local data in either frequency content or amplitude or both (Fedi et al., 2000). In the other words high frequency components is a subjective feature of all real data. The perception of what residual is and what it is not varies with the intent of the end use of the data what may be considered residual to one observer may be regional to another. This leads to the realization that no matter what the application is, a measured value will always have some amount of unwanted signal. As a result, the need for separating the unwanted portion from the portion of interest is essential to all users and is the motivational concept behind separation (Leblanc and Morris, 2001).

Although separation methods have sound basis for specific applications under specific conditions, each has variable degrees of success when applied to high frequency features such as aeromagnetic spike anomalies. A data spike is a single point anomaly whose magnitude is usually, but not necessarily, of significant deviation from the trend of the data. It is generally smaller in spatial extent and larger in amplitude than the local trend of the geologically sourced data. The ambiguity of this definition is a result of the signal associated with non geologic sources that cause the spike-like anomalies. These sources include acquisition errors, levelling, latitude, terrain, tides, drift etc. and shallow small anomalies.

Surface micro-anomalies create high-frequency portion at signal. Sometimes the purpose of the analysis is diagnosis of these shallow anomalies. In such a case low pass filter damage useful information of the data. Remember that random high frequency signals can not always describe the behaviour of gravity residuals; so the arithmetic is used to remove such high frequency features have limited application in practice.

Maximum (abs( main signal-long wavelength signal produced by SWT))= Maximum Residual (MR)

By applying the discrete stationary wavelet filter and soft thresholding all high frequency effects are removed. So, regression of the effects of surface anomalies should be maximal. Continuity of soft thresholding reduces the high frequency content of signal that is occurred by growing scales until the overall form of the signal has not been deformed.

An optimal separation also let the effect of deeper anomalies that were not seen because of micro anomaly is now evident. Minimum deviation of processed signal under wavelet thresholding occurs at lower scales. Going to larger scales causes separation of larger residuals. The signal to noise ratio or Regional to Residual Ratio (RRR) also decreases with increasing scale. Since the residual amplitude is in the denominator of the ratio, small

RRR is equivalent to large residual separation.

The shrinking process of the RRR continues until that all the original signal is remarked as residual. We seek smallest RRR until the amplitude of transformed signal (regional signal) are not less than one of detected signal as residual it means the best case is that RRR is unit or one.

# 4 SYNTHETIC GRAVITY DATA

## 4.1 Maximum Residual Separation at Minimum RRR

The simplest way to figure out the main concept of residual at gravity data is to consider a shallow smaller anomaly located over the bigger buried source (Fig.1).

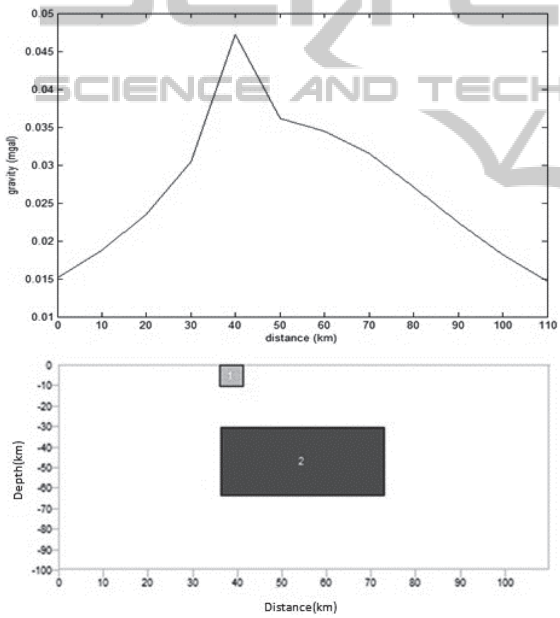


Figure 1: synthetic model composed of two prisms. Prism No.1 is nearer to the surface and smaller at size rather than the other.

Both No.1 and No.2 prisms have the density contrast of 0.1g/cm$^3$. Shallow anomaly causes spike-like effect at trace of deep structure and is recognized as residual in this example. Residual levels will not change much with the basic functions and more is the function of scale selection (compare results of Table 1 and 2).

We use Haar function at different scales to decide about the level in which the best separation result (unit or almost near unit RRR) is achieved.

