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ARTIFACTS REMOVING IN ULTRASONIC IMAGES BY FUSION PROCESSES

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Abstract: Allmost airborne ultrasonic images used in robotics have artefacts and distorstions, when comparing real objects with those presented in ultrasonic images. The differences between reral and reference images have various causes, as assymetries in directivity of ultrasonic transducers, reflections on the explored environment, non-linearities of the processing blocks. Previous works on the problem, showed that such distortions could be removed or attenutated by classical or adaptive filtering of ultrrasonic images. This paper presents the results artefacts removing made by image fusion approach and wavelet transform. Results are accurate and at the same level of quality, comparing with other explored methods, i.e. based on filtering.

Keywords: image, fusion, image fusion, ultrasonic image, signal processing.

1. INTRODUCTION[1]

Since the beginning of 1990's data fusion - in general - and image fusion - in particular – were been widely used in solving various problems from engineering, social and military application fields. Over time, image fusion was defined in various ways, (Zheng, 2011), e.g.: (i) a process dealing with data and information from multiple sources to achieve refined/improved information for decision making, (Hall and Llinas, 1997); (ii) the combination of two or more different images to form a new image by using a certain algorithm, (Genderen and Pohl, 1994); (iii) process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing, (Guest editorial, 2007); (iv) a process of combining images, obtained by sensors of different wavelengths simultaneously viewing of the same scene, to form a composite image. The composite image is formed to improve image content and to make it easier for the user to detect, recognize, and identify targets and increase his situational awareness, (Enhanced vision systems, 2013).

Ultrasonic imaging means 2D (static images) or 3D (video or dynamic images) representation of the environment, based on the ultrasonic waves. An element of the image (which could be assimilated as pixel) has an intensity proportional with the amplitude of the received signals, reflected by the surface of the objects from the explored environment, (Aiordachioaie and Frangu, 2012a, 2013). Such images have artifacts, coming from nonlinearities of the processing blocks, e.g. ultrasonic transducers and amplifiers. Some solutions use adaptive filtering, as described in (Aiordachioaie and Frangu, 2012b).

The present paper presents the results obtained by image fusion technique and based on Discrete Wavelet Transform (DWT). Firstly, in the second section, in section 2, the airborne ultrasonic images, including description of the problem and main causes, are introduced. In section 3 the importance of

[1]The content and the results of the paper are parts of the Nicoleta Cernat’s MSc dissertation, (Cernat, 2013). The structure of the paper and some improvements were proposed by Dorel Aiordachioaie.

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image fusion process is considered, in which it shows: definition, objectives, the demonstration that it is an important area, and the methods which are used. Section 4 describes the results obtained by fusion process of airborne ultrasonic images within the scope of artifacts removing.

2. ULTRASONIC IMAGES

The ultrasounds, in general, and ultrasonic images, in particular, have a lot of applications in various domains, starting with relatively old areas of industrial applications, and continuing with robotics and medical imaging.

Ultrasonic imaging means 2D (static images) or 3D (video or dynamic images) representation of the environment, obtained with ultrasonic waves. An element of the image (which could be assimilated as pixel) has an intensity proportional with the amplitude of the received signals, reflected by the surface of the objects from the explored environment.

In the field of mobile grounded robots, ultrasonic imaging is drastically limited by the absorption of ultrasound in air, and – as effect - the number of applications and results is still low. Practically, at least in robotics and for target recognition, frequencies over 150-200 kHz are rarely used.

Ultrasonic image generation could be obtained by using the element by element technique, by exploring various directions of the environment, on the directions were the objects are located. Exploring means pulse emission plus waiting and storage of the received echoes from environment during a fixed time window. Depending on target, the relative positions and amplitudes of the received echoes are changing in time. The set of recorded frames (in fact, static images) can be described by a 3D function $I = I(r,\theta,\varphi)$, where *r* is the range to target, θ and φ are angular coordinates (azimuth and elevation), and *I* means the intensity.

Fig. 1 presents the set of ultrasonic images (two cases) obtained by ROVIBAT-01, a biomimetic sonar head, described in (Aiordachioaie and Frangu, 2012a, 2013). For each object, a ball and a box, of similar size, around 14-15 cm, three images are presented: left, right and registered. The ultrasonic images have artifacts, by looking to the bottom of each image. These are introduced by ultrasonic transducers. The task of the image fusion process is to remove these artifacts by having, like a priori information, the type of the explored object.

