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An approach to image fusion implementing feature level fusion on seismic attributes

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Abstract – Image fusion is an important part of image processing, being performed on different levels of complexity. A feature, or attribute level fusion between two or more images, could be performed by combining the notions of image segmentation and mutual information in order to obtain the fused image. The first step of the proposed method is to decompose the input images into basic features using a connected-components algorithm, followed by the computation of the mutual information using one of the inputs as reference. The fusion method will be tested on synthetic images and further applied on seismic attributes.

Keywords: feature-level image fusion, image segmentation, mutual information, connected-components, seismic attributes.

I. INTRODUCTION

In image processing, image fusion, holds an important place due to the fact that it is a key processing method when dealing with the need to qualitatively and/or quantitatively improve the resulting image. We talk about image fusion when the input consists of at least two images. Usually irrespective of the number of input images, the output consists of a single image, representing the fused inputs, according to a specific fusion algorithm.

The concept of fusion is commonly applied with the purpose of combining the characteristics of complementary imaging sensors in order to enhance the final result. In our case, the goal is to combine different seismic attributes (seismic data obtained by processing, using various methods, the raw seismic images) hence obtaining a resulting image that yields more useful information than any of the input images.

Due to the particular nature of the seismic attributes, mainly to the fact that they contain localized information with very precise characteristics, the classical fusion approaches prove to be insufficient. Our goal was to implement a higher-level fusion method in order to evaluate its performance and compare the results with the ones obtained through low-level fusion methods.

A comparative analysis of the available feature-level fusion methods is presented in [1], concluding that for this particular type of images (i.e. seismic attributes) an expert system is best suited. The expert system designed to perform the feature-level fusion will use a priori knowledge about the characteristics of the input data, thus making it a task-oriented method, lacking the generality of low-level methods.

The image fusion method was developed to work with two input images, but as for almost every other fusion method the expansion to a greater number of inputs is straightforward.

The fusion is performed after a pre-processing of the input images. The pre-processing is comprised of two main steps: the first one consists in creating a mask of the input image in order to allow a further image decomposition; the second step is represented by a decomposition of the image based on the image mask generated in the first pre-processing step. The second step is performed by means of a connected-components algorithm [18], which decomposes the input based on an image mask (also obtained based on the input image) into elementary blocks or features.

After the pre-processing has been performed on both inputs, the feature level fusion algorithm is applied on the two sets of features obtained from the input images. The feature-level fusion algorithm is developed around the idea of computing the mutual information between the two sets of features and selecting the features based on a computed threshold [15]. One set of features is considered as reference in computing the mutual information and comparing the results with the threshold. Usually the image that contains more useful information or is less affected by noise or unwanted distortions is considered as the reference set.

The fusion method will be tested first on synthesis images, followed by a test on seismic attributes.

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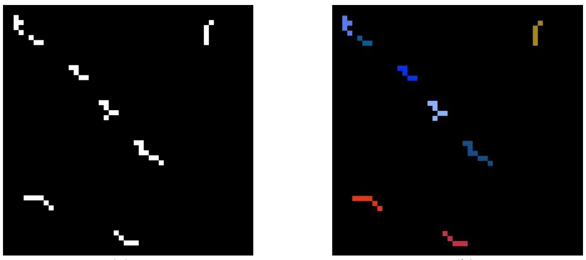
II. FEATURE EXTRACTION

Prior to performing the fusion at the feature level between the two inputs, a pre-processing of the input images is required. The first pre-processing phase consists of generating a mask based on the original input images. The input images are 8-bit grey level bitmaps, where 0 corresponds to “black” and 255 is associated with “white”. The resulting mask will divide the (0:255) range into a user-defined number of sub-ranges, where the value of a pixel from the resulting mask will be given by the number of the sub-range the pixel from the original image belongs to. Consequently, the resulting mask will have the same dimensions as the original image, the difference consisting in the fact that the value of its pixels will denote a certain sub-range of values of the original image.

The purpose of this mask is to further allow decomposition of the original image based on a connected components algorithm [18]. The decomposition algorithm was adapted for this type of images and it is detailed in [1]. It works on the image mask in order to find neighbouring pixels that belong to the same sub-range. The method is recursive in order to perform a step-by-step search in all four directions of neighbouring pixels for same sub-range pixels. Once all the pixels belonging to the same sub-range and connected to one another by at least one neighbouring pixel are found, by means of the connected-components method, they are considered as being a single entity also referred to as a feature. After the entire mask has been processed by the connected-components algorithm, a second mask will result, were the pixels belonging to the same feature will have as numerical value the index value of that feature, resulting from the labelling process.

