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Fast mosaicing method based on image resizing pre-processing

ABSTRACT

In recent years, mosaic images have found great success thanks to the increasing development in the field of imaging as well as the technological evolution of computer systems (camera, mobile, etc.). Mosaic images are obtained by merging several images of the same scene. The process incorporates several steps, each of which requires resources and execution time depending on the size, quality and resolution of the images used. In this paper, we propose a new image mosaic method that significantly reduces the execution time. The idea is to apply the stages of registration and search for the best inliers, necessary for the calculation of the geometric transformation, to the miniature of images. This allows the minimization of the overall processing time without altering the quality of the results. The experiment, on a database of images, shows that the proposed algorithm provides rapid results compared to similar methods. Also, we have extended our method to generate 360° panoramic images.

KEY WORDS
Stitching, mosaic, fast, sift, best inliers

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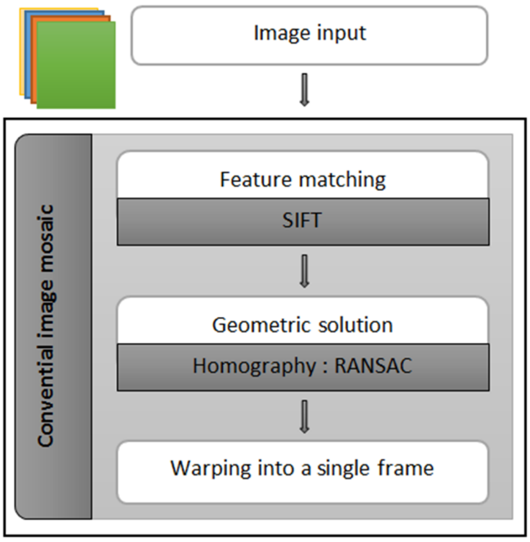
Introduction

Each and every day, digital images are used in various fields (such as computer vision, e-learning, security, etc.) and continue to reach other areas. Due to the limited vision field of digital camera sensors, only a small area can be captured of the real scene. To obtain a larger view of the latter, the reconstruction of the mosaic image becomes imperative. The current methods of image mosaic are numerous and are mostly based on the registration methods (Zitova & Flusser, 2003; Koo & Cho, 2011; Ghosh & Kaabouch, 2016) that make up the first step (Figure 1) in the image mosaic process and is also the most important one. Its role is to detect the remarkable objects in two or more images and compare them to detect existing matches that will in turn serve to create a geometric relationship between images. Despite their effectiveness, these methods remain costly in terms of processing time. The speed of image mosaicing depends essentially on the matching phase that consumes the largest part of the overall processing time. The matching process depends on the image size, texture, the number of control points that may exist (upon which the calculation of the geometric transformation is based). All of these factors influence the execution time of the mosaic process.

In this article, we propose a new method for creating a mosaic image that is similar, in the majority of steps, to the conventional methods (based on registration)

(Zitova & Flusser, 2003; Koo & Cho, 2011; Ghosh & Kaabouch, 2016). However, we apply the steps of matching and search for the best inliers (see section 3.2) to the miniature of the input images. In other words, the images used in the process of the mosaic will be resized to a lower scale. This way, the time consumed by the matching process and the search for the best inliers is reduced, which optimizes the overall time. Then we look for the equivalents (in the original images) of best inliers already detected (in the miniature images). Finally, we calculate the geometric transformation in order to realize the mosaic.



