# Enhanced SURF-Based Image Matching Using Pre- and Post-processing

Chenfei Zhang, Yaozu Wu, Ning Liu(✉), and Chongyang Zhang

Institute of Image Communication and Network Engineering,
Shanghai Jiao Tong University, Shanghai 200240, China
ningliu@sjtu.edu.cn

**Abstract.** SURF-based algorithms have been proved to be one of the most effective image matching methods. Considering the challenges induced by the poor illumination conditions or local-feature-similar noises, one enhanced SURF-based image matching method(E-SURF) using pre- and post-processing is developed in this work: pre- and post-processing is adopted to enhance the image matching performance in some challenging cases: Median filtering and Histogram linear transformation is adopted as the preprocessing to remove the isolated noises and amplify the illumination contrast, so that more SURF points can be found; After SURF matching, one LBP-based filtering is used to filter the possible false matching points using local texture features. Experimental results on some complicated images show that the proposed method can outperform the existing SIFT and SURF schemes.

**Keywords:** Image matching · SURF (Speeded Up Robust Features) · Local Binary Patterns (LBP) · Median filter

## 1 Introduction

With the development of automation technology, the object recognition application is widely used in the automatic production lines. To ensure the accuracy of object recognition, image matching algorithms stand on a vital position. One of the most effective algorithms for identifying several images with similar feature is SURF (Speeded Up Robust Features) [1]. Based on SIFT(Scale Invariant Feature Transform) method [2], SURF algorithm inherits the advantages of rotation invariant, scale invariant and affine invariant. In addition, it requires shorter running time and has better robustness for multiple images.

The traditional SURF algorithm is divided in three main steps, which can be sketched as finding interest point, forming descriptor and matching. There have been a large number of improved algorithms based on SURF algorithm proposed in the literatures(e.g. [6–12]). For example, an improved algorithm based on SURF uses a matching method of subset of features to improve the speed of registration [6]. Another example is that an improved SURF algorithm based on distance constraint improves the accuracy of matching [7]. When the


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image is formed with some rigid bodies, interest points can be detected easily, the matching time can be much shorter and the accuracy can be high enough. However, in some complicated cases, such as the images brightness is too low or too high to find enough interest points, the SURF-based matching methods may not perform very well. Another challenge is the noise, especially the noise that has similar local features with the interest points, which will cause the false matching [13,14].

Considering the above challenges, especially the poor illumination conditions and local-feature-similar noises, one enhanced SURF-based image matching method(E-SURF as short) using pre- and post-processing is developed to promote the robustness in these challenging cases: Median filtering and Histogram linear transformation is adopted as the preprocessing to remove the isolated noises and amplify the illumination contrast, so that more SURF points can be found. After SURF matching, one LBP (Local Binary Patterns) [4] based filtering is used to filter the possible false matching points using local texture features.

The paper is organized as follows. Section 2 describes the principle of E-SURF method, including the histogram linear transformation, LBP feature based filtering and median filtering. In Sect. 3, results are given and analyzed. Section 4 concludes the whole work.

## 2 Enhanced SURF-Based Image Matching Using Pre- and Post-processing (E-SURF)

The proposed E-SURF algorithm is divided in four main steps, which can be sketched as Median filtering, Histogram linear transformation, SURF-based matching, and LBP-based filtering (Fig. 1). The details of the three components (except the well-known SURF-based matching) are shown in the following subsections.

### 2.1 Histogram Linear Transformation and Median Filtering

The detector of SURF algorithm is based on the Hessian matrix, as well as the non-maximum suppression and scale space interpolation. In some extreme