3. IMAGE FUSION

Information fusion within source images can be classified as either redundant or complementary. Major advantages are of two types: improve reliability (by redundant information) and improve capability (by complementary information), (Zheng, 2011). Reliability is associated with redundancy of information between source bands, and capability is associated with complementary information between source bands. To obtain a much better picture in the end we must have in the source images large amounts of complementary information and less redundant information.

The objectives of image fusion schemes are to extract all relevant information from source images, don't introduce artifacts or inconsistencies which will distract human observers or the following processing and reliable and be robust to imperfections such as recording incorrect, (Hangan, 2011).

Image fusion is a perfect way to combine information from multiple sources or a single source to remove defects. The purpose of image fusion is to integrate different data in order to obtain more useful information.

To achieve image fusion, four stages must performed: signal level, pixel level, feature level, and decision level, (Zheng, 2011): (1) Signal level fusion combines signals from different sources to create a new signal which has a better signal-to-noise ratio in comparison with original signal; (2) Pixel level fusion is carried out on a pixel-by-pixel basis. This fusion is performed to improve the performance of image processing tasks, for example, segmentation. Each pixel from fused image is obtained from a set of pixels, which are in source images; (3) Feature level fusion is based on extracting the objects found in source images. Extracts the most important features from source images, for example, pixel intensities, edges or textures, and then merges these features; (4) Decision level fusion combines information resulted after applying several algorithms to get a final fused decision. The source images are processed separately for information extraction. Then information is combined with applying decision rules.

Over the years many methods have been proposed. The widely used methods include: (1) Intensity-Hue-Saturation (IHS) transform; (2) Principal Component Analysis (PCA); (3) Arithmetic combination (*Brovey transform*, *Synthetic variable ratio technique*, *Ratio enhancement technique*); (4) Multiscale transf. based fusion (*High-pass filtering method*, *Pyramid method*, *Wavelet and Curvelet transf.*); (5) Total probability density fusion; (6) Biologically inspired information fusion; (7) Artificial Neural Networks (ANNs).

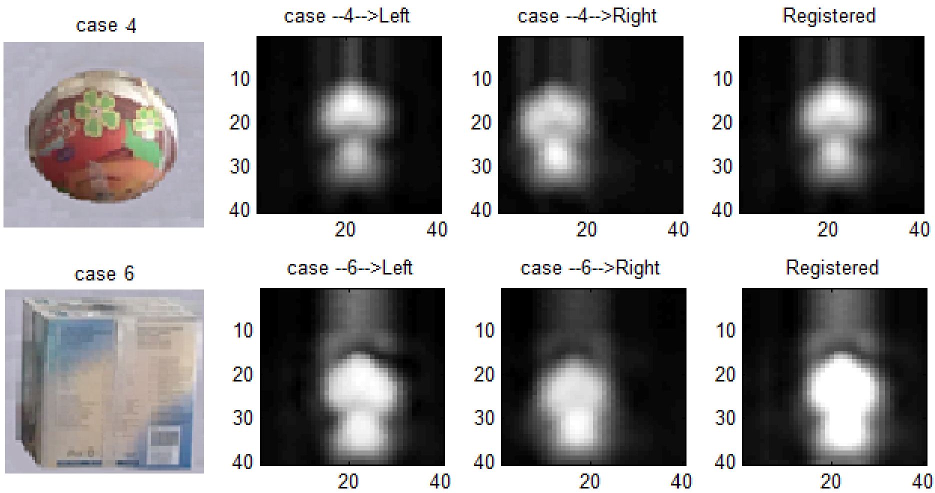

Fig. 1. Examples of airborne ultrasonic images obtained by ROVIBAT-01 biomimetic sonar head (Aiordachioaie and Frangu, 2012a; 2013)

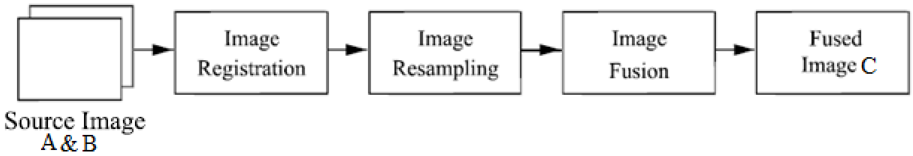

Fig. 2. Pre-processing tasks for image fusion

The literature of image fusion – in general – and – ultrasonic image fusion – in particular is quite generous. General discussions are present in (Mitchell, 2010; Stathaki, 2008), (Pajares and de la Gruz, 2004), or (Wang, *et al*, 2005). Details and results could be discovered by looking to some sample references, as e.g. from (Waltz and Waltz, 2009; Zheng, 2007; Burt and Adelson, 1983; Ukimura, 2011; Hamza, *et al*, 2005; Al –Wassai, *et al*, 2011; Elshafiey, *et al*, 2011; Liu, *et al*, 2004).

