Efficient Fuzzy based Image Mosaicing Algorithm for Overlapped Aerial Images

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Abstract: This article presents an efficient technique for aerial image mosaicing algorithm of overlapped pair of Unmanned Aerial Vehicle (UAV) images. Our algorithm is based on detecting some sparse distinguished set of pixels from captured image. Therefore, in the first stage, FAST algorithm was proposed for determining locations of feature pixels. Local binary pattern (LBP) technique is robust for describing features pixels, but it still suffers from different problems, such as noise and errors in interpolating values of surrounding pixels. Fuzzy logic theory partially solves the noise sensitivity problem associated with LBP approach, therefore; in the second part of this article, a robust method based on fuzzy logic technique was used to create Fuzzy Improved Local Binary Patterns descriptors (Fuzzy ILBPDs) for features matching purpose, after that; homography matrix will be estimated through the best associated features; in order to project the overlapped UAV images. The results of our algorithm maps for some benchmark and effective numerical comparisons with previous related works are presented in this paper.

1 INTRODUCTION

Unmanned aerial vehicles (UAVs) have become an increasingly familiar technology and have become smaller, more capable, and less expensive because of both military investment in the UAV industry and improved technology. Current generation UAVs can be transported in small vehicles and launched from a road or a small truck but are still large enough to be equipped with cameras and sensors that can provide low cost aerial information (Edward and McCormack, 2008) .The UAV based platform for photogrammetric and remote sensing; is a more flexible and easy way to provide high resolution images with lower cost. So building UAV based platforms is becoming a hot field throughout the whole world. For some aerial images, it is often necessary to analyze a complete scene section at high resolution which has large dimensions (a large number of pixels). However, in some cases the high resolution single image cannot be viewed even if using cameras with tens of millions of active pixels. The common approach of image mosaicing (Capel and Zisserman, 1998) is to acquire several images of parts of the scene at high magnification and assemble them into a composite single image which preserves the high resolution. The performance of an image mosaicing algorithm depends mainly on the performance of used techniques for features detection and matching .Since Local Binary Patterns Descriptors (LBPDs) (Ojala et al., 1996) provide good and robust description for the detected key points in two overlapped images, fast and good features matching can be obtained using the measured Hamming distance between two LBPDs, therefore, they are getting more and more popular over SIFT and SURF when combined with simple detector for the key point detection.

The aim of our study is to present and investigate the performance of a novel approach for LBP descriptors, because, most methodologies employed for creating LBP descriptors have little tolerance to uncertainty. The novel type of descriptors, which is more capable of dealing with such problems, can be

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developed by incorporating fuzzy logic (Dimitris et al., 2008), in the Local Binary Pattern methodology.

This article is organized in 6 sections. In section 2, some related works concerning some UAV image mosaic construction will be discussed as the state of the art. In section 3, the entire scheme for image mosaicing algorithm will be described. In section 4, the proposed Fuzzy Improved LBP method is described. In section 5, a comparative experimental evaluation reveals the advantageous performance of the proposed method in comparison to other methods applied on real aerial images. In section 6, conclusions and future perspectives are presented.

2 RELATED WORKS

Signal processing programs used on a PC are allowed for rapid development of algorithms, rapid debug and test application. Matlab is such an environment treating an image as a matrix, which allows optimized matrix. UAV image mosaicing, with high speed and robust accuracy, presents a significant challenge. Thus, there have been many researches in this area during the past few decades. In (Nemra, 2010), UAV was enabled to construct a reliable map of an unknown environment and localize themselves within this map without any user intervention. To construct this map; Adapted SIFT detector was used to extract and match features between all the images.