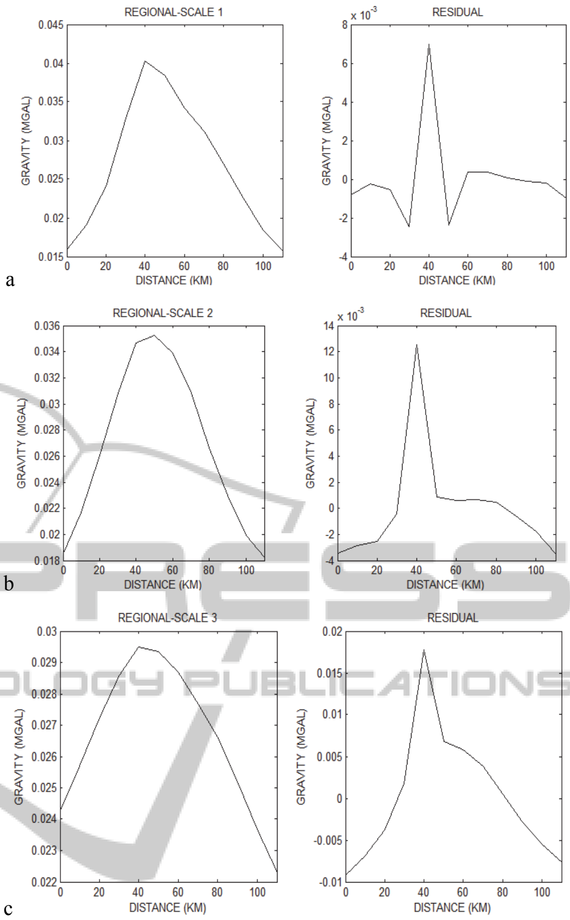


Figure 2: separation of synthetic data steps by wavelet transform. Three steps are due to scale 1, 2 and 3 are as shown in part a, b and c. a) Application of wavelet at scale 1 with Haar basis function. b) Result of wavelet at scale 2 with Haar basis function. c) Regional and residual signal reconstruction by wavelet at scale 3 with Haar basis function. At three above sections the separated residual signal, is shown at beside subplot.

Table 1: Maximum residual and regional to residual ratio provided at different scales for synthetic data (Fig. 1).

| Haar wavelet basis | | | | | |
|---|---|---|---|---|---|
| Scale 1 | | Scale 2 | | Scale 3 | |
| MR | RRR | MR | RRR | MR | RRR |
| 0.006 | 2.597 | 0.012 | 1.058* | 0.017 | 0.2991 |

The advantage of Haar function is exactly to detect two distinct wave number levels that accidentally this condition was occurred in this synthetic. It does not mean that we have reached a certain pattern and use only the Haar functions for always separation process.

The lowest regional to residual ratio, also not less than unit, is correspondent to the wavelet at scale 2 (Table 1). Among all functions, Haar produces the minimum acceptable RRR (Table 2). As shown at Fig. 2(b) high-frequency effect of prism No.1 is completely separated and regional signal contains only the expectable anomaly.

Table 2: regional to residual ratio for different wavelet functions at scale 2 for synthetic including two prisms.

| Wavelet basis functions | RRR |
|---|---|
| Haar | 1.058732010890705* |
| dmey | 1.863303773918932 |
| Db1 | 1.058732010890705 |
| Db2 | 1.453860116416355 |
| Db3 | 1.615515002033936 |
| Db4 | 1.710706620370309 |
| Db5 | 1.772346126748260 |
| Db6 | 1.814108360446961 |
| Db7 | 1.835009919059236 |
| Db8 | 1.843231484570417 |
| Sym1 | 1.058732010890705 |
| Sym2 | 1.453860116416355 |
| Sym3 | 1.615515002033936 |
| Sym4 | 1.710706620379929 |
| Sym5 | 1.772346126737329 |
| Sym6 | 1.814108360446384 |
| Sym7 | 1.835009919053853 |
| Sym8 | 1.843231484558451 |
| Coif1 | 1.468967960816310 |
| Coif2 | 1.727258582982356 |
| Coif3 | 1.826747213107115 |
| Coif4 | 1.846624829191316 |
| Coif5 | 1.855111352245451 |

## 4.2 Maximized Separation by Correlation Test

All three prisms at Fig. 3 have a density contrast of 0.1 g/cm$^3$ related to zero density of their surroundings. Shallow prisms can be seen as the agents that produce high frequency effects. Since prism No. 2 is larger at size, has created signal with bigger amplitude. Hence we expect that its trace is completely clarified purely at the higher scales of wavelet transform in which there is no effect of prism No.2 surly.