As specified in (Flusser, et al, 2007) , *"there is no "best" method; the choice of a proper method depends on the images and the fusion purpose."*

Limitations of existing fusion methods are presented in (Zhang, 2004). Analyzing the current state can be seen that, in worldwide, a common method is based on wavelets, but there are other methods approached, in addition, starting from the wavelet we can combine with other methods and so we obtain a better quality of image after merger. From the analysis of the available literature it can observe that to simple and robust image fusion method is based on DWT (Discrete Wavelet Transform). For this reason in this paper we have focused on the wavelet transform. After experiments, in order to evaluate the quality of fused image, after merger, it is calculated Root Mean Square Error (RMSE) for each wavelet, level and rule in part.

From structural point of view, image fusion needs two steps: (I) Fusion Analysis (by fusion rules) and Fusion Synthesis; (II) Pre-processing for fusion. After we have chosen the rule that we want to apply, so we know what we want to obtain at the output, before applying this method, we need a pre-processing for fusion. We need pre-processing and at output from fusion analysis, perhaps even and after fusion synthesis, so an iterative process must be considered some times.

The pre-processing structure is illustrated in Fig. 2. If there are two sources for obtaining images, the source image A may be very different from B, in this case applied IR (Image Registration) in that image in order to, for example, rotate, scale, and align the images. We can say that image registration is the correlation between the images before image fusion.

In fusion analysis step, input images are decomposed: choose a wavelet, choose the level N, decomposition is computed in the level N and at the output is obtained two sets of coefficients, approximation and detail (Zheng, 2011). The level N may be chosen according the desired performance at the output, this may be from 1 to 5. Synthesis means reconstruction of the two images into one image: it computed using the approximation coefficients from level N and detail coefficients from 1 to N.

The combination of the approximation and detail coefficients may be, (Zheng, 2011):

- Simple: 'max'(the maximum), 'min'(the minimum), 'mean'(the mean), 'img1'(the first element), 'img2'(the second element) or 'rand'(a randomly chosen element)
- Parameter-dependent: 'linear', 'UD_fusion' (Up-Down fusion), 'DU_fusion' (Down-Up fusion), 'RL_fusion' (Right-Left fusion), 'LR_fusion' (Left-Right fusion), 'UserDEF' (User-DEFined fusion)

Further we use fusion rules presented in Table 1 and Daubechies wavelet ’db2’were used.

Table 1. Fusion rules

Name	**The approximation coefficients** Selection Rule	**The detail coefficients** Selection Rule
max,max	Maximum	Maximum
min,max	Minimum	Maximum
max,min	Maximum	Minimum
min,min	Minimum	Minimum
mean,mean	Mean	Mean
mean,max	Mean	Maximum
max,mean	Maximum	Mean

2.1. Description of the fusion rules

Maximum Selection Rule

The images **A** and **B** are decomposed in rows and columns (low-pass (L) and high-pass(H) filtering). Then is applied down sampling at each level to obtain approximation (**LL**) and detail (**LH, HL** and **HH**) coefficients.

The steps for this rule are:

1: Read the two source images **A** and **B**.

2: Apply to each image wavelet decomposition till level N, to obtain approximation and detail coefficients, lev = 1,2..N, in this case N = 2.

3: Apply maximum selection rule, *'max'*, taking the maximum valued pixels from source images **A** and **B**. Following equation represents the approximation coefficients

$$LL_f^N(i,j) = \max\left(LL_A^N(i,j), LL_B^N(i,j)\right), \quad i,j = 1,2,... \tag{1}$$