A simple example of the pre-processing phase is illustrated in Fig. 1 using a synthesis image as input:



(a) (b)

Fig. 1 Original synthesis image (a) and connected-components result (b) – each feature is represented by a different colour

The second mask along with the original image will be further used to independently characterize each feature. The amount of information about a given feature can vary according to the level of complexity employed by the mutual information computation method. Mathematically, each feature can be represented by a feature vector, $f_i = [x, y, E, Id, N_O]$, $i = 0 \ldots N_F$, where the pair (x,y) represents the spatial coordinates of the “centre of gravity” of the feature, E the intensity value, Id the image number (in this case #1 or #2) and N_O, the feature index with respect to the set of features (N_F denotes the total number of features from an image). For a more precise characterization the orientation θ can also be used, thus fully characterizing a feature in the feature set F. In order to create the feature set F, both the original image and the second mask are used for extracting the characterizing parameters of each feature.

III. FEATURE RELEVANCE

Having extracted the features from the two input images, our next goal is to establish which are the relevant ones and which are redundant with respect to our desired outcome, that of a fused result. In order to establish feature relevance in a transparent manner, we will employ the notion of mutual information, method already successfully employed in feature selection schemes by [15] or [17].

A. *Mutual Information*

We denote by X and Y two random variables. Their mutual information can be defined in terms of their probability density functions *p(x), p(y)* and *p(x,y)* as:

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \qquad (1)$$

Based on the entropy, the mutual information between X and Y can also be expressed using the conditional probability $p(x|y)$. The entropy, H of X is a measure of its uncertainty (randomness) and it is defined as:

$$H(X) = -\sum_{x \in X} p(x) \log p(x) \qquad (2)$$

Given two variables, conditional entropy is a measure of the uncertainty when one of them is known. Therefore, the conditional entropy of X and Y can be expressed as:

$$H(X|Y) = -\sum_{y \in Y} p(y) \sum_{x \in X} p(x|y) \log p(x|y) \qquad (3)$$

The mutual information between X and Y can be computed from the entropy terms defined above as:

$$I(X;Y) = H(X) - H(X|Y) \qquad (4)$$

B. *Affinity notion*

The affinity notion from the mathematical point of view can be defined as a percentage leaning favourable of one set of values over another set pertaining to the same item in the set.

Having two features, each described by its parameters, we need to define a measure to compare them and to establish the degree in which they are similar to one another. A measure that quantifies this resemblance is the *affinity measure* defined in [16] and adapted by [15]. Since we are dealing with a particular type of images we need to define a particular model for the *affinity measure* that will quantify the resemblance between features with particular characteristics as the ones discussed. The model used to compute the affinity measure was used also by [15]:

$$A = e^{(-r/\sigma_r)} \cdot e^{(-\Delta/\sigma_e)} \tag{5}$$

This measure can be seen as a function of two variables: $Aff(f_1, f_2) = A$, where f_1 and f_2 represent features, f_1 from the first image and f_2 from the second image.

r denotes the spatial distance between the two features, in our case the Euclidian distance (other distances can also be used). This distance is computed based on the "centre of gravity" of each feature. σ_r is the normalization factor: $\sigma_r = R/w_1$, where R is the maximum possible value of r and w_1 is a weight factor that can be used to change the relative influence of the term in the affinity computation. Δ represents the absolute difference in intensity of the two features: $\Delta = |E_{f_1} - E_{f_2}|$. σ_e is the normalization factor: $\sigma_e = E/w_2$, where E is equal to the maximum possible value of the intensity. w_2, like w_1, is a weighting factor that can be used to change the relative influence of the Δ term.