Maximum residuals, regional to residual ratios and correlation coefficients of wavelet at four scales are given in Table 3. RRR at scale 3 is approximately unit and the smallest one is obtained again by Haar function at this scale like previous synthetic. The separation procedure is led to signal completely deformation when using wavelets at scale rather than 3. In this level whole change in signal shape is so much large that is not entitled residual of data by SWT likewise is more similar to original signal.

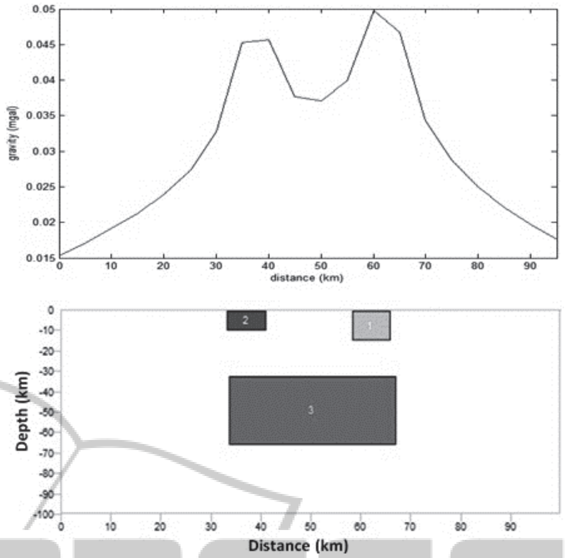


Figure 3: Synthetic model composed of three prisms. Prisms No.1 and No.2 are nearer the surface and smaller at size rather than No.3. Two spike-like anomalies created by shallow prisms, recognised as residuals which disturbs the Gaussian trend of prism No 3.

More assessment indicates the magnitudes of correlation coefficient of three first scales are closed each other and obey a decreasing trend while deviates or collapses suddenly at scale 4. If one can not obtain the desired RRR (more and round of unit) to achieve an appropriate scale, may use the correlation coefficient test. The scale, in which the correlation coefficient is deviated from the gradually decreasing trend, is suitable for maximum residual separation. This test for selection the best scale for separation could be useful when RRR from the first scale is less than one. Hence at such cases it is not possible to employ test of boundary value of one for RRR in which optimal value among all more and less than one RRR is selected.

The amplitude of separated signal as residual portion at larger scales goes to be larger. At scale 4 whole the original signal is introducing the residual position. The best scale is 3 in which the residual is completely is representative of its source's effect. Note that residual effect is masking the deep anomaly, and there is uncertainty at precise location of anomaly. We only determine locations of buried sources approximately near the horizontal extension of its actual position. Since wavelet unmasks trace of deep source and offers a more exact representation referenced to anomaly coordinates, a displacement in anomaly's location is natural and expectable.

