Data Cylinders in Medical Image Fusion

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ABSTRACT — **This paper compares two types of multiresolution data structure for data fusion, the data pyramid and the data cylinder. Data pyramids are well established, and in recent years non linear operators such as alternating sequential morphological filters have been used in their construction. The essential difference between pyramids and cylinders is that pyramids undergo subsampling at each level. This paper compares the fusion of medical images through pyramids and cylinders and also considers the effects of different sampling ratios.**

1 Introduction

Hierarchical data structures known as pyramids are well established for both image coding and data fusion. Early work [1] was based on linear filtering operations such as Gaussian and Laplacian kernels. More recently, morphological data pyramids have been used [2,3]. The advantages of morphological techniques are that they are faster to compute and that they provide a more graceful decomposition into image features than linear techniques [4].

In linear filtering the relationship between the filter size and sampling resolution is well established by Shannon's theorem. In the morphological case this relationship has been the subject of an evolving debate, [5, 6, 7,]. The latest results in this area [8,9] indicate that the sampling condition required by the theorems proposed in [5] and [6] are too strong, oversampling the signal by almost a factor of two. The new results provide critical sampling, in the sense that a similar condition cannot be obtained with more sparse sampling.

2 Medical Image Fusion

The use of data pyramids in the fusion of registered Computed Tomography (CT) and Magnetic Resonance (MR) scans of the human brain was demonstrated in [10,11]. The work describes an application of multiresolution morphological pyramids to the fusion of a stack of CT and MR data from the same patient. In this work the patient was specially scanned to allow registration of images.

In management of patients undergoing radiotherapy or skull based surgery, the information provided by magnetic resonance imaging (MR) and X-ray computed tomography (CT) is complementary. Normal and pathological soft tissue are better visualized by MR, while the structure of bone is better visualized by CT. A fusion scheme was described to combine information from different modalities through morphological pyramids.

3 Pyramid & Cylinder Fusion Schemes

A morphological pyramid is first produced for each of the input images. Then a morphological difference pyramid is constructed, for each of the above pyramids. This is achieved by taking the differences between the morphological images residing at successive levels in the original pyramid. An intermediate pyramid is constructed combining information from the two difference pyramids at each level. Finally, reconstruction of the intermediate pyramid, using appropriate morphological operations, produces the required fused image.

The morphological pyramid construction scheme is applied to each input image. The process which generates each image from its predecessor is called a Pyramid Construction (PC) operation, which is known as a reducing operation, since both resolution and sampling density are decreased. After the PC operation is applied, the new morphological image is sampled to generate the next level of the pyramid. This process is repeated to construct two pyramids, one for the MR data and one for the CT data. As well as being flat, the structuring element is also symmetric and it is used at each level during the pyramid construction process.

The difference pyramid is a group of difference images in which each image contains only details within a restricted range of scales and therefore contains only those image features lost from one filter step to the next. The difference pyramid can be computed as the difference between successive levels using an inverse morphological operation, called Pyramid ReConstruction (PRC), which is an expanding operation.

After a difference pyramid is constructed for both of the input images, a new intermediate pyramid, is produced. The new pyramid combines information from the two difference pyramids at each level. A fusing function is defined which determines how the values from each image are combined and results in the construction of the intermediate pyramid. Various fusing functions could be applicable but the one used in this paper took the absolute point by point maximum. Finally, the fused image was recovered from its difference pyramid representation through the reconstruction procedure of upsampling and addition. The final reconstructed image contains details of both input images regardless of scale.

For data cylinders the procedure is identical to that above with the exception that no subsampling takes place. In other words, instead of reducing both resolution and sampling density, only resolution is reduced. All levels of the data structure have the same number of samples, although they contain increasingly smoothed versions of the data. This can be observed in Figure 1, which shows the smoothed version of the CT and MRI images, as well as the fused image at each resolution level.