C. *Computing Mutual Information*

Consider the random variables I_1 and I_2 (X and Y for the general case); we have F_1 belonging to the domain I_1 that contains only features from the first image and F_2 belonging to the domain I_2 that contains features from the second image. The conditional probability based on the affinity measure between features from the set F_1 and features from the set F_2 can be defined as follows:

$$p(f_2|f_1) = \frac{Aff(f_2, f_1)}{\sum_{f_j \in F_2} Aff(f_j, f_1)}, \tag{6}$$
$$\text{where } p(f_2|f_1) \equiv p(I_2 = f_2 | I_1 = f_1)$$

The definition of the conditional probability in equation (6) enables us to measure the conditional entropy between I_1 and any feature $f_j \in F_2$. Using equation (3) this can be expressed as:

$$H(I_1|f_j) = -p(f_j) \sum_{f_i \in F_1} p(f_j|f_i) \log p(f_j|f_i) \tag{7}$$

where the distribution $p(f_j)$ can be considered as a prior distribution expectation of observing a given feature from the image space. Similarly, assuming $p(f_i)$ to be a known distribution (e.g. uniform), the entropy of I_1 can be computed as:

$$H(I_1) = -\sum_{f_i \in F_1} p(f_i) \log p(f_i) \tag{8}$$

In order to measure the mutual information $I(I_1; f_j)$ we can use equations (7) and (8) in equation (4). In order to obtain an estimate of the full joint mutual information $I(I_1; I_2)$ we consider each feature to be independent and we use the approximation suggested in [17], which is the mean of all mutual information values between features $f_j \in F_2$ and I_1:

$$I(I_1; I_2) = \frac{1}{|F_2|} \sum_{f_j \in F_2} I(I_1; f_j) \tag{9}$$

IV. FEATURE SELECTION USING MUTUAL INFORMATION

We now have to select the most relevant set of features from I_2 based on I_1. A feature selection problem similar to the one discussed here can be found in [17] and the intuition behind the solution of this problem is somehow similar to that one. The problem consists in seeking the subset of I_2 that maximizes the mutual information between I_1 and I_2.

If we assume the prior distribution of features $p(f_i)$ and $p(f_j)$ to be uniform, the entropy of I_1, equation (7), is constant. Wanting to maximize the mutual information is equivalent to finding a set of features from I_2 that minimizes the conditional entropy $H(I_1|I_2)$. Therefore, we seek those features from I_2 that minimize the randomness of the image features in I_1.

Using equations (7) and (8) we can rewrite equation (9) and also using the assumption of uniform distribution for $p(f_i)$ and $p(f_j)$, the conditional entropy of I_1 and I_2 can be expressed as:

$$H(I_1|I_2) \propto \sum_{f_j \in F_2} \left(-\sum_{f_i \in F_1} p(f_j|f_i) \log p(f_j|f_i) \right) \tag{10}$$

where the term in parenthesis can be interpreted as the entropy of the distribution of affinity between f_j and the features in F_1. In other words, this is the notion of relevance we need to define and use, because as already stated the entropy of affinity values is expected to be low only for f_j belonging to our region of interest.

Another problem that arises from this selection method is of finding the subset of features from F_2 that minimizes the mutual information, since there are an exponentially large number of subsets that would need to be compared. [15] suggests an alternate greedy heuristic search pattern that involves a simple incremental search scheme that adds to the set of selected features one at a time. The search method starts from an empty set of selected features, and with each new iteration the feature from I_2 that maximizes equation (9), is added to the set of selected features. This solution has one major drawback, though. The drawback being that it does not have a fixed stopping criterion, other then an upper limit provided as input by the user. A modified version that has a stopping criterion can be developed out of the presented greedy method:

1. Compute $I_{full} = I(I_1; I_2)$ where I_1 and I_2 are random variables defined over F_1 and F_2 respectively.
2. For each $f_j \in F_2$:
   a. $F_2^j \leftarrow F_2 - \{f_j\}$.
   b. Compute $I^j = I(I_1; I_2^j)$, where I_2^j is defined over F_2^j.
3. Select all f_j such that $I^j \le I_{full}$.

