# A Robust Corresponding Points for Uncalibrated Stereo Images 

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#### Abstract

There are many problems when we find matching points of stereo images using only the epipolar geometry. Therefore, we use a correlation technique to find an initial set of matched points, and then examine motion vectors to remove mismatched points among the candidates. Then the epipolar geometry can be accurately estimated using a well adapted criterion with the fundamental matrix. We also introduce a bucketing technique to optimize fundamental matrix, and apply F-guided matching method to find best matches for the images. The proposed algorithm has been widely tested with various scenes which have many repetitive patterns. The experimental results show that performance of our algorithm is better than that of RANSAC method.


Keyword: Robust Matching, Epipolar Geometry, Fundamental Matrix, Correlation, F-guided matching

## 1 Introduction

The accurate matching problem in different images of a single scene is an important issue in computer vision. We propose a robust method to find corresponding points for uncalibrated stereo images and motion vectors using a classical method[1] (correlation technique) based on the epipolar constraint. Our approach is to establish initial correspondences using a classical method and to remove mismatches by using motion vectors for uncalibrated stereo images. A classical method, correlation technique, is a typical matching method. The method however includes many mismatches. The proposed algorithm thus uses the median vector filter to get rid of the mismatches between two images. Then, we recover the epipolar geometry and compute the fundamental matrix by using the 8 -point algorithm in order to estimate the epipolar geometry [2][3]. By exploring the epipolar constraint, we also divide matched areas into buckets to reduce the selective redundancy of data set for 8 -point algorithm. F-guided matching method is then used to find the best matches for images.
The proposed algorithm has been widely tested with various scenes, and the experimental results show that performance of our algorithm is better than that of RANSAC method.

## 2 Proposed algorithm

The approach we propose in the paper describes as follows: First step is to use typical methods, Harris corner detection and correlation matching, to find initial candidates of matched correspondences selected extracting points from uncalibrated stereo images. Second step is to apply the median vector filter to remove mismatches in candidates. Third step is to divide matched areas into buckets to reduce the selective redundancy of data set for 8-point algorithm underlying the epipolar geometry. Fourth step is to compute the optimized fundamental matrix and then use F-guided matching method to find more matches between two images.

### 2.1 Matching correspondences

Before recovering the epipolar geometry, we must find corresponding points between uncalibrated stereo images. A corner detector is first applied to each image to process matching correspondences. Many corresponding points are then selected from each image. Points extracted matching correspondences between two images are thus feature points for each image. We use the well-known Harris corner detector[4] in our application.
This method allows us to provide feature points by estimating the gradient values for right and left image, $I R$ and $I L$, included the grey level and then to find
information of these points. In Harris detector, we set the value of proportional constant to 0.04 to provide discrimination against high contrast pixels within step edge.

### 2.2 Initial candidates of matched points

After Harris corner detector is first applied to each image to extract high curvature points, we find initial candidates of matched points by using a classical correlation technique. Given feature point $P_{1}$ of a right image $I R$, we use a correlation window of size $(2 N+1) \times(2 M+1)$ centered at the point and then select a rectangular search field of size $\left(2 D_{u}+1\right) \times\left(2 D_{v}+1\right)$ around the point in the left image $I L$. According as the correlation process is operated on a given correlation window $M_{1}$ in the right image and all matching points $M_{2}$ lying within the search area in the left image, a few candidates can be extracted from two whole images. The correlation score is defines as follows:
$\operatorname{Scor}\left(M_{1}, M_{2}\right)=\frac{\sum_{\mathbf{i}-N}^{N} \sum_{j=-M}^{M}\left[\mathbf{I}_{1}\left(\mathbf{u}_{1}+\mathbf{i}, \mathbf{v}_{1}+\mathbf{j}\right)-\overline{\mathbf{I}_{1}\left(\mathbf{u}_{1}, \mathbf{v}_{1}\right)}\right] \times\left[\mathbf{I}_{2}\left(\mathbf{u}_{2}+\mathbf{i}, \mathbf{v}_{2}+\mathbf{j}\right)-\overline{\mathbf{I}_{2}\left(\mathbf{u}_{2}, \mathbf{v}_{2}\right)}\right]}{(2 N+1)(2 M+1) \sqrt{\sigma^{2}\left(\mathbf{I}_{1}\right) \times \sigma^{2}\left(\mathbf{I}_{2}\right)}}$
where $\overline{\mathbf{I}_{\mathbf{k}}(\mathbf{u}, \mathbf{v})}=\sum_{i=-N}^{N} \sum_{j=-M}^{M} \mathbf{I}_{\mathbf{k}}(\mathbf{u}+\mathbf{i}, \mathbf{v}+\mathbf{j}) /[(2 N+1)(2 M+1)]$ is the average at point $(u, v)$ of $I_{k}(k=1,2)$, and $\sigma\left(I_{k}\right)$ is the standard deviation of the image $I_{k}$ in the neighborhood $(2 N+1) \times(2 M+1)$ of point $(u, v)$. The deviation is given by