Another strategy was proposed for registering and mosaicing UAV data "aerial images" (Ming et al., 2012), Firstly, the total number of the pyramid octaves in scale space was reduced to speed up the matching process; sequentially, RANSAC was issued to eliminate the mismatching tie points. The method described in (Cheng-Chuan et al., 2012) was to estimate the homography matrices that can precisely register UAV images onto the Google satellite map with less distortion. SIFT was used to perform image registration between consecutive UAV images. But this algorithm was a great challenging task due to quality mismatch between overlapped images. The method described in (Nagaraja et al., 2014) was proposed for construction of mosaic image from an underwater video sequence. Difference of Gaussian (DoG) technique, which is part of SIFT was used for feature detection, then; for each interest point, a texture descriptor was constructed using CS-LBP (Heikkila et al., 2006) technique to describe the key point. Then feature descriptors were matched using Nearest Neighbour Distance Ratio (NNDR) to measure the similarity.

3 IMGE MOSAICING

3.1 Features Detection

This stage is based on extracting a set of pixels (features) among the whole image pixels, then applying the necessary image analysis on these detected set of pixels. Points are the ideal features for image registration because their coordinates can be used directly to determine the parameters of the transformation function, and also due to their invariance to the image geometry and their facilities to be detected using simple detectors (Goshtasby et al., 2005).

3.2 Features Matching

Once the interest points have been extracted, the matching is to find for each point of an image, its correspondent in the other image knowing that the image points are projections of the real 3D points of the same scene. Several matching methods were proposed in the literature (Nemra, 2010), these methods can be classified into three categories: methods based on correlation comparison criteria, methods based on features descriptors and other methods based on features tracking.

3.3 Image Transformation

After finding the pairs of matched features, selecting an appropriate transformation model to compute the image alignments is an important step for image mosaicing (Patidar and Jain, 2011). Different types of transformations models exist for this purpose (Szeliski, 1994).but projective homography is the most general motion model for image mosaicing applications; where the scene is planar or almost planar and the camera undergoes a rigid motion.

3.4 Image Projection

Image warping is the act of projecting two overlapped images on each other according to a mapping between source image $I\ (x,y)$ and destination image $I'(x,y)$. Alignment of images may be imperfect due to registration errors resulting from incompatible model an assumption. Therefore, different blending techniques can be used to compensate these errors (Richard, 2006).

4 FUZZY IMPROVED LBP

Classical algorithm for Local Binary Patterns (LBP) is a binary system description which expresses the relationship of size of a gray image pixel point and its neighbour-hood pixels points; it was originally used to describe image texture information (Ojala et al., 1996). Nowadays, research workers put forward a lot of improved LBP algorithms that have been applied in features matching; face recognition, etc; and that because of its simple computation complexity and partial scale, rotation, and illumination invariance (Ning et al., 2007).

In LBP algorithm, every feature pixel in an image generates a single LBP code. Then a decimal value is calculated for the different LBP codes. The LBP codes forms the LBP feature vector, which characterize the image features. The LBP is based on hard thresholding of surrounding pixels, which makes features description sensitive to noise. In order to improve the LBP approach, we have considered fuzzy logic theory (Ying and Dali, 2006). Fuzzy logic resembles human decision making, with ability for finding precise solutions in approximate datasets collection.

The use of fuzzy logic in the LBP approach includes the transformation of the input variables to respective fuzzy variables, according to a set of fuzzy rules. Our proposed algorithm, which is presented in figure 1, is based on three fuzzy variables sets and four fuzzy rules, each one of these rules depend mainly on Hamming distance between the Improved LBP Descriptors.

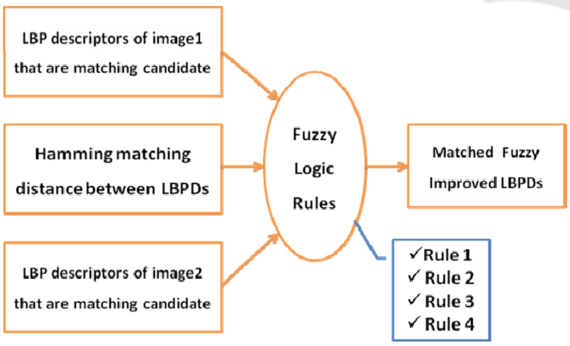

Figure 1: The used Fuzzy ILBPDs algorithm.