» **Figure 1:** *Structure of mosaicing method based on registration*

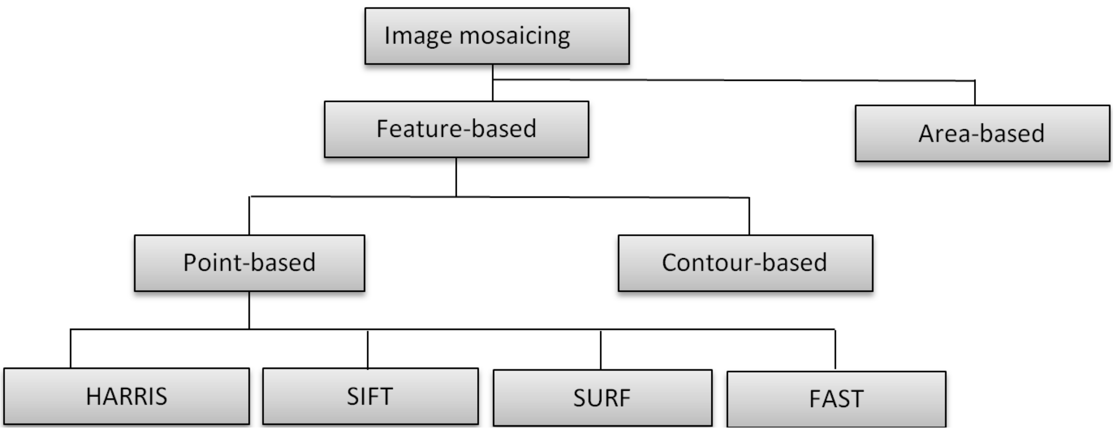
The paper is organized as follows: after this introduction, the related work is reviewed in Section 2. Details of the proposed approach are presented in Section 3. Experiments and results are discussed in Section 4, and the conclusion is in Section 5.

Related works

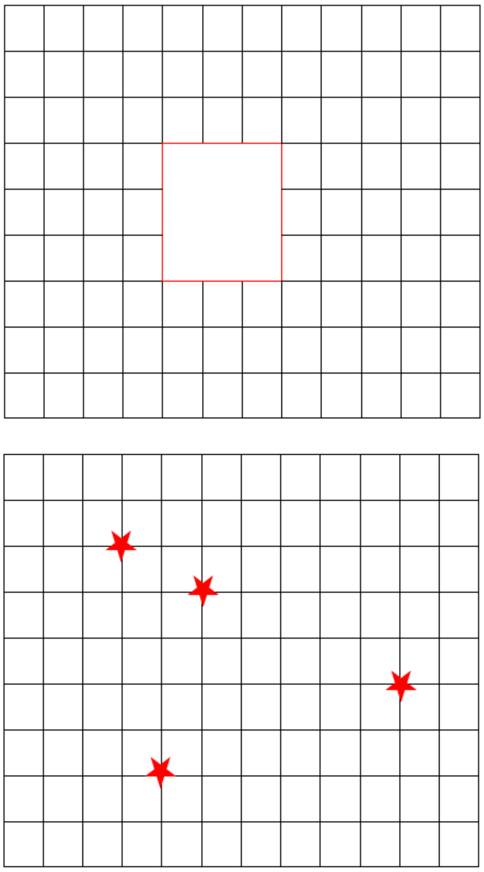
The image mosaic is a technique of combining two or more images in a wider visualization context. Many categories of mosaic algorithms (Figure 2) are able to take images, of the same scene, that overlap and to stitch them into a panorama. The techniques based on registration (Zitova & Flusser, 2003; Koo & Cho, 2011; Ghosh & Kaabouch, 2016) are still the most famous among others. This category of methods is based primarily on registration. So it is almost impossible to achieve mosaic reconstruction without the implementation of a robust and accurate registration system, which highlights the importance of this time consuming phase. Below is a brief presentation of registration techniques proposed in the literature and previous works.

The image registration techniques (Brown, 1992) can be grouped into area-based (Zitova & Flusser, 2003) (Figure 3.a) and feature-based methods (Zitova & Flusser, 2003) (Figure 3.b). Recently, with the appearance of a set of local feature descriptors techniques, feature-based methods have become increasingly used in image registration. The highlight of these methods is due to their invariance to rotation and scaling. So they can be used to match images with large deformations, while the area-based methods apply only to pictures in translation and on the same scale. These methods include Features from Accelerated Segment Test (FAST) (Trajković & Hedley, 1998; Rosten, Porter & Drummond, 2010), Scale-Invariant Feature Transform (SIFT) (Lowe, 2004; Laraqui, Saaidi & Satori, 2018) and Speeded Up Robust Features (SURF) (Bay et al, 2008).