$\mathbf{LL}_f^N$ is the fused, $\mathbf{LL}_A^N$ and $\mathbf{LL}_B^N$ are the input approximations, i and j represent the pixel positions. Further is calculated for the remaining coefficients, $\mathbf{LH}_f^{lev}$, $\mathbf{LH}_A^{lev}$, $\mathbf{LH}_B^{lev}$ are vertical high frequencies, $\mathbf{HL}_f^{lev}$, $\mathbf{HL}_A^{lev}$, $\mathbf{HL}_B^{lev}$ are horizontal high frequencies, $\mathbf{HH}_f^{lev}$, $\mathbf{HH}_A^{lev}$, $\mathbf{HH}_B^{lev}$ are diagonal high frequencies of the fused and input detail.

$$C_f^N(i,j) = D_f(i,j) * C_A^N(i,j) + \overline{D_f(i,j)} * C_B^N(i,j), \quad i,j = 1,2,... \tag{2}$$

$\mathbf{C}_f^N$ is the fused, $\mathbf{C}_A^N$ and $\mathbf{C}_B^N$ are the input approximations or detail, $\mathbf{D}_f$ a matrix of ones and zeros.

4: From Eq. (2) is enunciated a binary decision map.

$$D_f(i,j) = \begin{cases} 1, & d_A(i,j) > d_B(i,j) \\ 0, & otherwise \end{cases} \tag{3}$$

5: The fused transform with maximum selection pixel rule is obtained.

6: Consecution of fused coefficients provides the new coefficient matrix.

7: Implement inverse wavelet transform to reconstruct the image and display the result.

Minimum Selection Rule

The difference between maximum selection rule and minimum selection rule is Eq. (1), which becomes Eq. (4), taking the minimum valued pixels from source images **A** and **B**, and Eq. (3) becomes Eq. (5). Other steps remain the same.

$$LL_f^N(i,j) = \min\left(LL_A^N(i,j), LL_B^N(i,j)\right) \tag{4}$$

$$D_f(i,j) = \begin{cases} 1, & d_A(i,j) < d_B(i,j) \\ 0, & otherwise \end{cases} \tag{5}$$

This method does not gives good results after fusion, but by combining max-min, min-max or other combination the result will be another one, better or not, as explained in (Cernat, 2013).

Mean Selection Rule

As observed above in the two methods, steps (from step 1 to step 7) remain the same, only the fusion method change. For this method will be taken the mean valued pixels from source images, *A* and *B*, and binary decision map is the following.

$$LL_f^N(i,j) = mean\left(LL_A^N(i,j), LL_B^N(i,j)\right) \quad (6)$$

$$D_f(i,j) = 1 \quad (7)$$

The method can be applied, for example, to combine two human faces.

Randomly chosen element Selection Rule

The method will take a randomly chosen value from source images, *A* and *B*, and binary decision map is the following.

$$D_f(i,j) = \text{A Boolean random matrix} \quad (8)$$

For example:

$$R = rand\left(C_A^N(i,j)\right) \quad (9)$$

$$D_f(i,j) = \begin{cases} 1, & R < 0.5 \\ 0, & otherwise \end{cases} \quad (10)$$

The first element Selection Rule

In order to highlight this method, we will use the Minimum Selection Rule for approximation coefficients, Eq. (4) and (5), and for details will use the first element Selection Rule, as defined in Eq. (11).

$$C_f^N(i,j) = C_A^N(i,j) \quad (11)$$

Instead of $\mathbf{C}_A^N$ can be and $\mathbf{C}_B^N$ depending on the situation.

The second element Selection Rule

The second element Selection Rule for approximation coefficients is described by Eq. (12), and - for details - the Maximum Selection Rule is used, as defined in Eq. (1), (2) and (3).

$$C_f^N = C_B^N(i,j) \quad (12)$$

Instead of $\mathbf{C}_B^N$ can be and $\mathbf{C}_A^N$ depending on the situation.

Linear Selection Rule

The method has a parameter that allows us to select an image or to accord its value to obtain an output image, the formula is given below.

$$C_f^N(i,j) = C_A^N(i,j) * t + C_B^N(i,j) * (1-t) \quad (13)$$

If $t = 0$ then the picture that emerges is **B** and if $t = 1$ the result is **A**, otherwise $0 \le t \le 1$.