The fuzzy Improved LBPDs can be created by following these steps :

1) Detect points based features for each image using one of the robust detectors (FAST, Harris, SIFT ... etc).
2) Create LBP descriptors around the detected features using the first nearest eight neighborhoods pixels, and distance of one pixel from the center pixel.
3) Recreate LBP descriptors around the detected features using the second nearest eight neighborhoods pixels and distance of two pixels from the center pixel.
4) Repeat procedure (3), till the n^{th} nearest neighborhoods pixels and a specified *n* distance of pixels.
5) Put the obtained eight elements vectors from step (4) in one long binary vector of $(n \times 8)$ elements; and label them as Improved LBP Descriptors.
6) Apply Hamming distance to find the matching candidates, among the created Improved LBPDs of image 1 and the created Improved LBPDs of image 2.
7) Based on the calculated Hamming distances, and the matching candidates, apply fuzzy rules to choose the final matched Improved LBP descriptors among ILBPDs 1 and ILBPDs 2.

The obtained set of pairs of matched features from fuzzy based ILBP descriptors can be used for finding an appropriate projective transformation between overlapped images.

5 FUZZY ILBP BASED IMAGE MOSAICING ALGORITHM

Different algorithms were proposed for aerial image mosaicing. Since we are looking for robust algorithm, we have chosen a simple corner detector for features detection; and an improved LBP technique for features matching. Our contribution in this algorithm is integrating fuzzy logic theory in the stage of image mosaicing construction; in this stage; we have proposed to enhance the performance of LBP based features matching technique, by using fuzzy rules, in order to eliminate false associations.

5.1 FAST Corners Detector

The Features from Accelerated Segment Test (FAST) corner detector was developed by Rosten and Drummond in 2006; it has a simple and fast corner detection algorithm to find local invariant points. It finds corners in the image by comparing pixel gradients in a neighborhood of pixels.

FAST algorithm defines corner point as: (In the neighborhoods of a pixel, there are enough pixels in different region and their gray values are greater than or less than the central pixel's (Rosten and Drummond, 2006). The reason behind the work of the FAST algorithm was to develop an interest point detector for use in real time frame rate applications like SLAM on a mobile robot (e.g. UAVs), which have limited computational resources.

The Corner Response Function of FAST detection algorithm to judge whether a pixel is a corner point is defined as CRF as follows:

$$CRF = \sum_{x \in circle\ p} I(x) - I(p) \prec \varepsilon \qquad (1)$$

Where
p : means the central pixel;
I(p): means the gray value of pixel p;
I(x) : means gray value of the neighbour-hood;
ε :is a given threshold value.

If CRF is greater than a given threshold, this pixel point is considered as a corner point. However some pseudo corner points can appear with this algorithm (Rosten, 2011). To extract FAST corners, a grey scaled image is sufficient and allows much faster extraction than RGB one. In order to detect an existing corner, the grey scale of the pixels lying on the discrete circle is compared with the centre pixel p. If a certain consecutive number of differences lie above or below a certain threshold t, the considered pixel is marked as corner. The chosen threshold serves as parameter for controlling the total numbers of extracted corners in a given image (Rosten, and Drummond, 2005).

5.2 Improved LBP Descriptors

From the description of LBP technique, it is clear that it involves only simple arithmetic operations, since we are looking for good matching results with less calculation time; we have proposed to use a novel modified version of this technique; which satisfies our desires. Figure 2, illustrates the necessary steps to create eight elements LBP vector around a feature pixel of gray level of value 65.

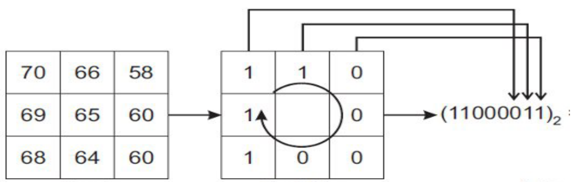

Figure 2: Construction of LBP descriptor.