$$
\begin{equation*}
\sigma\left(\mathbf{I}_{\mathbf{k}}\right)=\sqrt{\frac{\sum_{\mathbf{i}-N}^{N} \sum_{\mathbf{j}=-M}^{M} \mathbf{I}_{\mathbf{k}}^{2}(\mathbf{u}, \mathbf{v})}{(2 N+1)(2 M+1)}-\overline{\mathbf{I}_{\mathbf{k}}(\mathbf{u}, \mathbf{v})}} \tag{2}
\end{equation*}
$$

The score is an evaluation function to extract candidates from each image. When two correlation windows are identical, the score is 1 . Therefore, if the score of candidate points is higher than a given threshold, we can choose the point as an initial matched point. We set $N=M=7$ for the correlation, $D_{u}$ and $D_{v}$ for the search window are $1 / 10$ of the image width and height, and a threshold of the score is 0.8 , respectively.

### 2.3 Removing mismatches

We apply median vector filter to motion vector of the images to find mismatches among the initial matched points. This filter is founded on the constraint that image motion shows only a small variation across local regions. We therefore divide right and left image into four regions respectively, and then extract the median motion vector from each region by using the
median vector filtering. Each motion vector is compared with its neighbors. In the case of finding similar direction and length of motion vector for each region, correspondences are selected as initial candidates, otherwise it is discarded as mismatches. We apply the technique applied to matching algorithm proposed by Smith et al.[5] To compute direction and length of motion vectors, we find direction of the matched vector first within a threshold $T_{1}$ of the median angle, and then select motion vector within a threshold $T_{2}$ of the median length. Let the extracted median vector is $v$, and the other motion vectors are $v_{i}$ in each region, then we remove matched candidates as follows.
(1) $\left|\left|v_{i}\right|-\right| v \|>$ threshold of direction
(2) $\left|\arctan \left(v_{i}\right)-\arctan (v)\right|>$ threshold of direction

### 2.4 Epipolar Constraint

As shown in Fig. 1, let $C_{1}$ and $C_{2}$ be the optical centers of the first and second cameras, respectively. If a point $m_{1}$ is given in the first image, its correspondence in the second image is constrained to lie on a line called the epipolar line of $m_{1}$, represented by $l_{m 1}$. The line $l_{m 1}$ is the intersection of the epipolar plane defined by $\mathrm{m}_{1}, C_{1}$ and $C_{2}$.


Fig. 1 Geometry of epipolar lines
The relationship between two images means that the first image point $m_{1}$ may correspond to an arbitrary point on the semi-line $\mathrm{C}_{1 \mathrm{M}}$ and that the projection of $C_{1 M}$ on $I_{2}$ is the line $l_{m 1}$. Therefore, all epipolar lines of the points in the first image pass through a common point $e_{2}$ called the epipole. $e_{2}$ is the intersection of the line $C_{1} C_{2}$ with the line $I_{2}$. Generally, for each point $m_{1 k}$ in the first $I_{1}$, its epipolar line $l_{m 1 k}$ in $I_{2}$ is the intersection of the epipolar plane defined $m_{1 k}, C_{1}$ and $C_{2}$, with image plane $I_{2}$. Therefore, all epipolar planes confirm a pencil of planes containing the line $C_{1} C_{2}$.

This is the symmetry of the epipolar geometry. Conversely, the corresponding point in the first image of each point $m_{2 k}$ lying on $l_{m 1 k}$ must lie on the epipolar line $l_{m 2 k}$, which is the intersection of the same plane with the first image plane $I_{1}$. If a point m 1 and a point $m_{2}$ correspond to a single physical point $M$ in space, then $m_{1}, m_{2}, C_{1}$ and $C_{2}$ must lie in a single plane. This is co-planarity constraint[2]. Therefore, from the relationship between $C_{1}$ and $C_{2}$, the equation can be expressed as follows.

$$
\begin{align*}
& l_{\mathbf{m} 1}=F \mathbf{m}_{1} \\
& \mathbf{m}^{\mathrm{T}}{ }_{2} F \mathbf{m}_{2}=0 \\
& F e_{1}=F e_{2}=0 \tag{3}
\end{align*}
$$