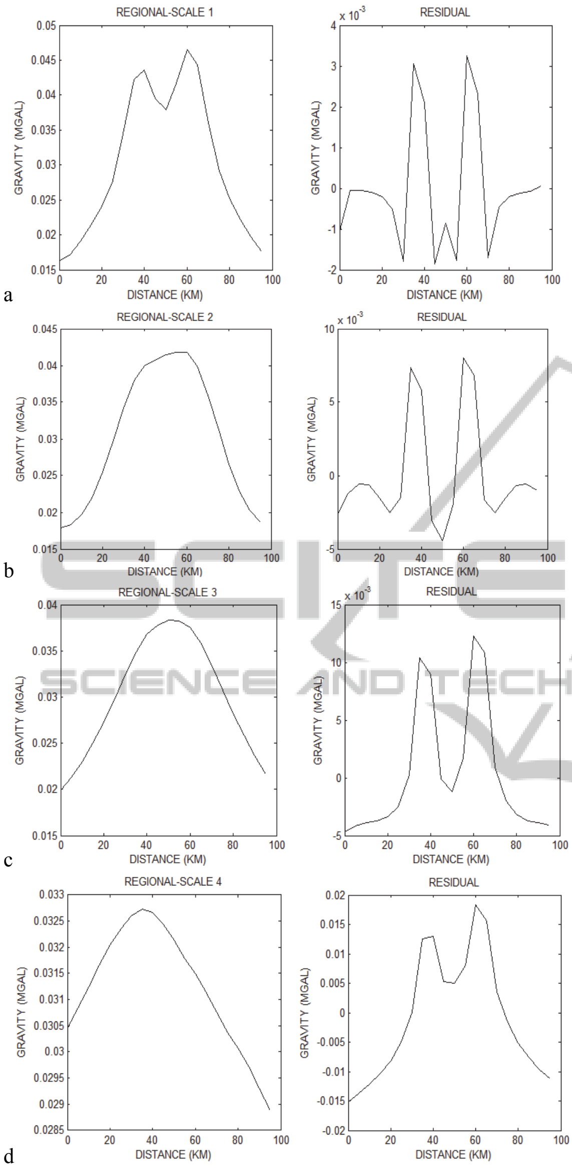


Figure 4: Four steps of separation are occurred by using higher scales. Result of wavelet application using Haar function at a) scale 1, b) scale 2, c) scale 3, d) scale 4. Beside subplot at each section is due to residual reconstruction.

# 5 APPLICATION TO REAL DATA

## 5.1 Real Data Separation by RRR Test

Real data belongs to Rodan city of Hormozgan province positioned in south of Iran. The region, in which data was acquired, has the area of almost 900 km$^2$ and has been located within 56º, 53´ and 57º, 24´ longitude and 27º, 33´ and 28º, 30´ latitude. The coordinates of basement in UTM system are 500000, 3060000. The data surveying was programmed in 10 lines, parallel to profile as shown at Fig. 5(a). This map has been positioned in reversed direction related to common NW. The data has been selected from a bigger lattice with 2000 km$^2$ hence the coordinates values have not started from zero in relative calculated local coordinates but the intervals have precisely been preserved the same. Some separated negative sources in Bouger map are seen while other geophysical and geological studies illustrate presence of a syncline in South-East corner of grid. We expect a uniform greater negative anomaly so apply maximum separation technique using RRR test to remove the largest micro-anomalies which have masked desired structure. Maximum separation should be done on data to check possibility of extract that desired geologic source from data.

Table 3: Maximum residual and regional to residual ratio and correlation coefficient, which are obtained at four scales, are correspondent to synthetic of three prisms. The coefficient at scale 4 is deviated suddenly from its decreasing trend.

| Wavelet 1-D Haar wavelet basis | | | |
|---|---|---|---|
| Scale 1 | | Scale 2 | |
| MR | RRR | MR | RRR |
| 0.0032 | 5.9264 | 0.0080 | 1.9216 |
| Correlation coefficient | 0.9917 | Correlation coefficient | 0.9506 |
| Scale 3 | | Scale 4 | |
| MR | RRR | MR | RRR |
| 0.0123 | 1.0827 | 0.0183 | 0.1145 |
| Correlation coefficient | 0.9361 | Correlation coefficient | **0.5903*** |

There are one hundred stations in grid which corresponded wave numbers in both horizontal and vertical direction is with very good approximation obtained. The overall look of the complete Bouger map shows undesirable effects that make it difficult to detect major anomaly. The RRRs were calculated for all scenarios by the 2-D stationary wavelet transform using different functions at different scales.

RRRs even for the lowest residual amplitude from separation process were not acceptable (were less than one) at scale 2 hence we put aside calculations of scale 2 to preserve time. Regional gravity map contains two positive anomalies in direction of South West to North East and a negative anomaly has been detected in the South-East area.