V. EXPERIMENTS

In order to test our feature fusion method we first need to define a series of synthesis images with a predictable outcome of the fused result in order to compare the ideal result with the one yielded by the fusion algorithm. In Fig. 2 we represent the two input synthesis images (a) and (b), along with the ideal result (c) and the result obtained through our method (d):

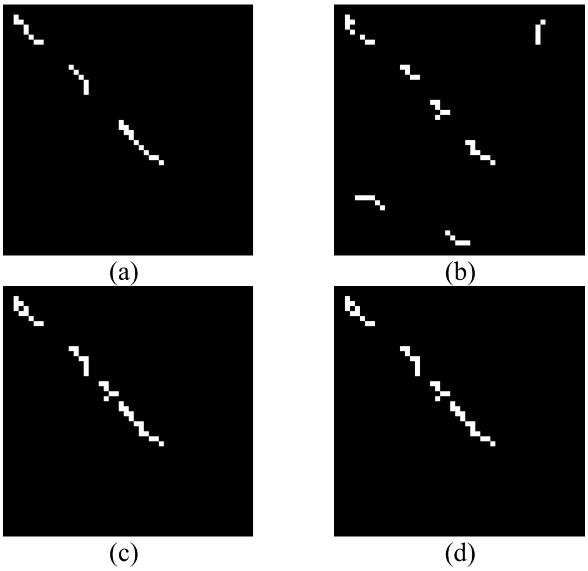


Fig. 2 (a) First input image; (b) Second input image (c) Ideal output; (d) Feature-level fusion result.

In order to evaluate the result and the degree of resemblance between the desired output and the one obtained by the fusion method, we will use the RMSD (*Root Mean Square Deviation*) measure to quantify the resemblance between the two results. RSMD is defined by the following equation:

$$RMSD(I_1, I_2) = \sqrt{E((I_1 - I_2)^2)} = \sqrt{\frac{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2}{n}} \qquad (11)$$

In this case the *RMSD*=0, meaning that the two compared images present no differences between them, concluding that for this test the fusion method yielded a result identical to the desired one.

Two important remarks need to be made: in the previous example the feature-level fusion offered better results than any of the low-level fusion methods, the RMSD being 0, meaning that there were no differences between what was obtained through this method and what was expected from the fused result; since this is a dedicated method, mainly to work on a certain type of images, i.e. seismic attributes, it lacks the wide application spectrum of other methods, therefore in some cases it yields results with a higher RSMD than the low-level methods.

For the test set represented in Fig. 2, we can see in Fig. 3 the graph of the computed values of the mutual information were the first image is considered to be the reference:

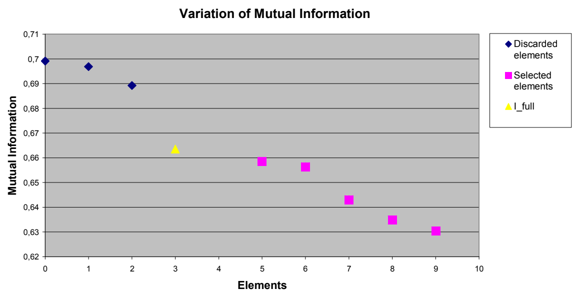


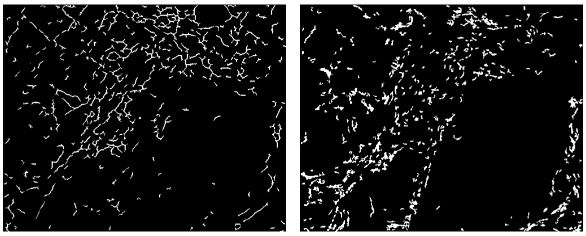
Fig. 3 Variation of Mutual Information

Only the features that are below the computed threshold (*I_full*) are selected as part of the fused output.

Our next example will use as input images two seismic attributes obtained through different processing methods from seismic images taken by means of SONAR. The attributes are called *Fault Maximum* [26] and *Coherence*. The goal of the fusion process is to combine the information contained by these two attributes into a single result that is qualitatively superior to either of them. Since we are dealing with fusion we should also mention the fact that the two attributes are spatially registered, meaning that they represent the same region of space hence we are talking about a spatial fusion with the purpose of enhancing the spatial detail.

As a last remark, we need to underline the fact that for real images we cannot define an ideal output, because that would imply that we already know something that we are trying to determine by means of image fusion, making the whole fusion process redundant, which is not the case.