### 2.5 Estimation of the Fundamental Matrix

RANSAC method has to select data set with purely random method. However, our algorithm extracts data sets with bucketing technique. To extract data sets, we have to calculate minimum and maximum coordinate of the matched points in the first image. And we divide the image into $\mathrm{b} \times \mathrm{b}$ buckets. Each bucket has a set of matched points. The buckets having no matched points are excluded. To generate a sub-sample of 8 points, we randomly select 8 different buckets, and then choose one matched point set in each selected buckets. Finally the selected 8 matched correspondences are applied to 8-point algorithm. [6][7][8]
To optimize the fundamental matrix, we use a nonlinear criterion by minimizing. The equation may be represented as follows.

$$
\begin{equation*}
\sum_{i}\left(d^{2}\left(\mathbf{m}_{2 \mathrm{i}}, \mathrm{Fm}_{1 \mathrm{i}}\right)\right) \tag{4}
\end{equation*}
$$

where $d\left(m_{2}, F_{m 1}\right)$ is the Euclidean distance between point $m_{2}$ and its epipolar line $F_{m 1}$. The fundamental matrix based on the epipolar geometry is iteratively calculated, and then we estimate the average epipolar distance errors for each the fundamental matrix. Consequently, the epipolar distance error represents the average distance between epipolar lines and matched points in second image.

### 2.6 F-guided Matching

The purpose of F-guided matching is to obtain additional matches consistent with the epiploar geometry. The epipolar constraint provides a more restrictive search region than that of unguided matching method. Therefore, a less severe threshold can be used for the matching attributes. In this case,
matching points are sought for unmatched corners by searching along the epipolar lines. This generates a large set of consistent matches. Using the corners computed on sub-pixel accuracy, the typical distance of a point from its epipolar line is decreased by $0.2 \sim 0.4$ pixels.

## 3 Experimental Results

A various types of scene, e.g. building, castle and valley, etc., have been used in our experiment. All test images are natural images and the resolutions are $512 \times 512$ respectively. We implement the proposed algorithm on personal computer system with Intel Pentium IV 3.0GHz CPU.
The results of each image are shown in Table. 1 and 2. For example, an input image is Figure 2. In the results, there are three figures that show the performance of correspondence by correlation, median vector filter and an iterative computation of the fundamental matrix, respectively.
Experimental results show that average distance error of our method is smaller than that of RANSAC method for the images. Moreover, after removing all mismatches, numbers of correspondence are also bigger than those of RANSAC method. For comparison of the two methods, we depict the numbers of correspondence in Fig. 3. For an evaluation of the proposed algorithm, we represent the epipolar lines in two stereo images and present an epipolar distance error for each image.

| Building Image <br> $512 \times 512$ | Proposed algorithm |  | RANSAC |
| :---: | :---: | :---: | :---: |
|  | Run time | Matching <br> points | Matching <br> Points |
| Correlation Matching | 0.170 sec | 77 |  |
| Median Vector filter | 0.020 sec | 74 |  |
| An iterative computation of <br> The Fundamental Matrix | 0.091 sec | 74 | 60 |
| Average distance error (pixel) |  | 0.438 | 0.496 |

Table. 1 After F-guided matches : 96 correspondences


Fig. 2 Natural Scene Image

| Natural Scene Image <br> $512 \times 512$ | Proposed algorithm |  | RANSAC |
| :---: | :---: | :---: | :---: |
|  | Run time | Matching <br> points | Matching <br> Points |
| Correlation Matching | 3.335 sec | 312 |  |
| Median Vector filter | 0.050 sec | 246 |  |
| An iterative computation of <br> The Fundamental Matrix | 0.735 sec | 246 | 223 |
| Average distance error (pixel) |  | 0.645 | 0.748 |

Table. 3 After F-guided matches : 325 correspondences


Fig. 3 Comparison of the two methods

## 4 Conclusion

There are many problems when we find matching points of stereo images using only the epipolar geometry. Therefore, we use a correlation technique to find an initial set of matched points, and then examine motion vectors to remove mismatched points among the candidates. Then the epipolar geometry can be accurately estimated using a well adapted criterion with the fundamental matrix. We also introduce a bucketing technique to optimize fundamental matrix, and apply F-guided matching method to find best matches for the images. The proposed algorithm has been widely tested with various scenes which have many repetitive patterns. The experimental results show that performance of our algorithm is better than that of RANSAC method.

## Acknowledgment

This research was supported by the Ministry of Education, Seoul, Korea, under the BK21 project.

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