Table 4: Regional to residual ratio at scale 1 for real data of syncline.

| Wavelet basis functions | RRR | Wavelet basis functions | RRR |
|---|---|---|---|
| Haar | 1.0750 | Bior2.4 | 1.1145 |
| dmey | 1.0574* | Bior2.6 | 1.1106 |
| Db2 | 1.0863 | Bior2.8 | 1.1032 |
| Db3 | 1.1314 | Bior3.1 | 1.1195 |
| Db4 | 1.1134 | Bior3.3 | 1.1214 |
| Db5 | 1.1005 | Bior3.5 | 1.1077 |
| Db6 | 1.1016 | Bior3.7 | 1.0984 |
| Db7 | 1.0906 | Bior3.9 | 1.0922 |
| Db8 | 1.0858 | Bior4.4 | 1.1139 |
| Db9 | 1.0859 | Bior5.5 | 1.1101 |
| Db10 | 1.0828 | Bior6.8 | 1.0953 |
| Sym2 | 1.0863 | rbio1.3 | 1.1213 |
| Sym3 | 1.1314 | rbio 1.5 | 1.1194 |
| Sym4 | 1.1189 | rbio 2.2 | 1.0936 |
| Sym5 | 1.0993 | rbio 2.4 | 1.1159 |
| Sym6 | 1.1026 | rbio 2.6 | 1.1139 |
| Sym7 | 1.0954 | rbio 2.8 | 1.1083 |
| Sym8 | 1.0901 | rbio 3.1 | 1.1730 |
| Coif1 | 1.1076 | rbio 3.3 | 1.1341 |
| Coif2 | 1.1130 | rbio 3.5 | 1.1158 |
| Coif3 | 1.0977 | rbio 3.7 | 1.1021 |
| Coif4 | 1.0872 | rbio 3.9 | 1.0941 |
| Coif5 | 1.0815 | rbio 4.4 | 1.1098 |
| Bior1.3 | 1.1276 | rbio 5.5 | 1.1014 |
| Bior1.5 | 1.1308 | rbio 6.8 | 1.0925 |
| Bior2.2 | 1.1032 | * | * |

Some anomalies persist on their previous locations despite great changes and some have moved a little referenced the previous ones. This event is as above mentioned natural and expectable.

## 5.2 Separation of Real Data Due to Cavity using Correlation Coefficient Test

This real data which is located in west of Iran is due to region that some other methods illustrate presence of karstic phenomena (cavity) in it. From negative anomalies which have been seen along each other, it is found that the cavity has been located along the north-south direction. Furthermore negative anomalies which are correspondent to cavity are discontinued at width of 215.5 m. this discontinuity causes ambiguities in presence of cavity. The proposed method in this study is used for data which is led to results shown in Table 5.

Since values for RRR at scale 1 are less than unit the minimum RRR test can not find the proper scale for optimal wavelet application and then also optimal separation. Less than unit RRRs indicate original form distortion that vanish geologic phenomenon which are accessible by appropriate separated data. In this case, we choose the best scale for residual effect removal by correlation coefficient test.

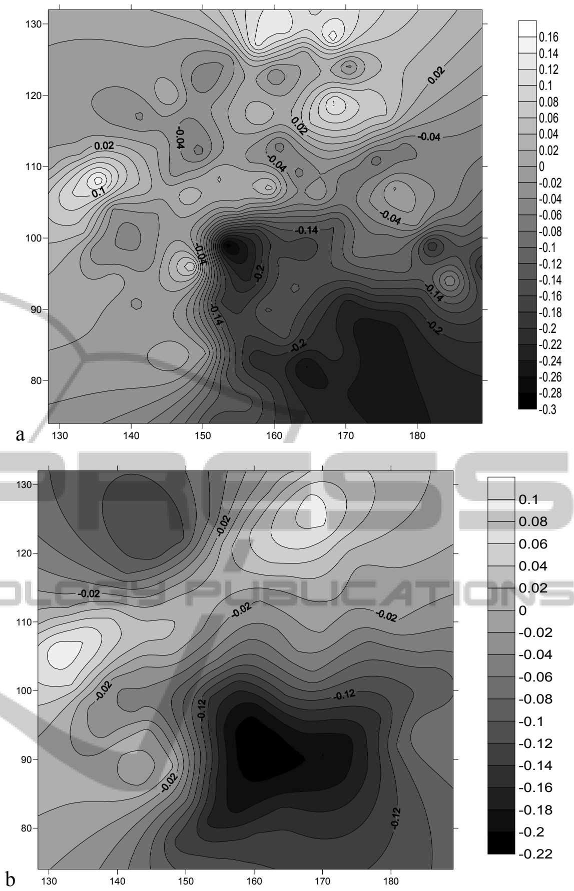

Figure 5: a) Bouger map of original data. b) Cleaned regional data in which a syncline is clearly detected.