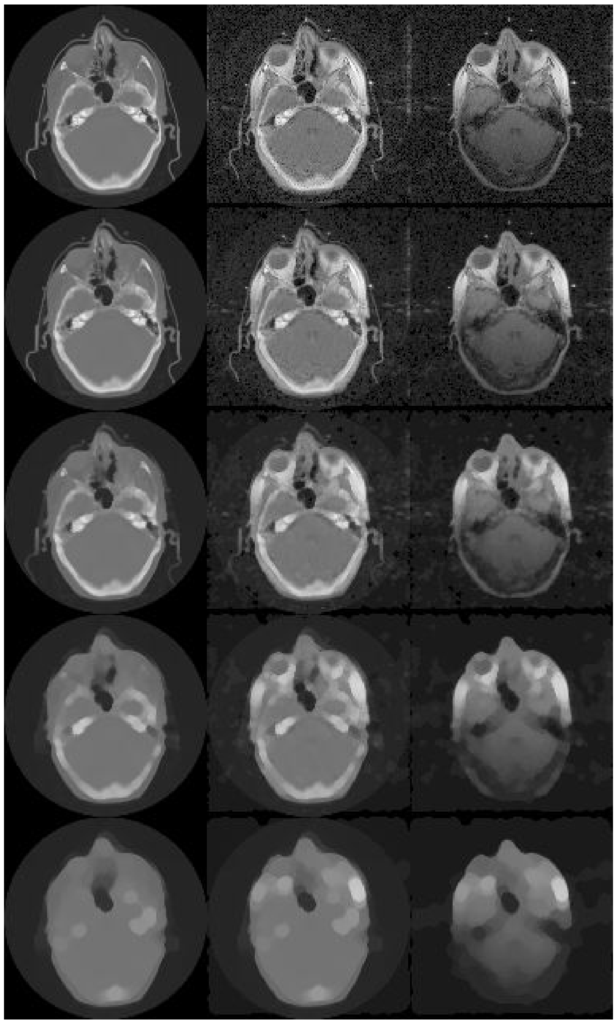

Figure 1: Images used in the Cylinder Fusion. Left Column: progressive smoothed CT images; Right Column: Progressive smoothed MRI images; Center Column: fused images at each resolution level.

4 Critical Sampling

When using the pyramids for data fusion, designing an appropriate filter becomes an important issue. The filters employed in morphological fusion to date have been based on the existing knowledge relating morphological filtering and sampling[7]. New results on morphological sampling [8,9] show that a less restrictive filtering (or more sparse sampling) can provide the same bounds on reconstruction error. This raises the question of whether a less severe filtering process should be applied, pushing the sampling rate to the limit. According to the Critical Morphological Sampling Theorem [8], a 2x2 structuring element should be used in the filtering process prior to a decimation by a factor of 2, instead of a 3x3 structuring element as required in [7].

The principle of multiresolution image fusion is to split the details of the source images in different resolution levels. A stronger filter will keep too much detail in the first (higher resolution) difference image. On the other hand, by oversampling the lower resolution images, the effects of edge shifting (typical of morphological sub-sampling) can be reduced. In the pyramid structure, grouping too much detail in the same pyramid level (by using a stronger filter) will lead to poor detail preservation. On the other hand, pushing the sampling rate to the limit (e.g., by using critical sampling) will increase the number of artifacts produced in the fusion process.

In this application, subsampling has the only objective of saving resources (i.e., memory and computation). If there is no resource limitation,