The category of mosaic methods based on registration includes several techniques. First of all, we start with Brown and Lowe method (Brown & Lowe, 2007) considered the reference method in this category. It is based on SIFT algorithm and RANdom SAmple Consensus (RANSAC) method (Márquez-Neila et al, 2016; Misra et al, 2012). It also recognizes several panoramas in a set



» **Figure 2:** *Classification of mosaic methods based on registration* of unordered images. In (Zaragoza et al, 2014) a new estimation technique called Moving Direct Linear Transformation (DLT Moving) is able to adjust or refine the projection and greatly reduce ghosting without compromising the geometric realization of the mosaic image. In paper (Zhou & Luo, 2012), the authors introduce a representation of a multi-view image mosaic algorithm based on the CSIFT detector (Color Scale Invariant Features). The authors of (Saeed et al, 2015) propose a unified scheme, which manages two transformations. A recent approach of image mosaic that is based on Voronoi diagram at the moment of matching and the phase of projection to replace the random choice of Ransac method was proposed in (Laraqui et al, 2017). A method of the mosaic image based on a camera-auto calibration technique has been proposed in (Baataoui et al, 2015).


a)
b)

» **Figure 3:** *a) area-based matching, b) feature-based matching*

Our approach

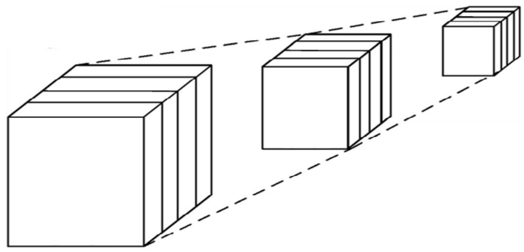
The majority of image mosaic methods based on registration follow the following steps:

- Detect and match keypoints (using Sift)
- Find the best inliners and estimate optimal homography *H* (using RANSAC)
- Project onto a sruface (alignment)

In this paper, we propose an improvement of image mosaic methods based on the steps previously cited. This improvement is intended to minimize the calculation time without compromising the quality of the mosaic results.

Matching

To search for matching points between the input images, we used SIFT (Lowe, 2004) because it is invariant to rotation, scale changes and affine transformations. It is clear that the step of matching consumes the larger part of the execution time in the process of the mosaic. This has led researchers, in this area, to look for alternative methods such as seam-based mosaic techniques (Pan and Wang, 2011; Zeng et al, 2014). In this article we offer a solution to reduce the calculation time of matching phase. This is possible by resizing the input images to a lower scale that reduces the time consumed in this step.



» **Figure 4:** *Image resizing scale. Inspired from (Shin et al, 2016)*

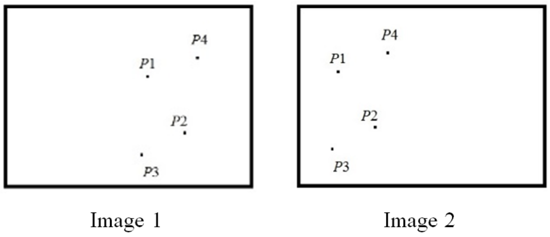
We will resize the input images to a scale *S* that ranges from 0 to 1. Figure 4 shows the size of an image with respect to the value of *S*.

Find the best inliers

After the matching phase, we get a set of matching pairs between images. At this stage, we search for the best inliers (available within the matches found) upon which the computing of geometric transformation *H* will be based (using Ransac algorithm (Márquez-Neila et al, 2016; Raguram, Frahm, & Pollefeys, 2008; Misra et al, 2012).