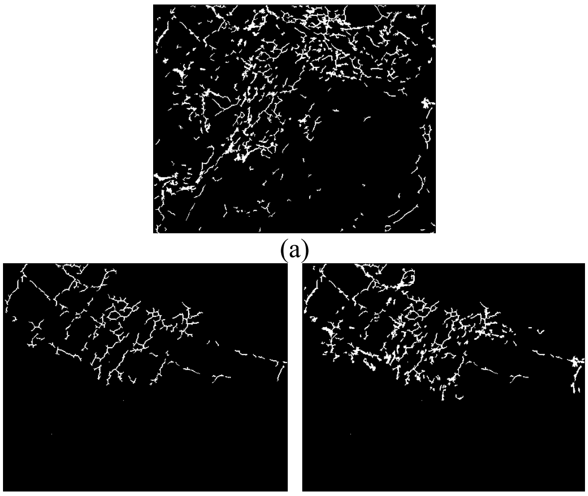
Fig. 4 presents the two attributes used in our tests.



(a) (b)

Fig. 4 (a) Fault Maximum attribute; (b) Coherence attribute

Since we cannot define an ideal result we can base our conclusions on an expert's opinion, in our case a geologist who can properly evaluate the fused result. Also based on an expert's opinion, the reference image is chosen to be the *Fault Maximum* attribute, described in detail in [26]. The fused result can be furthermore improved by defining the region of interest for our reference image. Fig. 5 represents the fusion result for the images in Fig. 4, where the (a) is considered as reference, and also the reference image with the region of interested defined and the fusion result in this case:



(a)

(b) (c)

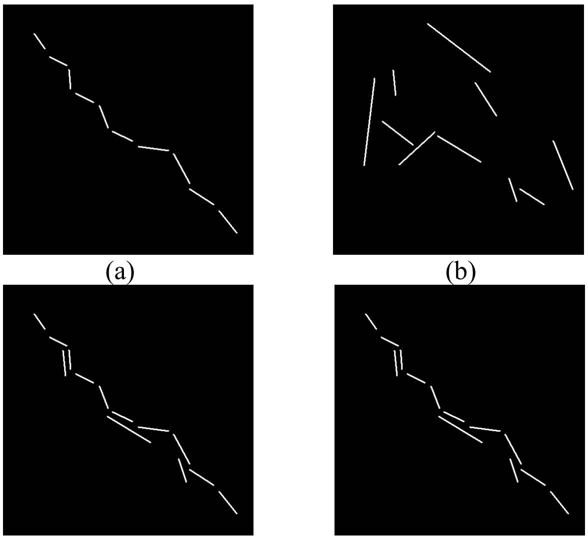
Fig. 5 (a) Fusion result between the two attributes; (b) Fault Maximum attribute with a defined region of interest; (c) Fusion result between (b) and Coherence attribute

As it can be observed from Fig. 5 (c) the fusion result increases qualitatively when we define a region of interest for the reference image. Even so, the fusion result strongly depends on the image that is selected as reference.

A final experiment will be presented for the case where we expand the *affinity notion* in order to include also the orientation of a feature given by its relative angle θ:

$$A = e^{(-r/\sigma_r)} \cdot e^{(-\Delta/\sigma_e)} \cdot e^{(-\alpha/\sigma_\alpha)} \tag{12}$$

For this example we will use once again a set of synthesis images, this time also with a strong orientation characteristic. The input images are represented in Fig. 6:



(a) (b)

(c) (d)

Fig. 6 (a) First synthesis image; (b) Second synthesis image; (c) Ideal output; (d) Fusion result;

An important remark for this example is that the selectivity of the fusion process increases when we take into account, in computing the mutual information, the orientation of the features. The RMSD between the ideal and the fusion result is 0.

At the moment the extended model works only for synthesis images, but as a further development of the method, a fully operational algorithm can be developed such that to work one a more complex type of images such as seismic images.

V. CONCLUSIONS AND REMARKS

The main purpose of the work presented in this paper was the development of a mid-level image fusion method as an alternative to the existing low-level ones and a performance analysis of this method using as a reference benchmark the well-established low-level methods. And extended set of comparative tests between the feature-level fusion method and some of the most robust low-level fusion methods is presented in [1]. Based on the tests presented in the EXPERIMENTS section, we can conclude that, as long as we are taking into account the fact that our method is a task oriented one, the results prove to be promising and open a new direction in image fusion, offering an alternative to the classical methods. The concept of mutual information has already been used in some applications involving image fusion [15], [17], but the full extent of its usability has yet to be discovered and implemented in future fusion algorithms.

Further work can be done in order to improve the selectivity of the method by increasing the complexity and number of parameters that characterize each feature. In this way the feature selection can be done with increased accuracy ensuring that only the desired features from the second set will be selected for the fusion process.

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