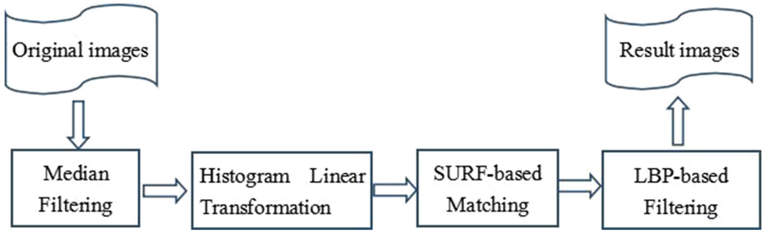


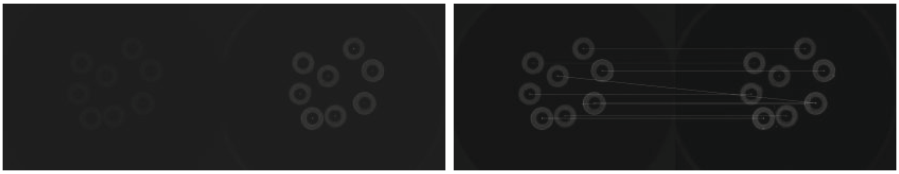

**Fig. 1.** The flow chart of the proposed E-SURF algorithm

conditions like the left image in Fig. 2(Left), the contrast of the image is too low to detect enough interest points(For the image in Fig. 2(Left), no interest points can be detected) [15]. Given an image with low contrast like that, the gray values of that images histogram are within a very small range, which causes the failure of interest point detection. FOR those extreme conditions, we use Histogram linear transformation to enhance the contrast of images. Since the maximum range of gray value is [0,255], we enhance the contrast of the image by widening the gray value range. This is achieved by using Histogram linear transformation [3]. Before matching, images are processed with Histogram linear transformation. That is defined as follows

$$\begin{aligned} r' &= \tfrac{r'_b - r'_a}{r_b - r_a}(r - r_a) + r'_a, && r \in [r_a, r_b] \\ r' &= r'_a, && r \in [r_{min}, r_a] \\ r' &= r'_b, && r \in [r_b, r_{max}] \end{aligned} \tag{1}$$

where $r \in [r_a, r_b]$ is the gray value range of the original image, $r \in [r'_a, r'_b]$ is the gray value range of the transformed image, $r$ is the original gray value, and $r'$ is the transformed gray value.

After a series of experiments, [0,110] is chosen for the empirical value of $r \in [r'_a, r'_b]$ . The contrast of the image becomes strong enough for the interest point detection after Histogram linear transformation (Fig. 2(Right)): For the image in Fig. 2(Left), no interest points can be detected due to the low illumination; while all the center points of the circle objects can be detected as SURF points when histogram linear transformation is applied (Fig. 2(Right)).



(a) (b)

**Fig. 2.** Illustration of SURF detection without (Left) or with histogram linear transformation (Right)

In the SURF algorithm, a matching pair is detected if its Euclidean distance is closer than 0.7 times the distance of the second nearest neighbor. Inevitably, some similar but different interest points are matched because they meet the threshold. Histogram linear transformation is used to reduce those false positive matches. Consider the threshold, Histogram linear transformation can enhance the contrast and enlarge the discrepancy in gray value between pixels, which can make most of the false positive matches do not meet the threshold. Hence,

**Table 1.** Comparison of correct matching rate for different filters

| | Median filter | Bilateral filter | Mean filter | Gaussian filter |
|---|---|---|---|---|
| Figure 4(a) | 87.50% | 54.35% | 75.00% | 75.00% |
| Figure 4(b) | 96.15% | 90.00% | 90.32% | 93.33% |
| Figure 4(c) | 79.49% | 45.76% | 46.77% | 40% |

Histogram linear transformation allows for more detected interest points and gives a significantly increase in correct matching rate.

In many times, there is much noise in the original images which make the matching interfered. The isolated noises, such as salt-and-pepper noises, will make up as corner points and result in false matching easily. Because we focus on the interest points, the impulse noises are most likely to cause the mismatches. Comparing to other useful filters, the median filter has better performance in our experiments. The comparison is shown in Table 1. Thus, median filter algorithm can be a proper method of removing those noises before the Histogram linear transformation [5].

The median filter algorithm can be divided into two steps. Firstly of all, put the gray-level value of a pixel and its eight adjacent pixels in numerical order. Then, obtain the mid-value and assign these nine pixels the mid-value [19,20]. The formula of median filter is shown as follows

$$g(m,n) = \underset{i,j \in S}{Median}[f(i,j)] \tag{2}$$

where S corresponds to a $3 \times 3$ block revolved around the center pixel.