The RANSAC algorithm permits the estimation of parameters of a mathematical model by random sampling. The basic assumption is that the data consists of "inliers", i.e., data whose distribution can be explained by some set of model parameters, and "outliers" which are data that do not fit the model. The best inliers are inliers that have obtained the best scores compared to the others

In the case of homography (Brown, 1992; Szeliski, 2006), We need four pairs of points. Figure 5 shows the best inliers found between the resized images.



» **Figure 5:** *Best inliers between resized images (image 1 and image 2)*

At this stage, we need to combine the original images to their original sizes. Therefore, the use of resized images stops here. We will look for the coordinates of the best inliers (previously found in the resized images) in the original images (Figure 6).

This occurs by the multiplication of *C* (coordinates) of each point found (in the resized images) by the inverse of *S* to obtain C' which represent the positions in the original image (Equation 1).

$$C' = C \times S^{-1} \tag{1}$$

With:

- C : The coordinates of the best inliers in resized images.
- C': The coordinates of the best inliers in the original images.
- S : Scale value.

For more precision, the four pairs ofoints found are matched by SIFT (Lowe, 2004).

Calculate the geometric transformation and alignment

At the end of SIFT, we get a list of match pairs. From these data, we want to determine as precisely as possible the homography matrix *H*, which links our two images.

We need to determine eight parameters. It is therefore necessary and sufficient to have four pairs of points to determine *H*. It has the following form (Equation 2):

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} . \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{2}$$

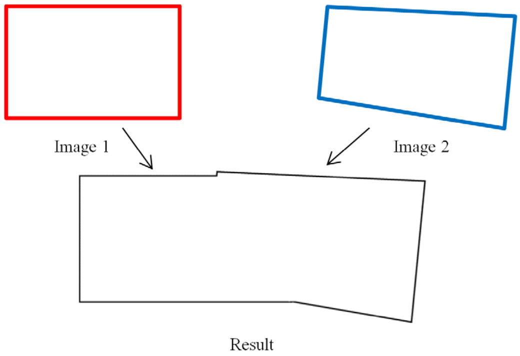
The optimal matrix is the one that obtained a lower projection error score compared to the others

So far, we have obtained the best inliers necessary for the calculation of the transformation *H*. This transformation will link the original images based on the equation 3.

$$p_{ki} \sim H_{ij}\, p_{kj} \tag{3}$$

With p_{ki} the point *k* of image *i*, p_{kj} the point *k* of image *j* and H_{ij} represents the geometric transformation of 3x3 size which connects the images *i* and *j*.

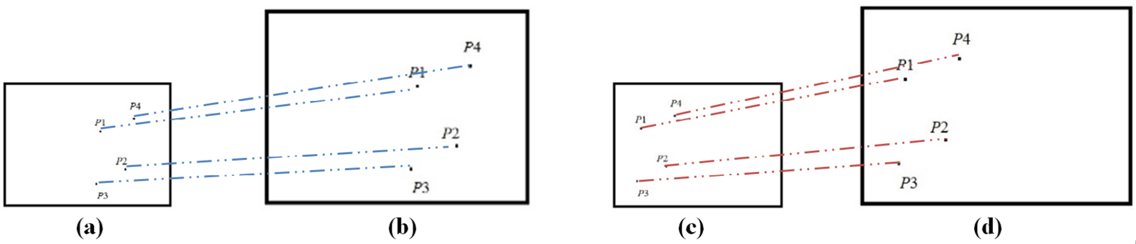
The last step is merging the two images in a single frame that represents an enlarged view of the scene (Figure 7)



» **Figure 7:** *Alignment of the two images on a plane surface*

Experimental results

To show the effectiveness of our approach, we carried out the tests on a database of images (Brandt, 2010). Also, we have compared our method with the existing methods ((Brown & Lowe, 2007) in the case of two images and (Wang et al, 2016) in the case of panorama) in terms of execution time, allocated memory and quality of results. We implemented our approach and existing



» **Figure 6:** *a) Best inlier in miniature of image 1 b) Best inlier in original image 1 c) Best inlier in miniature of image 2 d) Best inlier in original image 2* methods, using Matlab 2014b and a computer system characterized by: Intel (R) i3 2.2 GHz with 6 GB of RAM.