In our case we have used window size of eight elements for creating the LBP descriptors, but many different sizes of neighbourhood can be used, each element of LBP can be obtained by comparing central the pixel with its eight neighbours, as given in equation 2:

$$LBP(i) = \begin{cases} 1 & if \quad g_{p,i} \succ g_c \\ 0 & if \quad g_{p,i} \prec g_c \end{cases} \qquad 1 \le i \le 8 \qquad (2)$$

Where:
$\boldsymbol{g_c}$ is the detected interest point.
$\boldsymbol{g_{p,i}}$ is one of the eight pixels around g_c .

By concatenating N eight elements LBP vector, we can get a long (8 × N) binary vector called Improved LBP descriptor, in which N depends on the chosen radius from the detected point features to the central feature pixel.

5.3 Hamming Matching Distance

Improved LBPDs depend only on increasing radius; and keeping at each time eight pixels in the neighbours. If two ILBPDs are compared, small distance value context between them is a sign of good match ability, the distance between two ILBDs is measured using the Hamming distance, which is a simple bitwise exclusive or (XOR) instruction (Zhou, 2014) . Hence, computation and matching of ILBDs can be implemented efficiently. For two feature points, p_{ij} and $p_{i'j'}$ from images i and i' respectively, we can compute the matching distance as given by equation 3:

$$d_S(p_{ij}, p_{i'j'}) = d_{ham}(\widehat{h}_{ij}, \widehat{h}_{i'j'}) \qquad (3)$$

Where
$\widehat{h}_{ij}, \widehat{h}_{i'j'}$: refers to *ILBPD1 and ILBPD2.*
d_{ham} : Hamming distance between ILBPDs.

In the ideal case; the Improved LBP descriptors of the matched features should be completely coinciding, in other words, the distance between them should be zero. Some relation should be made to avoid mismatching due the noise in the binary vectors. For that, we have imposed to use fuzzy logic theory to eliminate some false association.

5.4 Fuzzy Improved LBPDs

The fuzzy logic theory is used in our work; to determine the correct matches between two overlapped images. The inputs to the fuzzy logic for every pair of matched key points which are defined by ILBP descriptors are as follows:

1) The measured Hamming distance (d_H) between every two ILBP descriptors.
2) Belongingness of the ILBP descriptor to its region (R1) in image 1.
3) Belongingness of the ILBP descriptor to its region (R2) in image 2.

The belongingness of an ILBP descriptor in R1 is given by the measured correlation criterion of features of the created binary descriptors with features of image 2 .Similarly belongingness of ILBP descriptor in R2 is also defined as vice versa. The membership functions for input variable 'Hamming distance measure' is defined as 'low', and 'high' (see Figure 3 (a)). The input variable 'belongingness' is defined by sigmoid function, shown in Figure 3 (b). Output variable is defined by