### 2.2 LBP-Based Filtering

Another problem in traditional SURF algorithm is incorrect estimation for matching interest points [16]. In a realistic scenario, there will be many similar corner points and noise in an image. For better object description, extracted features should have distinctiveness, which means a special value to distinguish the detected interest points and any other points [21]. With the traditional SURF description based on the Haar wavelet feature, which has good robustness to region directionality, the features of interest points are defined as the sum of Haar response values in a small region. The description described by a sum means that it focuses on the directionality but has less rotation variant. So when meeting some interest points having similar feature, those points will be matched each other directly and there is no method to filter disturbance points. To overcome this problem, mismatches should be corrected and interest points should have not only directional feature, but also texture feature. Therefore, local Binary Patterns, referred to simply as LBP is taken into consideration [4]. LBP can extract feature from a $3 \times 3$ block to make interest points have their own region texture feature, as well as ignore the scaling of gray level. The region texture feature is closely related to better rotation invariant. So LBP-based filtering can be used as one post-processing to remove the error matching points which have similar Haar wavelet feature but different LBP feature. In the procedure of matching, most of similar corner points and noises will be distinguished for different LBP feature. The formula of LBP-based filter is shown as follows

$$LBP_9value = \sum_{i=0}^{8} f(g_i - g_c) \times 2^i, f(x) = \begin{cases} 1 & x \geqslant 0 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where $g_c$ corresponds to the gray-level value of the chosen interest point and $g_i$ to the gray-level value of the adjacent eight pixels revolved around the interest point.

An example chart of LBP feature extraction is shown in Fig. 3. There is a 3×3 block revolved around the template interest point in the top left hand corner in figure (b). In figure (a), one block is similar to the template block and another one is acquired by 180° rotation from the former block. For traditional matching method, it is obvious that both of the interest points in figure (a) are matched to the template interest point in figure (b) because their Haar wavelet feature is almost the same. However, only one matching is correct. Then for LBP feature filtering, the LBP values of those two interest points in figure (a) are different. [17]. Just obtain the difference of two digital numbers extracted from two images. ‘5’ is the chosen threshold for the difference. Only one difference is less than the pre-set threshold. Therefore, only one pair of interest points is matched. So the LBP feature can be used to filter the mismatched points.

## 3 Experimental Results

In this section, the results of the experiment as well as the comparison are presented and illustrated using a standard evaluation set and an industrial object recognition application. In this paper, all the experimentations are conducted using Opencv2.4.9 with a 2.8 GHz Core i5 processor and a 4 GB of memory.