Image mosaicking

In this section, we will test our approach by a database (Brandt, 2010) of 10 sequences. Each contains two images of size 1024 x 683px.

In order to show the robustness and the effectiveness of our approach compared to other techniques, the obtained results are compared with the results of method (Brown & Lowe, 2007). It is based on the SIFT detector and RANSAC method. This reference method (Brown & Lowe, 2007) widely used in comparison with other mosaic techniques. The general principle of the method has been replicated in several recent papers such as (Mills & Dudek, 2009; Ma et al, 2015). Our approach improves this method by using miniature images in the matching phase (as explained in section 3).

Figure 8 illustrates the pairs of images from the database Adobe System (Brandt, 2010) (4 sequences among 10). The scale value S applied in our approach, on the test images, was 0.25 (25% of the real size of images).

Figure 9 represents the results obtained by the two approaches. These results do not contain any processing such as interpolation (Allène, Pons & Keriven, 2008), deletion of intensity change and deghosting (Uyttendaele, Eden, & Skeliski, 2001) in order to test the reliability of the two methods and measure exactly the real calculation time.

In terms of mosaic reconstruction quality, both methods provide satisfactory results and are almost identical. This can be explained by the fact that the two methods are able to find the best inliers able to calculate an optimal geometric transformation. Also, the results confirm the reliability of our approach and the preprocessing used (image resizing) does not alter the quality of the mosaic.

Since the methods based on registration suffer at the level of time consumed during the matching phase the main, our approach, however, reduces the computation time without affecting the quality of results by applying the phases of matching and search for the best inliers (by RANSAC) to the miniatures of images. The process results in a considerable reduction of the processing time. Below, we present a comparison of the number of inlier matches detected, the time consumed in matching phase and finally the memory used as well as the overall duration of the process.