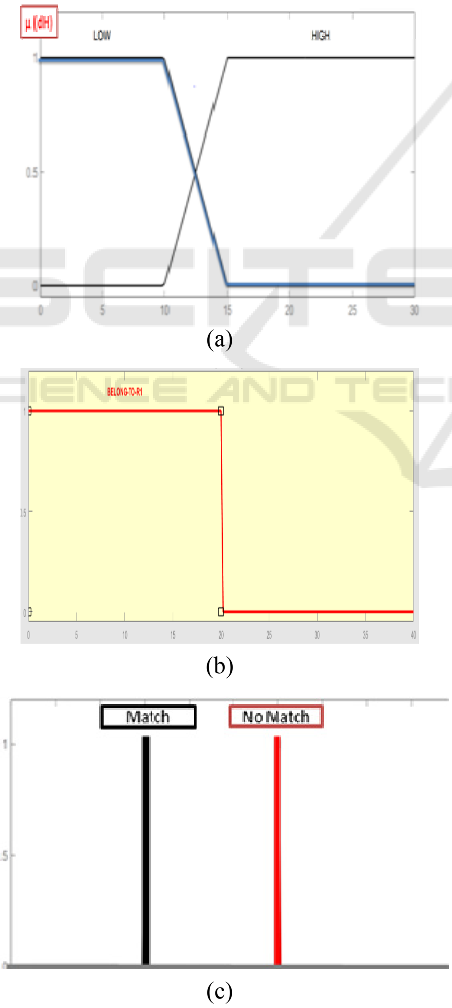

Figure 3: (a) The 1st input membership function 'hamming distance'(d_h). (b) The 2nd input membership function 'Belongingness to R1/R2'. (c) The output membership function 'match/ no match'.

Gaussian functions for 'match', 'low' and 'no match' (see Figure 3 (c)). For each matched features of overlapped images using ILBP descriptors, a Hamming measure and correlation criterion (in our case we have used Sum of Absolute Difference) are calculated, then, fuzzy logic which is discussed in previous section is used to find if the key points are said to be semantically matched or not.

The following are the fuzzy rules used for the proposed system to determine the matching decision. The defuzzification method used in our case for the output is centroid method.

1. If (d_H is low) and (r1 is belong) and (r2 is belong) then (ILBPDs match).
2. If (d_H is high) and (r1 is not belong) and (r2 is not belong) then (ILBPDs do not match).
3. If (d_H is low) and (r1 is not belong) and (r2 is belong) then (ILBPDs do not match).
4. If (d_H is high) and (r1 is belong) and (r2 is not belong) then (ILBPDs do not match).

During the matching process, the distance between the ILBP descriptors for two image features is computed with Hamming distance and the correlation score is calculated to determine the belongingness of ILBPDs. Then these distance and scores are used as the crisp inputs of the fuzzy system. The membership values of the measured hamming distance is found for two fuzzy set Low and High, and the membership values for the calculated correlation scores is found for two fuzzy set either belong or not. The rules are evaluated and finally the output decision is obtained from the zero order Sugeno type output membership function (singleton) as a Match or No Match.

5.5 Homography Estimation

Homography or projective transformation is the suitable image mapping model for image mosaicing purpose, which is a planar transformation with 8 degrees of freedom. Each pair of point correspondence generates 2 linear equations for the elements of H and hence 4 correspondences are enough to solve for the homography directly (Capel and Zisserman, 1998).

If more than 4 pairs are available, a solution for element of H can be estimated using a linear least-square method. Matrix H can be defined as follows:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{4}$$

Each pair of matched features gives two linear equations:

$$\begin{aligned} x'(h_{31}x+h_{32}y+h_{33})-h_{11}x-h_{12}y-h_{13}=0 \\ y'(h_{31}x+h_{32}y+h_{33})-h_{21}x-h_{22}y-h_{23}=0 \end{aligned} \quad (5)$$

Hence, N pairs of points generate $2N$ linear equations, which may be arranged in a matrix design as follows:

$$AH=0 \quad (6)$$

The solution for H is the one-dimensional kernel of A, which may obtained from the SVD. For N>4 points, this equation will not have an exact solution. In this case, a solution may be obtained which minimizes the algebraic residuals, $r = AH$, in a least-squares sense, by taking the singular vector corresponding to the smallest singular value.

5.6 Backward Image Warping

Using homography matrix, overlapped images were warped (figure 4); we have determined bounds of the new combined image where the corners of left image would fall in the coordinate frame of the right image. This was done by multiplying homography on the corner point coordinates. Then we have attempted to lookup colors for any of these positions we got from the left image as given by this equation:

$$x = H^{-1} * x' \quad (7)$$

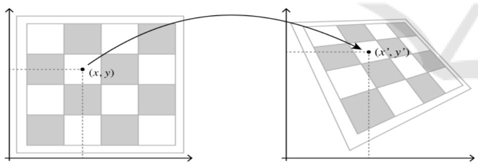

Figure 4: Backward image warping.