Up - Down Selection Rule (UD)

For beginning the size of images, **s**= *size(*$\mathbf{C}_A^N$*)* = [s_1, s_2] is needed, and then build the following matrices. Is generates a linearly spaced vector **x**, with values from 0 to 1.

$$\mathbf{x} = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} = \begin{bmatrix} 0 & 0 & \dots & 1 \end{bmatrix}_{1xs_1} \quad (14)$$

After that is formed the matrix which give the up-down fusion.

$$\mathbf{P} = \begin{bmatrix} x_1 & \dots & x_1 \\ \vdots & \ddots & \vdots \\ x_n & \dots & x_n \end{bmatrix} = \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 1 & \dots & 1 \end{bmatrix}_{s_1 x s_2} \quad (15)$$

If t is not equal to 1, **P** becomes:

$$\mathbf{P} = \mathbf{P}^T, \quad t \ge 0 \quad (16)$$

and, finally, the image fusion is:

$$C_f^N(i,j) = C_A^N(i,j) * (1-\mathbf{P}) + C_B^N(i,j) * \mathbf{P} \quad (17)$$

Down - Up Selection Rule (DU)

It is calculated same as Up-Down Selection Rule, but the Eq. (17) becomes Eq. (18).

$$C_f^N(i,j) = C_A^N(i,j) * \mathbf{P} + C_B^N(i,j) * (1-\mathbf{P}) \quad (18)$$

Left-R ight Selection Rule

Starting from Up - Down Selection Rule Eq. (15) will become Eq. (19).

$$\mathbf{P} = \begin{bmatrix} x_1 & \dots & x_n \\ \vdots & \ddots & \vdots \\ x_1 & \dots & x_n \end{bmatrix} = \begin{bmatrix} 0 & \dots & 1 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix}_{s_1 x s_2} \quad (19)$$

The image fusion is the same, eq. (17).

Right - Left Selection Rule

Starting from DU Selection Rule eq. (15) will become eq. (19), as shown above. The image fusion is the same, eq. (18).

User-Defined Selection Rule.

In this method user can choose how to fuse the two images

4. ULTRASONIC IMAGE FUSION

Results of the fusion of airborne ultrasound images are presented. For each distorted ultrasonic image, a reference (target) image is considered, which is free of distortions. This can be obtained by simulation (a synthetic or artificial approach) or could be obtained by post processing of the real, distorted images.

The objective of the fusion is to remove the artifacts and to decrease the distortions, in such a way the fused image is closer to the target image.

For this paper we present four cases, as it is given in Table 2.

Table 2. Source images

Case	Target image name	Source Images A & B	
1	box_right	Target box	box-right
2	box_left	Target box	box-left
3	ball_right	Target ball	ball-right
4	ball_left	Target ball	ball-left