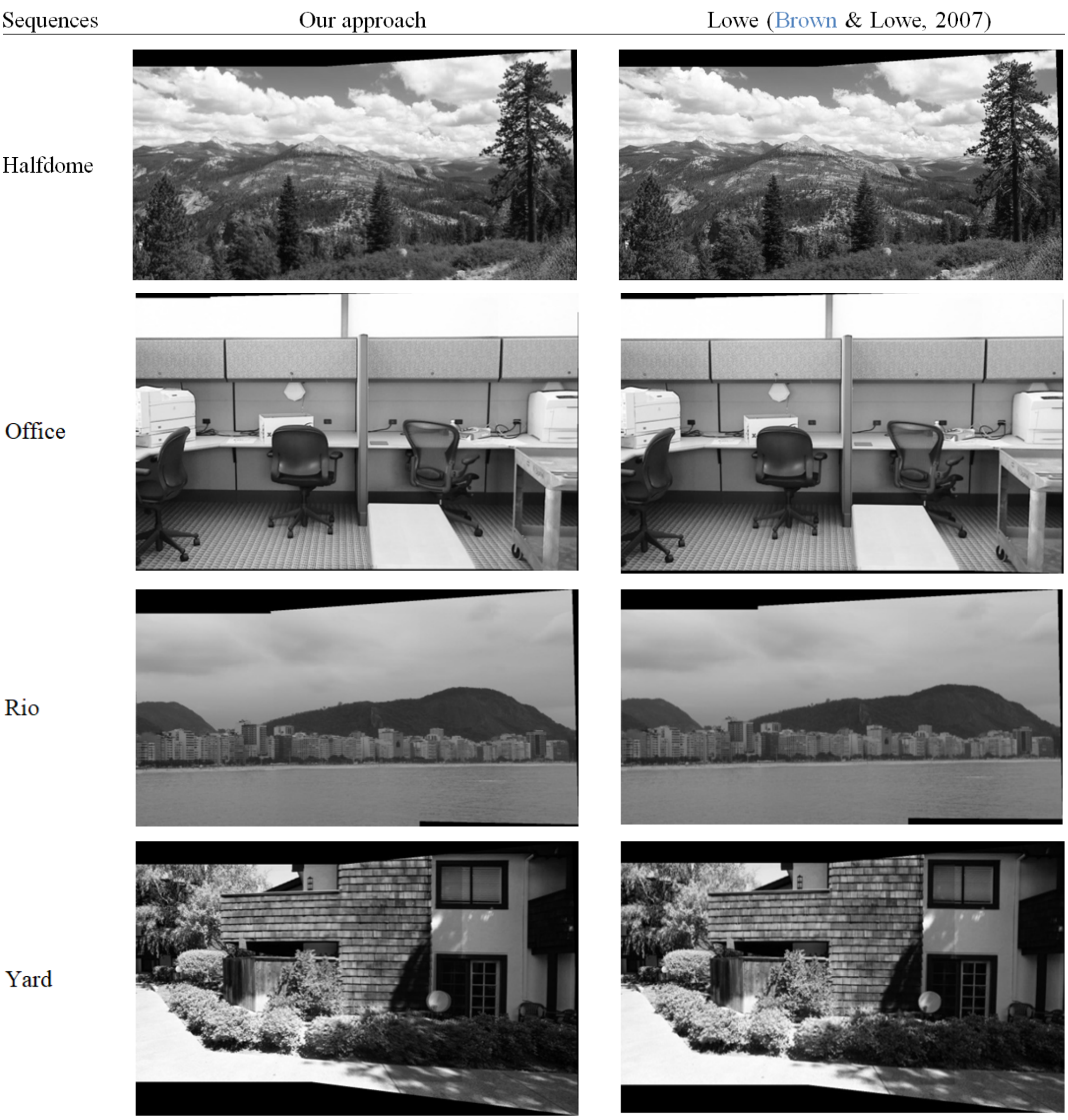
Figure 10 shows the number of matched points detected by our method and method (Brown & Lowe, 2007). The reduction varies between 75.96 and 95.07% of detected points. This reduction is due to the process of image resizing which reduces the number of pixels constituting the image. Naturally, the number of inlier matches will be reduced as well.

Figure 11 shows the time consumed during the matching phase of the two methods. The reduction varies between 85.76 and 90.89% in favor of our approach. The size reduction of the processed images and the reduced number of inlier matches detected minimize the matching time.

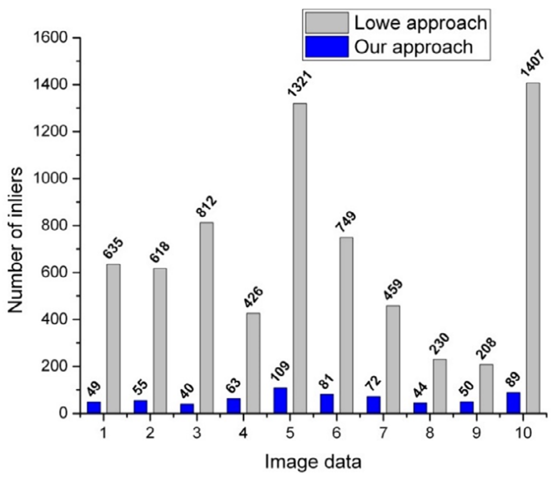
Figure 12 summarizes the overall calculation time during the mosaic process. The figures obtained are the average of 5 consecutive executions of the program. The results obtained show that our approach provides a very short time compared to method (Brown & Lowe, 2007). In numbers, time reduction, based on the data used, varies between 52,93 and 71,80 % in favor of our approach. This is due to the minimization of matching time and search of best inliers.

