Oral Presentation

The 7th TSME International Conference on Mechanical Engineering
13-16 December 2016

AME0016

Automatically Enhanced UAV Images for Infrastructure Inspection

Chen-Ming Kuo[1], Po Ting Lin[1,*], Chun-Hsin Kuo[1], Chinnapat Thipyopas[2], Vis Sripawakul[2], Stung Hao Yang[1], Yi-Chi Hsieh[1], Wei-Hao Lu[1] and Shu-Ping Lin[1]

[1] Department of Mechanical Engineering, Chung Yuan Christian University, 200 Chungpei Road, Chungli, Taoyuan, Taiwan 32023
[2] Department of Aerospace Engineering, Kasetsart University, 50 Ngamwongwan Road, Chatuchak, Bangkok, Thailand 10900
[*] Corresponding Author: potinglin@cycu.edu.tw, +886-983033147

Abstract

Public infrastructures such as bridges are important for transportations between different places. However, many of those infrastructures were built at more than 50 years ago. The aging managements and damage assessments are required to ensure safe operations of these old bridges. Unmanned Aerial Vehicle (UAV) technologies have been utilized for infrastructure inspections in the past few years. It provides necessary visual information of the damage assessment and it is safer than human inspections. We have designed and made a UAV equipped with a camera for the collection of high-resolution images. To further reveal more information of the damage condition from the captured images, the Fuzzy Automatic Contrast Enhancement (FACE) method was utilized to maximize the image quality. Because the UAV images can be taken under various circumstances, it is usually a lot of works to manually adjust the image quality for better visual observation. FACE has been proven that it is capable of finding the maximum image contrast without any human settings. Real tests of automatically enhanced UAV images of cracks on the wall show the potential locations of the damages. As predicted by the proposed method, severe damages occur at the expected locations at six months later.

Keywords*:* Infrastructure Inspection, Unmanned Aerial Vehicle, Fuzzy Automatic Contrast Enhancement.

1. Introduction

In many developed countries in US and Europe, most bridge are most built before and after World War Two, where in Asia, for example, Japan, most bridges are built during the first Tokyo Olympics in 1970s. If just looking at In the US alone, 70% of bridges and roads are built prior to 1935 in which regular inspections is required by the FHWA [1-3].

Now looking at Asia, Korea estimated that around 12,000 bridges require safety inspection tests on an annual basis [4]. Different countries has slightly different regulation for bridge inspection, however, Visual inspection techniques are currently the most common primary methods used to evaluate the condition of the majority of the nation's highway bridges. During the visual inspection mission, the inspector just simply just looks at the structure and records its damage level both analogously or digitally. The method also including counting the number of surface cracks and measuring the maximum widths of the crack lines it is possible. The tasks sounds and look relative simple, but it can be also very difficult, dangerous and costly when the structure is in complex shape like bridge or target area is highly elevated above ground [1-5]. Very often visual inspection will require some specialized equipments, which are mostly large, heavy, expensive and complex, as shown in Fig. 1.

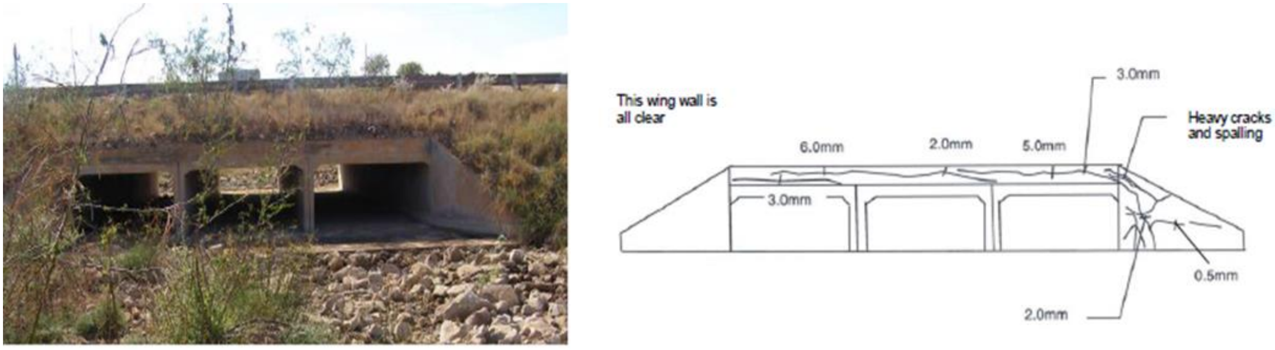
To summaries the visual inspection tasks in different countries, the two most important and fundamental steps are (1) identifying damage (such as cracking and corrosion) and (2) generating the damage map for further evaluation of safety of the bridge. For example, in Australia, level one bridge inspection [6] requires the inspector to identify the damage and its location respect to the structure in order to generate the damage map when it is possible. A sample of the bridge and generated damage map report are shown in Fig. 2. Lastly, all the visual inspection mission require inspectors being on site, and if mission involves uses of special trucks, climbing or going into water [7-9], which can be dangerous and costly.