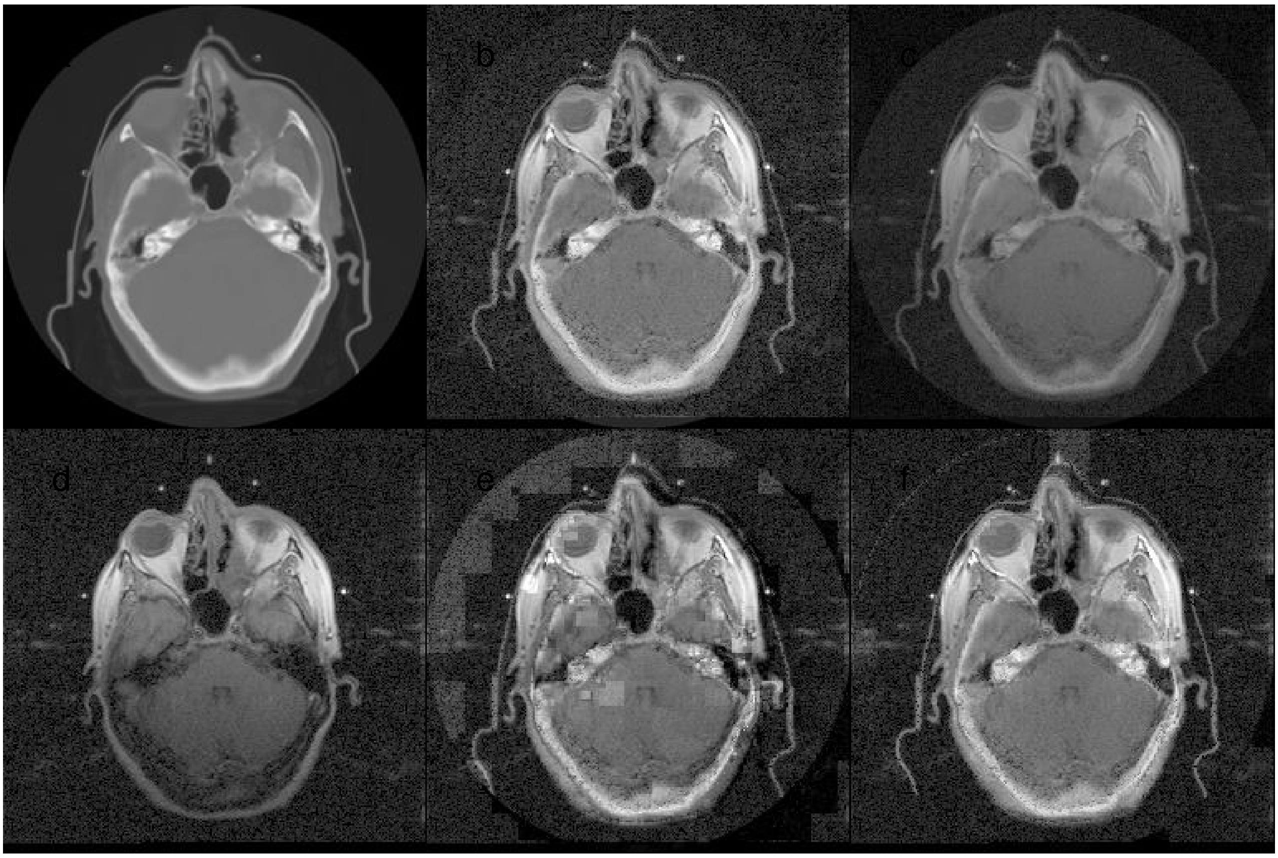

Figure 2: 256x256 images: a) original CT image; b) fused using morphological cylinders (i.e., no subsampling); c) linear combination (MRI+CT)/2; d) original MRI image; e) fused using Critical Morphological Subsampling; f) fused using Haralick's sampling.

there is no advantage on subsampling. Therefore, the ideal relation between filtering and subsampling will depend solely on the characteristic of the environment under consideration.

5 Results

The fusion schemes described above were implemented for both pyramids and cylinders. The pyramid schemes were carried out for both Haralick's and critical morphological sampling. input MRI and CT images are shown in Figures 2-a and 2-d.

For the Haralick sampling pyramid, the successive opening and closing was carried out within a 3 x 3 structuring element prior to a downsampling by a factor of 2. For critical sampling the same downsampling was preceded by filtering with a 2 x 2 structuring element.

The results are given in Figure 2, which shows the input MRI and CT images, the images fused through pyramids using critical and sub-critical sampling, fused using a cylinder structure, and using linear averaging. In order to study the fine detail, an area around the eye is given in Figure 3 for the same images. Notice the blocking effects produced by the pyramid-based fusion, which is more significant for the critical sampled pyramid.