Figure 13 shows the use of memory by different methods and indicates that our method uses less memory compared to LOWE's technique (Brown & Lowe, 2007). This reduction varies between

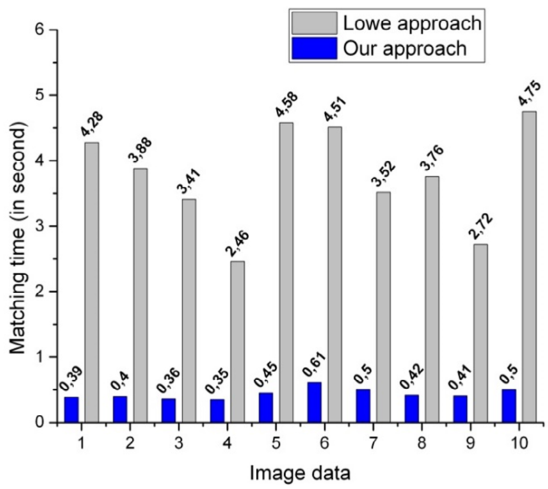
» **Figure 8:** *Four sets of sample images*



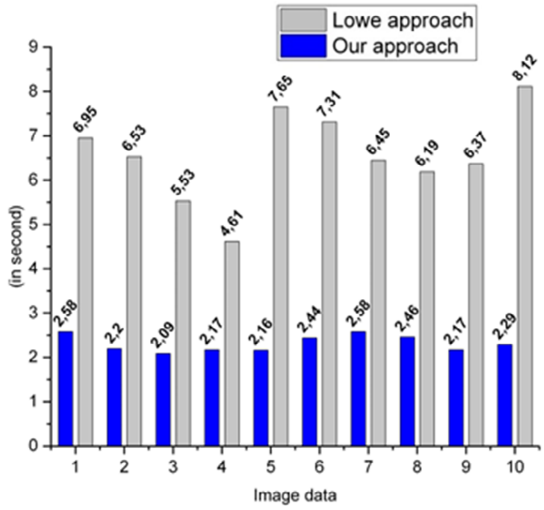
» **Figure 9:** *Results of the mosaic obtained by the two methods*



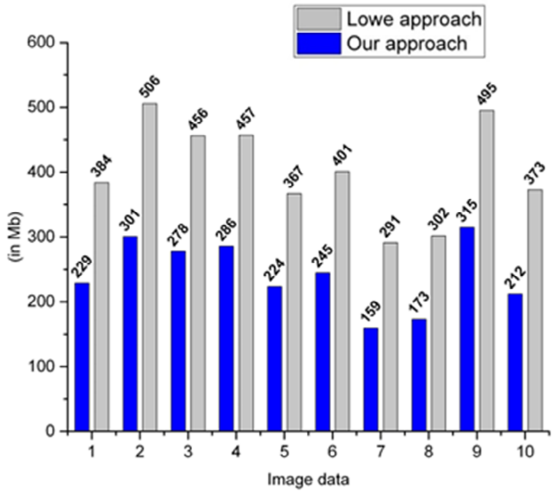
» **Figure 10:** *Number of inlier matches*



» **Figure 11:** *Matching calculation time of both approaches*



» **Figure 12:** *Total calculation time of both approaches*



» **Figure 13:** *Total used memory of both approaches*

25.28 and 30.51%. These results confirm the previous ones and prove that our method is faster than Lowe's, and even consumes less resources.

Panorama

The panorama is an aspect of the mosaic which assembles more than two images in a surface (flat (Kamali et al, 2011), spherical, (Lovegrove & Davison, 2010), cylindrical (Wu, Wang & Wang, 2005) ...).