Fig. 3 shows the UAV [10] that we built for the bridge inspection. The UAV carries a camera that captures high-resolution images. The positioning of the UAV and the image acquisition are synchronized by our developed integration system. Each image is taken with a GeoTag (information of UAV positioning including GPS position). However, there are still many factors (including the nature of the object material, calibration parameters for the image capture device, conditions of insufficient ambient light, etc.) that are likely to cause low-contrast images [11].

Contrast enhancement is one of the most important image processing technologies that could improve the quality of the captured low-contrast image. When the color intensity excessively concentrates in specific areas of the intensity histogram, the details and features in the concentrated area become less distinguishable leading to low contrast of the image [12]. Contrast enhancement is one way to improve the image quality and find out the details of the hidden information at the low-contrast area of the image. This paper uses the Fuzzy Automatic Contrast Enhancement (FACE) [13] to improve the image quality without the needs of human settings.

(a) (b)

Fig. 1. Specialized equipments for bridge inspection: (a) Inspectors can reach the bottom of the bridge aided by the equipment. (b) A photo of real disaster of falling equipment occurred in the past.



(a) (b)

Fig. 2. An example of bridge inspection in Australia: (a) photo of the inspected bridge, (b) the damage map generated by visual inspection [6].

Fig. 3. Infrastructure inspection using our developed UAV equipped with a camera.

2. Unmanned Aerial Vehicle (UAV) for Infrastructure Inspection

The UAV that built by CYCU is capable of performing inspection missions both autonomously or by remote controls. The full inspection system includes Command, Control and Communications (C3) Systems [14]. The UAV types focused by this paper are mainly octocopters and quadcopters. However, even two robots are in different size, weight and control method, both were designed and built by modular design concept; therefore, different module/parts can be shared between two robots. Very typical example is that the autopilot systems for both robots are the same and the interfaces are identical. Thus, one can move the autopilot system from vehicle to vehicle easily by only performing firmware updates. Since the communication protocol between robots and Ground Control Station (GCS) are the same, therefore there is no need for any software update when switching to different. GCS software is written in C and C#, which run on Microsoft Windows Operating System (apart from Win8 mobile phone OS at time when this project is performed). Communication between the vehicles and GCS is done wirelessly by standard RF module; hence, operator/pilot could easily monitor vehicle's status such as, attitude and other flight information during mission.

As for payload control such as camera or gimbal direction could be done via GCS (or done by pilots RC remote direct). The images captured from digital camera were too large for real-time wireless transfer to ground; therefore, high-quality images were stored on board of the camera. In order to assist the operator to know what and where he/she is capturing photo, the camera were fitted with Video output chip to send the reduced resolution image from camera to ground station in real time. Actions of camera triggers were recorded with both a blackbox on board of the vehicle (recording time, and GPS location when camera shutters are triggered) and GCS wirelessly.

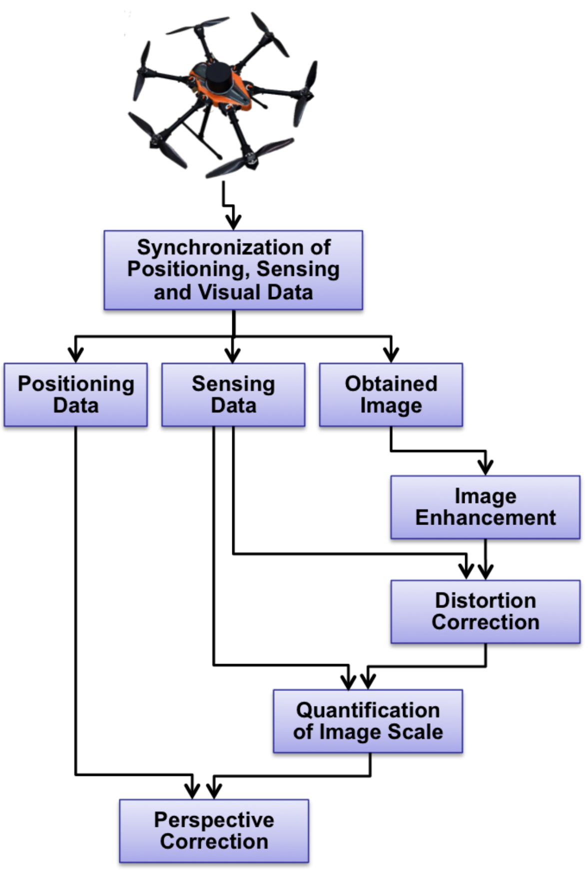


Fig. 4. Integration in our UAV inspection system.