6 Discussion

Where pyramids are used purely for data fusion purposes with no data compression objectives, the role of sampling is uncertain. Apart from reducing the intermediate volume of data what advantage, if any, does a pyramid have over a data cylinder? In the cylinder the various levels of filtered image are fused without intermediate subsampling.

We observed that sampling does indeed cause a deterioration in the quality of the fused image, by introducing blocking effects. The heavier the sampling the more severe the blocking. The image with the least artifacts is therefore that resulting from matching through a cylinder structure. The critical sampling procedure gives the most noticeable artifacts as it pushes the sampling to its limit.

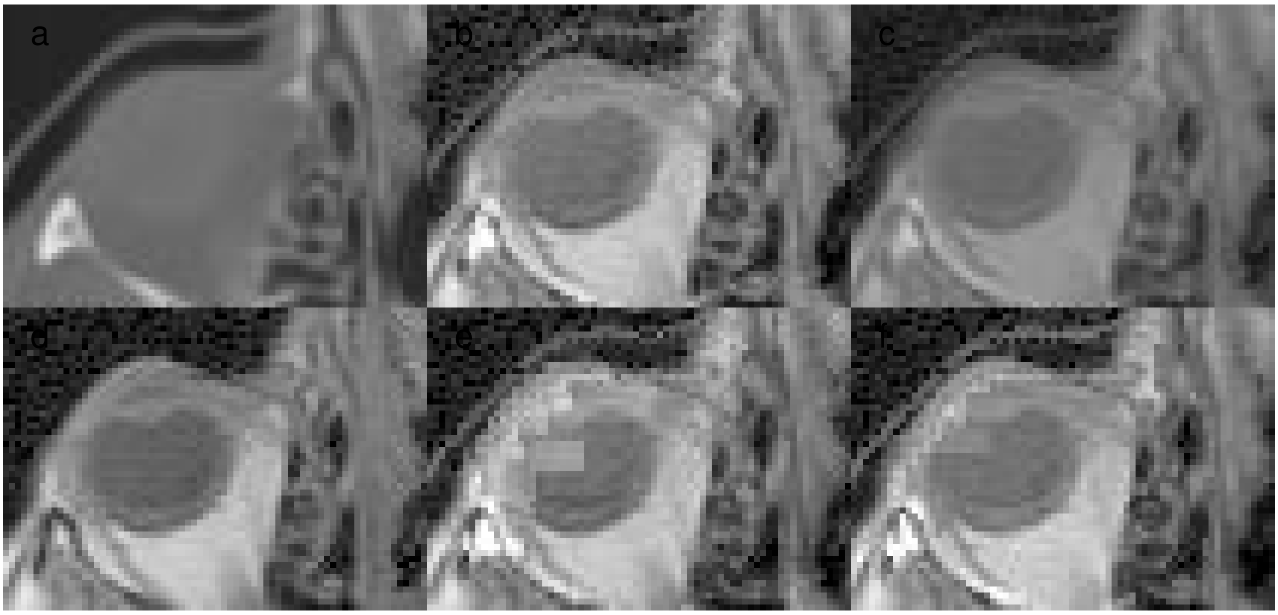

Figure 3: Detail region from Figure 2: a) original CT image; b) fused using morphological cylinders (i.e., no subsampling); c) linear combination (MRI+CT)/2; d) original MRI image; f) fused using Critical Morphological Subsampling; e) fused using Haralick's sampling.

7 Conclusions

In this paper we have addressed some of the questions concerning cylinders, pyramids and sampling. In particular, we have implemented a data fusion process based on cylinders, and compared this with previous results derived from pyramid structures with different degrees of sampling.

In the case of the data cylinder, each of the difference images consist only of details of the original images, and very little information has been generated by edge uncertainty, showing an advantage over previous fusion algorithms, where edge uncertainty information may mask true image details.

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