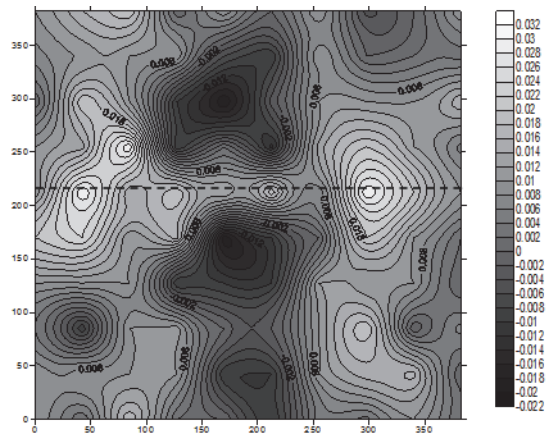

Figure 6: it seems that there is a karstic phenomenon in north-south direction. The dashed profile crosses the low density zone vertically. There is no certain symptom of low density in trend of data in that profile.

Table 5: Maximum residual and regional to residual ratio and correlation coefficient provided by wavelet at different scales for real data of cavity.

| 2-D Wavelet with basis function of Haar | | | |
|---|---|---|---|
| Scale 1 | | Scale 2 | |
| MR | RRR | MR | RRR |
| 0.017 | 0.510 | 0.023 | 0.142 |
| Correlation coefficient | 0.787* | Correlation coefficient | 0.5469 |
| Scale 3 | | Scale 4 | |
| MR | RRR | MR | RRR |
| 0.025 | 0.064 | 0.035 | 0.002 |
| Correlation coefficient | 0.2401 | Correlation coefficient | 0.089 |

Because of large amplitude of residuals, from the first step RRR of 2-D wavelet transformed images are less than 1. Suitable scale is that its correlation coefficient has not yet deviated form its decreasing trend suddenly. Note that big scale and small RRR test fails when their magnitudes are very small because of extra big residuals.

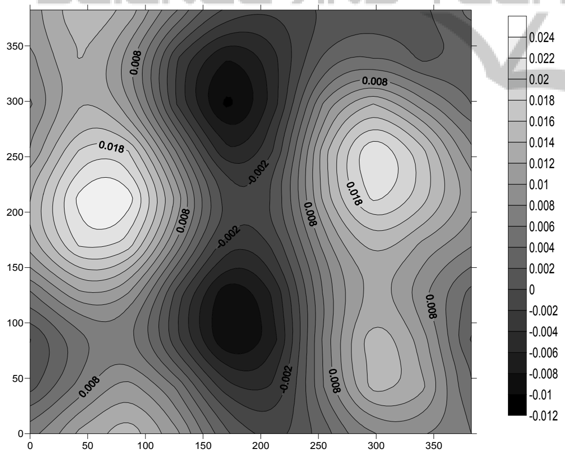


Figure 7: regional map of data which has been shown at Fig. 6. Appropriate scale is 1 and the proportional wavelet function is dmey.

# 6 COMPARISON OF 1-D AND 2-D WAVELET RESULTS FROM SEPARATION PROCESSING

We used 1-D wavelet transform for separation of data corresponds to profile as shown in Fig. 6. According to the RRR test, Haar wavelet function at scale 3 is known appropriate for maximum residual separation; its result is offered at Table 6. The result of 2-D wavelet which has been applied on data (for comparison of 1 and 2-D results, the gravity trace of the same profile has been selected from 2-D wavelet map) indicates the application of scale 1 for obtaining optimal separation is suitable.

We mean the same results as if both 1-D and 2-D wavelet produce data which are geologically interpreted the same and their trends are correlated relatively. To check this we produce outputs provided by wavelet at some more scales. Some RRRs of various separation levels which provided by both 1-D and 2-D wavelet at alternative scales are less than unit which causes to be ignored them as unacceptable geologic correlated tools for separation. Therefore, we are able to prepare and visualize transformed signal and map at any scale but some of them suffer significant geologic and geophysical interpretation. We use optimal results of one and two dimensional by both tests to calibrate the comparison and find out the relation in two dimensions. Fig 8a and 8c are 1-D wavelet transform of data due to profile shown at Fig. 6 at scales 4 and 5. Results of 2-D wavelet transform are brought in Table 5 and are shown at Fig. 9.