After the built the initial UAS, some quick inspection were conducted for a steel truss bridge, as shown in Fig. 2. The trial mission lasted less than 10 minutes with a total collection of 300 photos from two different cameras with different resolutions. Due to the accessibility of the site, only the one side of the bridge (east) is inspection east side of the bridge is inspected and facade map has been created, However, even with details of more than 60 million pixels on facade map, some details of the bridge are still not in good resolution. Enhancement of the image quality becomes essential for the success of the inspection mission.

Fig. 4 shows the integration of our UAV inspection system. The details about the quantification of image scale and perspective correction can be found in the reference [10]. The synchronization of positioning, sensing and visual information is the first core technology of our UAV. This paper introduces how the captured images can be enhanced for more details about the structure damages.

3. Fuzzy C-Means Clustering

The Fuzzy Automatic Contrast Enhancement (FACE) [13] was developed in the same research group and has been shown to be effective on improvement of image quality. It has been shown that FACE is capable of revealing the fine details in the original image without creating artificial artifacts or producing large hue shifts. Fig. 5 shows an example that can be found in the reference [13].

FACE utilizes a Fuzzy C-Means (FCM) clustering process to classify the pixels with similar colors together. A universal contrast enhancement variable (UCEV) is optimized to maximize the image entropy automatically without the need of human-defined control parameters. The above two processes are expected to enhance the image contrast without the productions of artifacts and unwanted noises.

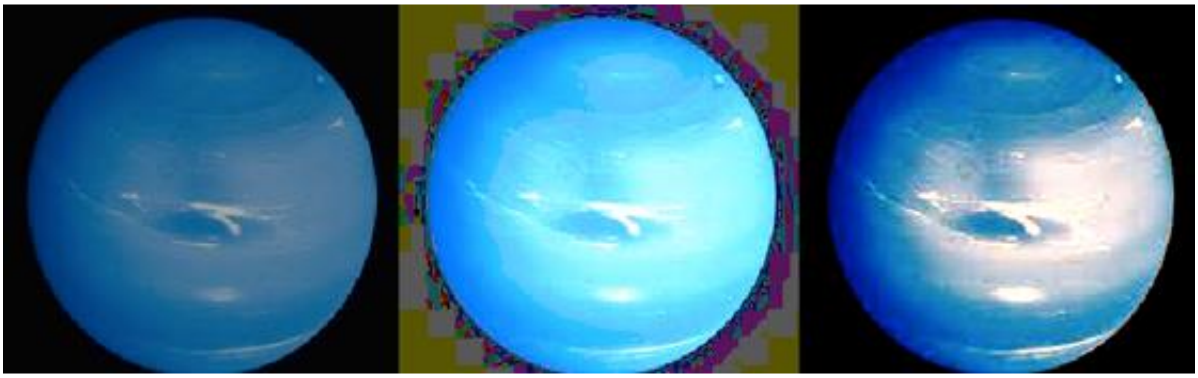
Suppose there are N image pixels, $\mathbf{x}_i$ for $i = 1 \ldots N$, and they are to be clustered into K groups, the center of each group is denoted as $\mathbf{c}_j$ for $j = 1 \ldots K$. The parameter u_{ij} represents the belongingness of the i^{th} pixel in the j^{th} cluster. For exact clustering methods such as K-Means [15-18], u_{ij} is either 0 or 1 (i.e. 0 stands for not belonging; 1 stands for belonging). This paper utilized Fuzzy C-Means (FCM) [19] to allow non-exact belongingness of pixels in every clusters. In other words, u_{ij} can be any real number in the interval of $[0,1]$.