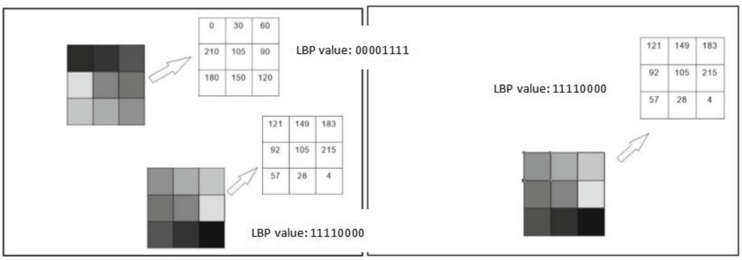



**Fig. 3.** The flow chart of the proposed E-SURF algorithm

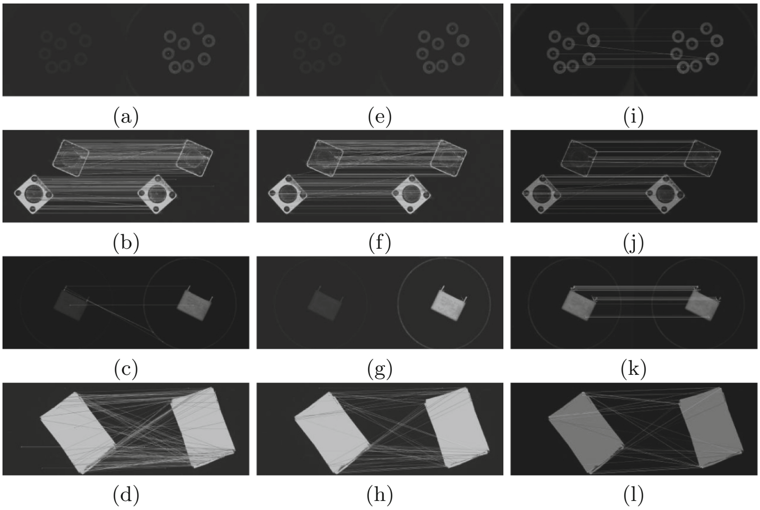



**Fig. 4.** Images from top to bottom: (a) (b) (c) (d) are matching results using original SIFT algorithm; (e) (f) (g) (h) are matching results using SURF algorithm; (i) (j) (k) (l) are results using SURF with pre-processing (Median Filtering and Histogram Linear Transformation)

**Table 2.** Comparison of detected points number, correct matching pairs number, and correct matching rate for the first group of test images (First line in Fig. 4)

| First test group (First line in Fig. 4) | SIFT (Fig. 4(a)) | SURF (Fig. 4(e)) | SURF with pre-processing (Fig. 4(i)) | Proposed E-SURF (Fig. 5(a)) |
|---|---|---|---|---|
| Detected points | 0 | 0 | 9 | 8 |
| Correct matching pairs | 0 | 0 | 8 | 8 |
| Correct matching rate | 0 | 0 | 88.90% | 100% |

### 3.1 Results for SURF with Pre-processing (Median Filtering and Histogram Linear Transformation)

We tested our algorithm using some industrial images. Due to space limitations, we selected four groups of typical images. For Histogram linear transformation (HLT), it is compared to the difference of SURF [1], and SIFT propose by Lowe [2]. The comparison results are shown in Fig. 4, Tables 2, 3, 4 and 5.

**Table 3.** Comparison of detected points number, correct matching pairs number, and correct matching rate for the second group of test images (Second line in Fig. 4)

| Second test group (Second line in Fig. 4) | SIFT (Fig. 4(b)) | SURF (Fig. 4(f)) | SURF with pre-processing (Fig. 4(j)) | Proposed E-SURF (Fig. 5(b)) |
|---|---|---|---|---|
| Detected points | 255 | 197 | 78 | 33 |
| Correct matching pairs | 221 | 170 | 75 | 33 |
| Correct matching rate | 86.67% | 86.29% | 96.20% | 100% |

**Table 4.** Comparison of detected points number, correct matching pairs number, and correct matching rate for the third group of test images (Third line in Fig. 4)

| Third test group (Third line in Fig. 4) | SIFT (Fig. 4(c)) | SURF (Fig. 4(g)) | SURF with pre-processing (Fig. 4(k)) | Proposed E-SURF (Fig. 5(c)) |
|---|---|---|---|---|
| Detected points | 5 | 0 | 12 | 6 |
| Correct matching pairs | 2 | 0 | 12 | 12 |
| Correct matching rate | 40.00% | default | 100% | 100% |

Table 2 gives the comparison for the first test group (Fig. 4(a), (e), (i)). As can be seen, when the images have very low contrast (the case of first group), the original SIFT and SURF algorithm cannot detect any interest points but the E-SURF method can detect enough interest points due to the enhanced pre-processing using Histogram linear transformation.

Table 3 gives the comparison for the second test group (Fig. 4(b), (f), (j)). In this case, the correct matching rate of proposed algorithm is about ten percent higher than that of SURF or SIFT, and the most important correct matching pairs can also be retained.

Table 4 gives the comparison for the third test group (Fig. 4(c), (g), (k)). As we can see, SIFT and SURF do not work well in this case. But the E-surf method can detect enough interest points and improve the correct matching rate to 100%.

**Table 5.** Comparison of detected points number, correct matching pairs number, and correct matching rate for the fourth group of test images (Fourth line in Fig. 4)

| Fourth test group (Fourth line in Fig. 4) | SIFT (Fig. 4(d)) | SURF (Fig. 4(h)) | SURF with pre-processing (Fig. 4(l)) | Proposed E-SURF (Fig. 5(d)) |
|---|---|---|---|---|
| Detected points | 224 | 83 | 38 | 4 |
| Correct matching pairs | 31 | 14 | 11 | 3 |
| Correct matching rate | 13.84% | 16.00% | 28.95% | 75.00% |

In most conditions, our algorithm performs well in the interest point detection and matching. But in some extreme conditions like the group in Fig. 4(d), (h), (l), the proposed algorithm improves the correct matching rate but also has some problems in the interest point matching (Table 5). In some conditions like Table 3, the number of the matching pairs decreases a bit after our algorithm. But there are still remaining enough correct matching pairs to achieve the image matching [2].