Table 6: Maximum residuals, RRRs and correlation coefficients for different scales provided for cavity.

| Wavelet 1-D basis function Haar | | | |
|---|---|---|---|
| Scale 2 | | Scale 3 | |
| MR | RRR | MR | RRR |
| 0.0036 | 3.1472 | 0.0060 | 1.2766* |
| Scale 4 | | Scale 5 | |
| MR | RRR | MR | RRR |
| 0.0103 | 0.5726 | 0.0125 | 0.2720 |

Trends of regional portion by 1-D wavelet transform at scales 4 and 5 are matched one by one with proportional result of 2-D wavelet transform at scales of 2 and 3. These anomalies are provided by surface micro-anomalies; see b and d sections of Fig. 8. Since there are more stations (with smaller intervals rather than other profiles) on individual profile rather than other data acquiring lines, its corresponding signal is smoother rather than ones which are extracted from other grid lines of data.

Result at each scale of 2-D is proportional to ones by 1-D wavelet at scale with second next number. It means 2-D wavelet at scale 1 is corresponding to 1-D wavelet at scale 3 and so on. Finally, 2-D wavelet at scale 1 and its corresponding 1-D wavelet at scale 3, show the path of cavity clearly.

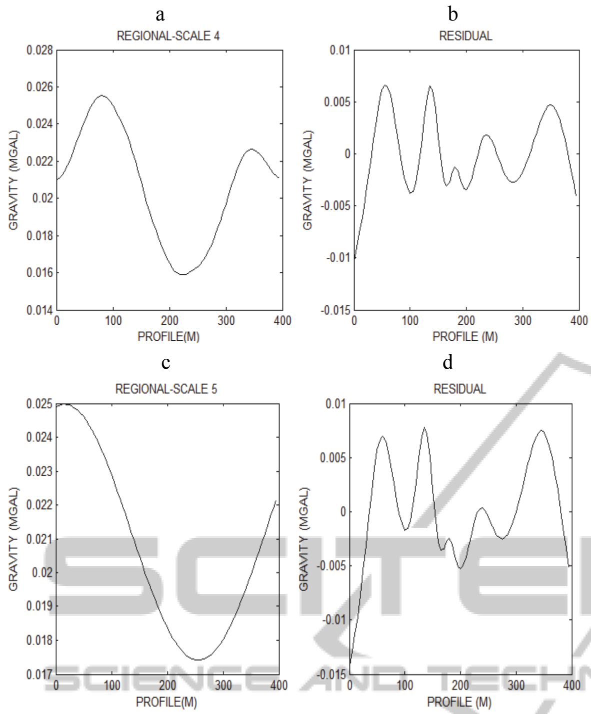


Figure 8: a) 1-D wavelet transform at scales 4. b) Residual reconstruction at scale 4. c) Result of application of 1-D wavelet to data at scale 5. d) Residual reconstruction at scale 5.

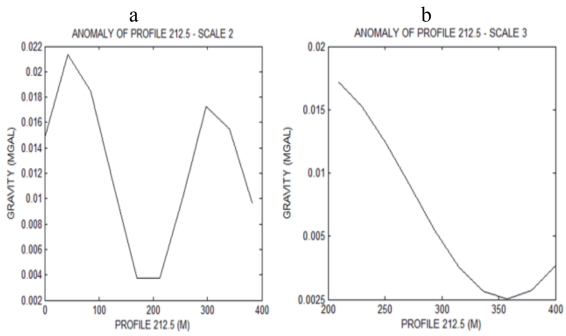


Figure 9: a) Trend of data of profile like that in fig. 6, correspond to regional map produced by 2-D wavelet transform at scale 2. b) Trend of data of profile like that in fig. 6, correspond to regional map produced by 2-D wavelet transform at scale 3.