5.7 Interpolation Blending Technique

It is a simple approach, in which; the pixel values in the blended regions are weighted average from the two overlapping images. Sometimes, it is better to take more than two neighbor pixels in interpolation process. In our case, we have used the bilinear interpolation algorithm; which is slightly more sophisticated interpolation method, it interpolates pixel value from the nearest four mapped source pixels, and this simple algorithm produces excellent results.

6 SIMULATION RESULTS

Matlab is a powerful software platform which can be used for the development of several applications. In our case, due to the provided image processing predefined functions with Matlab toolbox; Matlab software is suitable for the development of complex image processing algorithms such as image mosaicing algorithm. To test the proposed image mosaicing algorithms, we have used Matlab running on a computer that disposes 4 GB of RAM, CPU of Intel i7 generation and Intel graphic card. We tested our image mosaicing approaches on the images of Aerial Robotics Data sets (AerialRobotics, 2014). Figure 5; shows the used overlapped aerial images, which have overlapping percentage of about 30 %.

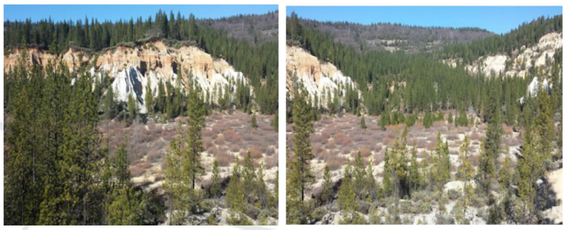

Figure 5: The two overlapped UAVs images.

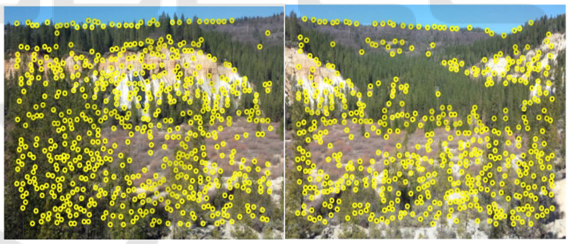

Figure 6: The detected features using FAST algorithm.

Figure 6 shows the detected corners features in the two images, in which we can see that repeatability condition is well verified using this type of points based features.

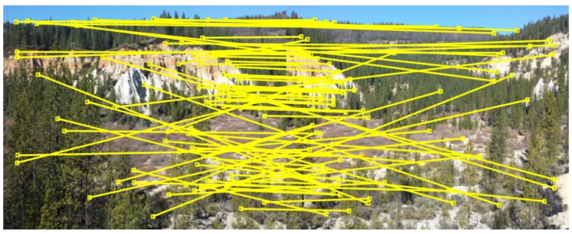

Figure 7: Features matching using LBP.

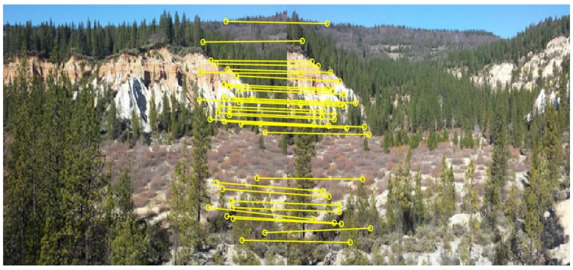

Figure 8: Features matching using fuzzy ILBP.

Figure 7 shows the obtained features correspondence between the input images; using LBP descriptors, in which we can notice the existence of a lot of incorrect matches. But with the fuzzy ILBPDs; we can visually notice that this approach provides good matching results as shown in figure 8. After homography estimation, we have used this transformation matrix to warp images as shown in figure 9. The black gaps are because images aligned after undergoing geometric corrections most likely require further processing to eliminate remaining.