### 3.2 Results for E-SURF (Pre-processing + SURF + Post-processing (LBP Filtering))

After the gray scale linear transformation, the accuracy of circular matching and the rectangle matching has been improved apparently, and the number of points of incorrect estimation has reduced slightly. In order to remove the error matching points which have similar Haar wavelet feature but different texture features, LBP-based filtering can be used as one effective post-processing.

Figure 5 gives the matching result using proposed E-SURF (Pre-processing + SURF + Post-processing). See Fig. 5(a), the mismatched point has been removed and the accuracy is up to 100% (last column in Table 2). In Fig. 5(b), it is obvious that all the remained match-lines are correct and the accuracy is also up to 100% (last column in Table 3). In Fig. 5(c), as can be seen, all the matching pairs are correct and some redundant matching pairs are suppressed (last column in Table 4). In the case of the fourth test images (Fig. 5(d)), the matching accuracy of the rectangle objects has achieved 75% with the proposed E-SURF, compared with the accuracy of less than 30% with the traditional SIFT and SURF methods (Table 5).

One of the disadvantages of the proposed E-SURF is that the matched SURF points will reduced greatly due to the filtering in pre and post processing,

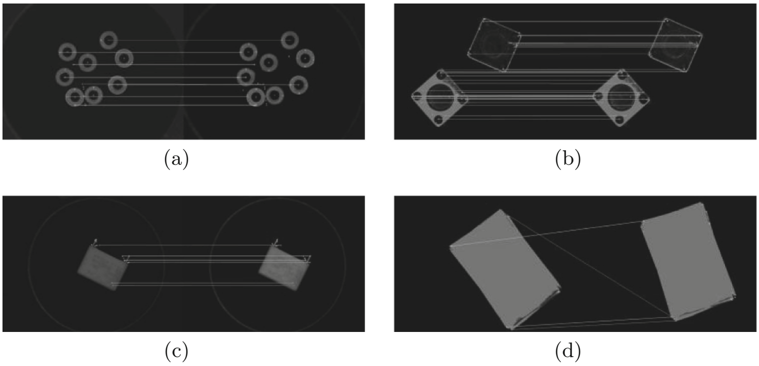


**Fig. 5.** Image matching result using the proposed E-SURF (Pre-processing + SURF + Post-processing).

especially for the case of fourth test group (only four pairs are left, Fig. 5(d)). But as the conclusion pointed out in [2], the ability to detect small objects in cluttered backgrounds requires that at least 3 features be correctly matched from each object for reliable identification. In all the cases, more than 3 pairs of points can be detected. So the image objects can be matched correctly.

## 4 Conclusion

We have presented a more accurate and robust algorithm based on SURF. With median filtering and histogram linear transformation as preprocessing, and LBP feature based filtering as post-processing, the proposed E-SURF algorithm is suitable to detect interest points with the image for very low contrast or very low brightness, and it can improve the correct matching rate at the same time. Future work will concentrate on eliminating the effect of fuzzy edge, increasing interest points in multiple rectangle matching, and reducing the time complexity by graph model.

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## References

1. Bay, H., Tuytelaars, T., Gool, L.: SURF: speeded up robust features. In: Leonardis, A., Bischof, H., Pinz, A. (eds.) ECCV 2006. LNCS, vol. 3951, pp. 404–417. Springer, Heidelberg (2006). doi:10.1007/11744023_32
2. David, G.: Lowe: distinctive image features from scale-invariant keypoints. IJCV **60**(2), 91–110 (2004)