We will test the performance of our approach compared to method (Wang et al, 2016) using the cylindrical projection which can reach up to 360°. The test is performed on Adobe System database (Brandt, 2010) (two sequences of images) and two real image sequences. To avoid errors that may occur during panorama creation, especially between images that suffer from a reduced overlapping area, we have opted to use a scale value of 0.5 (50% of full size). Figure 14 shows the characteristics of sequences used (name, size and number of images) and the results obtained.

The results obtained are satisfactory and almost identical to the results of Wang method (Wang et al, 2016). This confirms the results obtained previously.

Still, the results obtained in the sequences Mountain and Mountain 2 present some anomalies in terms of consistency in colors intensity (the sequences have suffered at the time of acquisition). Therefore, a post-treatment multi band blinding (Allène, Pons & Keriven, 2008) is employed to minimize the visibility of seams between images, vignetting and enhance the rendering. Figure 15 shows the result of the sequence Mountain 2 post processed.

a. Our approach

b. Wang Approach (Wang et al, 2016)

(a)

(b)

Sequence name : Hotel | Image size : 1024 x 768px | Number of images : 8

» **Figure 14 (part 1):** *Results of panoramic images obtained by our approach (a) and Wang Approach (b)*

(a)

(b)

Sequence name : Goldengate Image size : 600 x 900px Number of images : 6

(a)

(b)

Sequence name : Mountain Image size : 800 x 1200px Number of images : 13

(a)

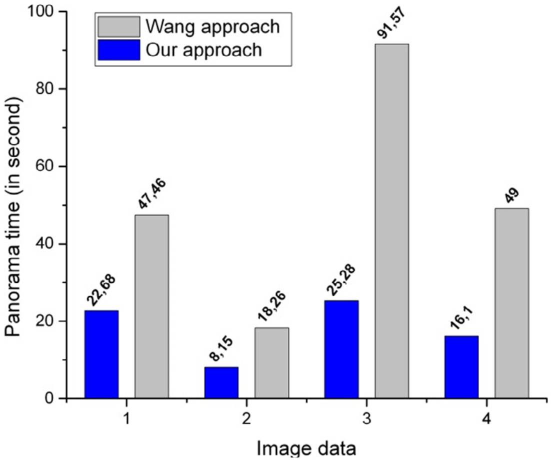
(b)

Sequence name : Mountain 2 Image size : 600 x 920px Number of images : 12

» **Figure 14 (part 2):** *Results of panoramic images obtained by our approach (a) and Wang Approach (b)*

» **Figure 15:** *Post-processed panorama for sample Mountain 2*

Figure 16 represents the time of generating the panoramas in both methods. Our method provides a calculation time reduced on all of the sequences used. The reduction varies between 52.21 and 72.39% (following the sequence used). So our method preserves the quality of the mosaic and minimizes considerably the calculation time.



» **Figure 16:** *Total calculation time of both approaches*

Our approach provides a reduced calculation time compared to existing methods (Brown & Lowe, 2007) in case of two images and (Wang et al, 2016) in the case of panorama. This is due to the use of the miniatures of images during the phases of matching and the search for the best inliers, which reduces the execution time. Note that, the scale value *S* used depends essentially on the image size, the size of the overlap area between the images and the number of inliers that may exist. In the case where we use a very low value of *S*, the number of inliers may decrease at a rate that does not detect the best inliers reliable for estimating transformation *H*. To overcome this problem, it is preferable to avoid the use of the input images with a very low overlap area.

Conclusion

In this article, we have proposed an improvement of the methods of image mosaic based on registration, namely SIFT, Harris, Fast and SURF being the most popular ones in the field. The purpose of this contribution is to propose a time efficient reconstruction method that triumphs existing approaches, without having to compromise the quality of mosaic. The results obtained show that our method was able to preserve the quality of the reconstruction despite the reduction of the calculation time by up to 71% and the memory by around 30%. This reduction allows mosaic methods based on registration to invade other computer vision areas requiring real-time processing. The use of this method should be of great benefit for low memory devices. Experimental results on synthetic and real data show the performance and effectiveness of our approach.

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