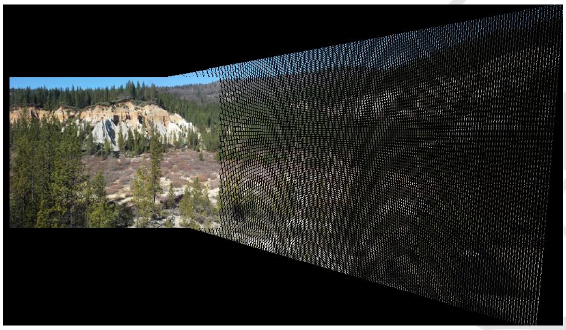

Figure 9**:** The obtained mosaic using backward warping.

That is why; we have used an interpolation blending technique, based on bilinear interpolation to get seamless image mosaic, which is shown in Figure 10.

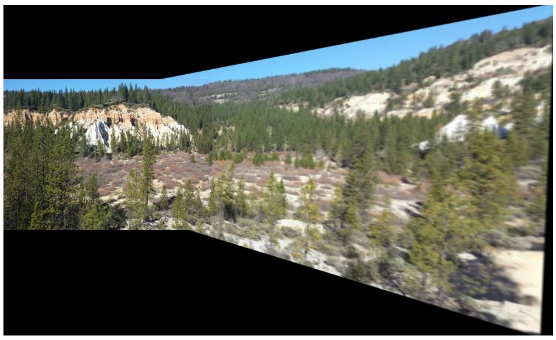

Figure 10: The blended mosaic using interpolation.

- *RESULTS DISCUSSION*

Our method was compared visually and numerically with recent state-of-the-art algorithm in the literature. Performance evaluations in terms of computation time show success of our algorithm. In (Taygun et al., 2016), by the same simulation tools, SIFT point detector was used for extracting images salient elements, and BRIEF descriptor was used to describe and match key-points. The matching results, show that big difference in calculation time between our algorithm and that of (Taygun et al, 2016), which is due to the simplicity of calculation using fuzzy ILBP Descriptors; contrary to SIFT/BRIEF descriptors.

Since visual comparisons can be subjective, a numerical evaluation of the algorithms is also necessary. To evaluate the algorithm performances, feature matching errors present in the results of each method are calculated in terms of recall (Hassaballah et al., 2016)**,** which depends mainly on the ratio between number of inliers and outliers. The following table summarizes the comparison of our simulation results and compares it to other results obtained by using the same simulation platforms.

Table 1: Comparison of simulation results.

Methods	Features1	Features 2	Recall
CS-LBP (Nagaraja et al, 2014)	262	274	0.71
SIFT (Lowe, 2004)	256	243	0.62
SURF (Bay et al, 2008)	233	263	0.68
Our Method	345	326	0.73

7 CONCLUSIONS

LBPDs based matching technique has different advantages such as tolerance against illumination changes, computationally simple and efficient. The main drawback of LBP is that by increasing the radius from the detected interest point, the algorithm is not too robust. In order to overcome this drawback; we have proposed to extend version of LBP into fuzzy improved LBP. The fuzzy ILBP descriptors outperform the existing local descriptor for most of the test cases, especially for images with severe illumination variations and they capture better gradient information than original LBP. We recommend for future work using other type of images such as IR areal images.

REFERENCES

Edward D., McCormack., 2008. ‘The Use of Small Unmanned Aircraft by the Washington State Department of Transportation’. Washington State Transportation Commission.

Capel D., Zisserman A., 1998. “Automated Mosaicing with Super-resolution Zoom”. Robotics Research Group, Department of Engineering Science.University of Oxford Oxford OX1 3PJ, U.K.

Ojala, T., Pietikäinen, M., Harwood, D., 1996. “A comparative study of texture measures with classification based on featured distribution. Pattern Recognition”, Vol. 29, pp 51-59.

Dimitris K., Iakovidis., Eystratios G., Keramidas., Dimitris Ma., 2008. ‘Fuzzy Local Binary Patterns for Ultrasound Texture Characterization’. International Conference Image Analysis and Recognition ICIAR Image Analysis and Recognition, pp 750-759.

Nemra A., 2010. “Robust Airborne 3D Visual Simultaneous Localisation And Mapping”. PHD Thesis . Cranfield University.