3. Gonzalez, R.C., Woods, R.E.: Digital Image Processing. Prentice Hall, Upper Saddle River (2007)
4. Ojala, T., Pietikinen, M., et al.: A comparative study of texture measures with classification based on feature distribution. Pattern Recogn. **29**, 51–59 (1996)
5. Tukey, J.W.: Exploratory Data Analysis (Preliminary Ed.). Addison-Wesley, Reading (1971)
6. Juntai, Z., Yonghong, L.: An improved SURF algorithm for image registration. Journal of Hunan University of Technology, March 2011
7. Hongbo, L.: An improved SURF algorithm based on distance constraint. J. Syst. Simul. **16**(12) (2014)
8. Suqing, G., Xunjun, T., Chengxia, H.: Improved algorithm of image registration based on SURF. J. PLA Univ. Sci. Technol. (Nat. Sci. Ed.), August 2013
9. Weidong, Y., Hongwei, S., Zhanbin, Y.: Robust registration of remote sensing image based on SURF and KCCA. J. Indian Soc. Remote Sens. **42**(2), 291–299 (2014)
10. Seung Hyeon Cheon, I.K., Ha, S., Moon, Y.H.: An enhanced SURF algorithm based on new interest point detection procedure and fast computation technique. J. Real-Time Image Proc., 1–11 (2016)
11. Lukashevich, P.V., Zalesky, B.A., Ablameyko, S.V.: Medical image registration based on SURF detector. Pattern Recogn. Image Anal. **21**(3), 519–521 (2011)
12. Sun, W., Shen, Q., Liu, C.: SURF feature description of color image based on gaussian model. In: Li, K., Li, J., Liu, Y., Castiglione, A. (eds.) ISICA 2015. CCIS, vol. 575, pp. 275–283. Springer, Singapore (2016). doi:10.1007/978-981-10-0356-1_28
13. Wu, Z., Xu, P.: A fast gradual shot boundary detection method based on SURF. In: Wen, Z., Li, T. (eds.) Practical Applications of Intelligent Systems. AISC, vol. 279, pp. 699–706. Springer, Heidelberg (2014). doi:10.1007/978-3-642-54927-4_66
14. Abeles, P.: Speeding up SURF. In: Bebis, G., et al. (eds.) ISVC 2013. LNCS, vol. 8034, pp. 454–464. Springer, Heidelberg (2013). doi:10.1007/978-3-642-41939-3_44
15. Mok, S.J., Jung, K., Ko, D.W., Lee, S.H., Choi, B.-U.: SERP: SURF enhancer for repeated pattern. In: Bebis, G., et al. (eds.) ISVC 2011. LNCS, vol. 6939, pp. 578–587. Springer, Heidelberg (2011). doi:10.1007/978-3-642-24031-7_58
16. McGuinness, K., McCusker, K., O'Hare, N., O'Connor, N.E.: Efficient storage and decoding of SURF feature points. In: Schoeffmann, K., Merialdo, B., Hauptmann, A.G., Ngo, C.-W., Andreopoulos, Y., Breiteneder, C. (eds.) MMM 2012. LNCS, vol. 7131, pp. 440–451. Springer, Heidelberg (2012). doi:10.1007/978-3-642-27355-1_41
17. Janusch, I., Kropatsch, W.G.: Persistence based on LBP scale space. In: Bac, A., Mari, J.-L. (eds.) CTIC 2016. LNCS, vol. 9667, pp. 240–252. Springer, Cham (2016). doi:10.1007/978-3-319-39441-1_22
18. Wei, Y., Lin, G., Sha, Y., Yonggang, D., Pan, J., Jun, W., Shijun, L.: An improved LBP algorithm for texture and face classification. SIViP **8**(Suppl. 1), 155–161 (2014)
19. Pitas, I., Venetsanopoulos, A.N.: Median filters. In: Nonlinear Digital Filters. The Springer International Series in Engineering and Computer Science, vol. 84, pp. 63–116. Springer, New York (1990)
20. Smolka, B., Szczepanski, M., Plataniotis, K.N., Venetsanopoulos, A.N.: Fast modified vector median filter. In: Skarbek, W. (ed.) CAIP 2001. LNCS, vol. 2124, pp. 570–580. Springer, Heidelberg (2001). doi:10.1007/3-540-44692-3_69
21. Abdel-Hakim, A.E., Farag, A.A.: CSIFT: a SIFT descriptor with color invariant characteristics. Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recogn. **2**, 1978–1983 (2006)