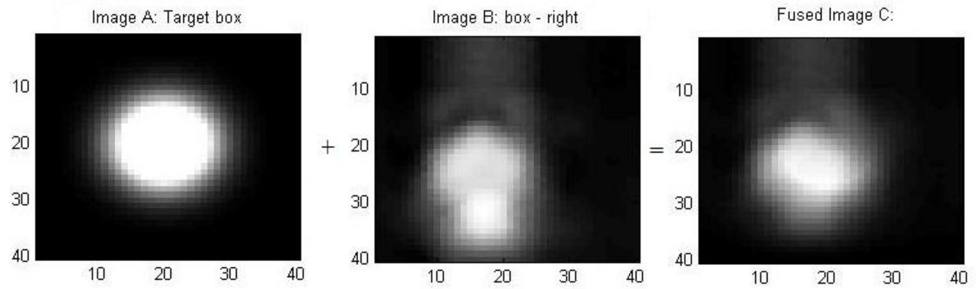

Fig.3. Source image (box_right). Fused Image Down-Up Selection Rule

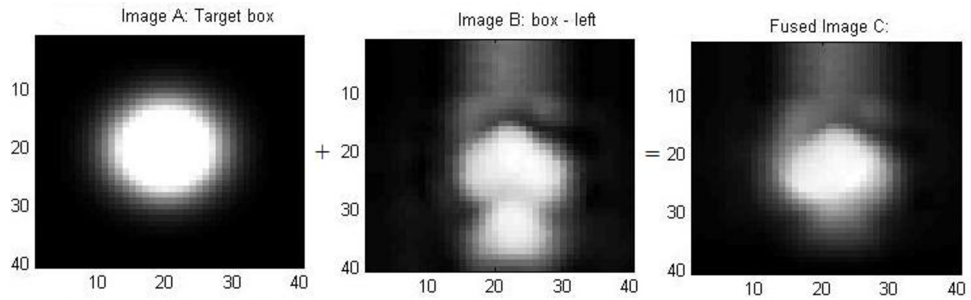

Fig. 4. Source image (box_left). Fused Image Down-Up Selection Rule

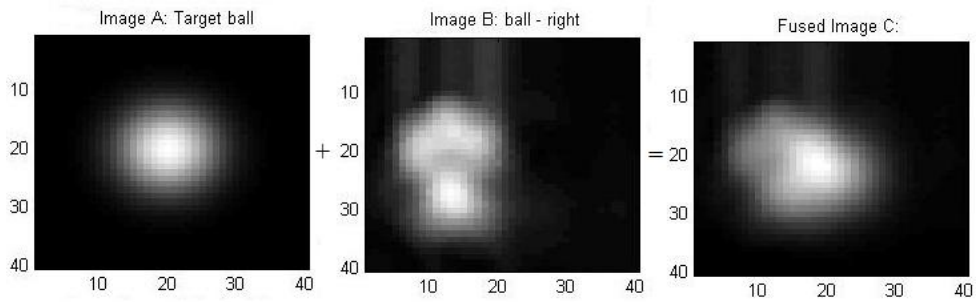

Fig. 5. Source image (ball_right). Fused Image Down–Up Selection Rule

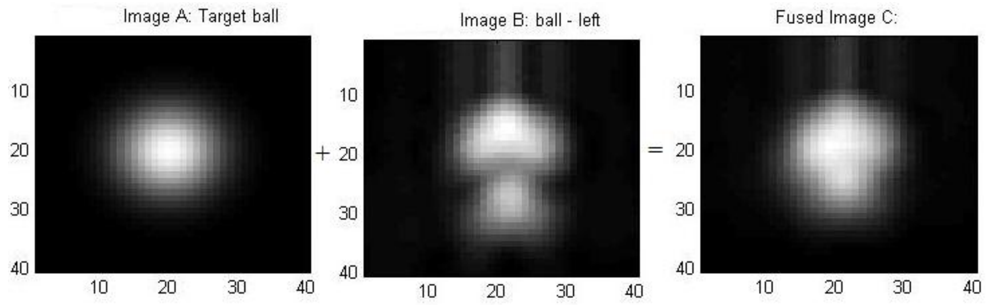

Fig. 6. Source image (ball_left). Fused Image Down–Up Selection Rule

a) For case #1 (box_right image**)** the following steps were used: 1. Load source images; 2. Apply the fusion method, DU selection rule. The result is shown in Fig. 3. As can be seen, the result is better then original. After applying DU fusion it can be seen that the defect is almost removed, and the upper part is kept.

b) For case #2 (box_left image), the same steps were as above. The result is shown in Fig. 4. The result is appreciated as good, the same quality as previous. After fusion the defect is almost removed, and the upper part is kept.

c) For case #3 (ball_right image) were used the same steps, explained for the first case. The result is shown in Fig. 5. The result is good, after fusion the defect is almost removed, and the upper part is kept. But, for a better result, a preprocessing step is necessary to align the two objects before fusing.

d) For case #4 (ball_left image) were used the same steps, explained for the first case The result is shown in Fig. 6. As can be seen, the result is good, after fusion the defect is almost removed, and the upper part is kept. As we can see, because the objects were aligned the result is much better then case #3.

A quantitative analysis is made based on RMSE (Root Mean Square Error) between the target and fused images. The results are presented in Fig. 7 and confirm the qualitative results presented above.

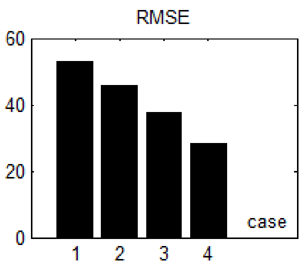

Fig. 7. Quantitative analysis of the fused images, cases 1 to 4

5. CONCLUSIONS

The objective of the paper was to remove the artifacts of airborne ultrasonic images, obtained with a biomimetic sonar head, by using image fusion and wavelet transform. A set of four case studies were considered, representing images of two objects, from the left and the right side. For each object a target object (image) is considered, as reference. The two images merged according to the decision rule for the approximation and detail coefficients. The decision rule is chosen according to what we want to get after the merger. Even it was not applied in this work, image fusion needs pre-processing, because the source images should have the same structural characteristics (size, resolution, representation, etc.). For application fusion with ultrasound images, and for the imposed artifact, the chosen Down-Up fusion rule provides acceptable results and in line with other results reported in literature. For other types of artefacts or to shaper more the fused image, other rules could apply and also more fusing.

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