# 7 CONCLUSIONS

The residuals in gravity data which are due to shallow micro-anomalies create high-frequency effects in the original signal. Discrete stationary wavelet transform was applied to separate them from regional effect to clarify its trace. We want to separate maximum residuals in amplitude that can be interpreted as the biggest shallow anomalies. Maximum scale which provides minimum and not less than unit RRR has been determined for optimal separation. We call this condition establishment of RRR test that is introduced as credible technique for maximum residual separation. If from the first scale RRR is less than unit (this often happens in 2-D wavelet) we choose the scale that correlation coefficient has not still deviated from its decreasing trend. Less than unit RRRs causes distortion of regional signal or map from original form.

Application of test to synthetic gravity data illustrated the usefulness of this technique for maximum residual separation using above mentioned tests. Separation of real data was led to detect of syncline. 1-D and 2-D transforms was applied on data of a Karstic area. We applied 2-D wavelet transform using correlation coefficient test that unmasked cavity (karst path) trace. It was seen that 1-D wavelet results are similar with 2-D ones in manner that 2-D wavelet at any scale is one by one related to 1-D wavelet at second next scale (two times). The advantage of wavelet is basis function alternation that makes it possible to identify and separate any shape and size micro-anomalies.

# ACKNOWLEDGEMENTS

The first author would like to appreciate encouraging guidance of Dr. H. Siah Koohi, at University of Tehran for his valuable feedback.

# REFERENCES

Coifman, R. R., and Donoho, D. L., 1995: Translation-invariant denoising, in Antoniadis, A., and Oppenheim, G., Eds., Wavelets in statistics: Springer-Verlag, 125–150.

Deng, X. Y., Yang, D. H., Peng, J. M., Guan, X., Yang, B. J., 2011: Noise reduction and drift removal using least-squares support vector regression with the implicit bias term, Geophysics, Vol. 75, No. 6, pp. V119–V127

Donoho, D. L., 1993: Nonlinear wavelet methods for recovery of signals, densities, and spectra from indirect and noisy data, in Daubechies, I., Ed., Different perspectives on wavelets: Proc. Symp. Appl. Math, 47, 173–205.

Donoho, D. L. Johnstone I. M., 1994: Ideal spatial adaptation by wavelet shrinkage, Biometrika, Vol. 81, pp. 425-455.

Fedi, M., Lenarduzzi,L., Primiceri, R., Quarta,T., 2000: Localized Denoising Filtering Using the Wavelet Transform Pure appl. geophys. VOL157, pp 1463-1491.

Fedi, M., Primiceri, R., Quarta, T., Villani, A. V., 2004: Joint application of continuous and discrete wavelet transform on gravity data to identify shallow and deep sources, Geophys. J. Int. VOL156, 7-21.

Leblanc, G. E., Morris, W. A., 2001, Denoising of aeromagnetic data via the wavelet transform, GEOPHYSICS, VOL. 66 NO. 6 , Pages 1793-1804.

Moreau, F., Gibert, D., Holschneider, M., and Saracco, G., 1999: Identification of sources of potential fields with the continuous wavelet transform: basic theory: J. Geophys. Res., 104, B3, 5003–5013.

Neumann, M. H., and Von Sachs, R., 1995: Wavelet thresholding beyond the Gaussian i.i.d. situation, in Antoniadis, A., and Oppenheim, G., Eds.,Wavelets in Statistics: Springer-Verlag, 301–329.

Ridsdill-Smith, T. A., and Dentith, M. C., 1999: The wavelet transform in aeromagnetic processing: Geophysics, 64, no. 4, 1003–1013.

Saito, N., 1994, Simultaneous noise suppression and signal compression using a library of orthonormal bases and the minimum description length criteria, in Foufoula-Georgiou, E., and Kumar, P., Eds.,Wavelets in geophysics: Academic Press, 299–324.

Soares, J. C., Tenorio, L., Li, Y. G., 2004: “Efficient automatic denoising of gravity gradiometry data,” Geophysics, Vol. 69, No. 3, pp. 772-782.

Yan. P., Wu, Y., 2011: Application of wavelet threshold denoising method in gravity data processing, IEEE, International Conference on Multimedia Technology (ICMT),pages 2972-2975.

Zou, C. C., Yang, X. D., Pan, L. Z., 1999: A new technique for denoising log curve on the basis of wavelet transform, Geophysical and Geochemical Exploration, Vol. 23, No. 6, pp. 462–466.