Ming Li., Deren Li., Dengke F., 2012. “A Study on automatic UAV image mosaic method for paroxysmal disaster”. International Archives of the Photo grammetry, Remote Sensing and Spatial Information Sciences. Melbourne, Australia.

Cheng-Chuan, C., Shih-Ming, H., and Ching-Chun, H., 2012. “Image Registration among UAV Image Sequence and Google Satellite Image Under Quality Mismatch” The 12th International Conference on ITS Telecommunication. PP 311-315.

Nagaraja, S., Prabhakar, C. J., and Praveen Kumar, P. U., 2014. (Parallax effect free mosaicing of underwater video sequence based o texture features) . Signal & Image Processing: An International Journal (SIPIJ) Vol.5, No.5.

Heikkila, M., Pietikainen, M., and Schmid, C., 2006. “Description of Interest Regions with Center-SymmetricLocal Binary Patterns”, In Computer Vision, Graphics and Image Processing, ICVGIP 2006, vol. 4338, pp. 58-69.

Goshtasby, A. A., 2005.“2-D and 3-D Image Registration for Medical, Remote Sensing, and Industrial Applications”. Published by John Wiley & Sons, Inc., Hoboken, New Jersey. Published simultaneously in Canada.

Patidar, D., and Jain, A., 2011. “Automatic Image Mosaicing: An Approach Based on FFT”. International Journal of Scientific Engineering and Technology. Page 1-4 .Vol 1. Issue 1. India .

Szeliski, R., 1994. “Image Mosaicing for Tele-Reality Applications”. Technical Report series. Cambridge Research Laboratory.

Richard, S., 2006. “Image alignment and stitching: a tutorial”, Found. Trends. Comput. Graph. Vis. 2 .pp1–104.

Ojala, T., Pietikainen, M., and Harwood, D., 1996. “A comparative study of texture measures with classification based on feature distributions”, Pattern Recognition, vol. 29, no. 1, pp. 55-59.

Ning, S., Zhenhai, J., and Cairong, Z., 2007.“ Gender classification based on local binary pattern”. Journal of Huazhong University of Science and Technology .pp 177-181. Chinese.

Ying, B., and Dali, W.,2006. “Fundamentals of Fuzzy Logic Control”. Publisher: Springer, Londo pp 17-36.

Rosten, E., and Drummond, T., 2006.“ Machine learning for high-speed corner detection”. European Conferen-ce on Computer Vision. pp 430-443. Graz, Austria.

Rosten, E., 2011. “FAST Corner Detection Homepage”. http://svr- www.eng.cam.ac.uk/ er258/work/fast.html.

Rosten, E., and Drummond, T., 2005. “Fusing points and lines for high performance tracking”. In Proceedings of the International Conference on Computer Vision (ICCV). pp 1508-1511.

Zhou, Z., 2014. “FPGA Implementation of Computer Vision Algorithm”. A thesis submitted in partial satisfaction of the requirement for the degree of Master of Science in Electrical Engineering. University of California (Riverside).

AerialRobotics Dataset,. 2014.. ftp://www.aerial robotics.eu/ accessed: 2014-03-30.

Taygun, K., Alper, Y., and Mustafa, U., 2016. ‘A new approach to real-time mosaicing of aerial images’. Elsevier Jornal of robotic and autonomous systems.

Hassaballah, M., Abdelmgeid, AA., and Hammam, A., 2016. “Image Features Detection, Description and Matching”. Springer International Publishing Switzerland.

Lowe, D. G., 2004. “Distinctive Image Features from Scale-Invariant Keypoints”, International Journal Computer Vision, 2(60), pp.91-110.

Bay, H., Ess, A., Tuytelaars, T., and Gool, L. V., 2008. “Speeded-Up Robust Features (SURF)”, Computer Vision and Image Understanding, 113(3), pp. 346-359.

APPENDIX

The obtained results of applying our algorithm on other aerial images “Hakekasa data set “from (AerialRobotics, 2014):