A recursive approach [13] in Eqs. (1) and (2) ensures the optimal fuzzy clustering can be determined.

$$\mathbf{c}_j = \frac{\sum_{i=1}^{N} u_{ij}^m \mathbf{x}_i}{\sum_{i=1}^{N} u_{ij}^m} \tag{1}$$

$$u_{ij} = \frac{1}{\sum_{l=1}^{K} \left[\frac{\left\| \mathbf{x}_i - \mathbf{c}_j \right\|}{\left\| \mathbf{x}_i - \mathbf{c}_l \right\|} \right]^{\frac{2}{m-1}}} \quad (2)$$

Eq. (1) determines the center of the j^{th} cluster based on the given belongingness of pixels. Eq. (2) then determines the belongingness parameter u_{ij} based on the given cluster center points. The recursive process continues until convergence. This paper uses $m=3$ for best performances [20].



(a) (b) (c)

Fig. 5. An example that was shown in the reference [13]: (a) original image, (b) enhancement by Histogram Equalization (HE) [21], (c) enhancement by FACE.

4. Entropy Maximization for Contrast Enhancement

A universal contrast enhancement variable (UCEV), α, is to be optimized for maximum contrast of the determined images. By increasing the UCEV, each pixel point is moved to a new position away from the center of the belonging cluster and it is given by:

$$\mathbf{x}'_i \equiv \mathbf{x}_i + \alpha \sum_{j=1}^{K} u_{ij} \left(\mathbf{x}_i - \mathbf{c}_j \right) \quad \forall\, i = 1 \ldots N \quad (3)$$

where α acts like the step size of a line search along a fuzzy combination of directions away from the cluster center points. A positive value of α broadens the distribution of image pixels leading to contrast enhancement (or brightening in some color spaces). A negative value of α indicates shrinking coverage of pixel distribution, which may be useful for correcting the photos that are too bright.

The final step of the FACE is to find the optimal enhancement of the image contrast. A global measurement, entropy J [22], is maximized with respect to α, as shown below:

$$\underset{\alpha}{Max} \quad J(\alpha) = -\sum_{\mathbf{x} \in \Omega} \left[p\left(\mathbf{x}'(\alpha)\right) \log_2 p\left(\mathbf{x}'(\alpha)\right) \right] \quad (4)$$

where p is the probability density of the distribution of newly determined set of image pixels $\mathbf{x}'$, obtained from Eq. (3); Ω is the gridding set for computing the image entropy, i.e. the measure of unpredictability of pixel distribution. Larger entropy represents higher "randomness" of the pixel distribution and greater variance between image pixels; therefore, the optimization process in Eq. (4) ensures to enhance the image contrast.

The expansion of the pixel distribution should be constrained within the investigated color space. In this paper, the moved pixel points that exceed the bounds of the color space stay on the bounds. Therefore, the increment of image entropy stops when some pixel points accumulate on the bounds. A greater value of α will cause greater accumulation of pixel points on the bounds and lower variance between pixel points, i.e. a lower value of entropy. This is why a maximum of entropy exists when the entropy maximization strategy is used.

4. Results of Automatically Enhanced UAV Images

Fig. 6 (a) shows an image that was captured by the UAV system we developed. One operator controlled the UAV system collaborating with one inspector. The inspector found the cracks while checking the real-time streaming video, which was wirelessly sent from the UAV to the GCS. The image was then captured with synchronized UAV positioning information that will be used for future verification and required maintenance.

Our implement of FACE, shown in Fig. 6 (b) shows good realization of crack locations and prediction of potential damages. There is actually a clear vertical crack spanned from the top of the image to the bottom, which cannot be easily seen in the original image. Furthermore, it has been found there is also a horizontal crack spanned from the left of the image all the way to the right. The new finding provides more information about the structure health than what was observed by human eyes. The minor marks revealed by FACE are the locations of potential cracks. Next section will show how the proposed methodology can be utilized to predict the crack locations and real tests confirm our findings.

(a)

(b)

Fig. 6. Automatically enhanced UAV image for inspection: (a) original image of cracks on the wall, (b) enhancement result.

5. Prediction of Crack Locations Using Automatically Enhanced UAV Images

The importance of the image enhancement can be seen in following real inspection cases: The original inspection mission were carried out by using octocopter to record the surface damage of the building, where in Fig. 7 left, large crack area can be seen. From the inspection results, one can expect that the boxed area have the most significant damage as the concrete is popping out. After 6 month, the same area shows very large damage Fig. 7 Right, and even area not in red boxes are also damaged. However, if now using image enhancement method proposed in this paper, results can be seen in Fig. 8 middle (please compare with right). Green boxed area in Fig. 8 shows the significant damage area that after using image enhancement, which shows a good match with Fig. 8 right.

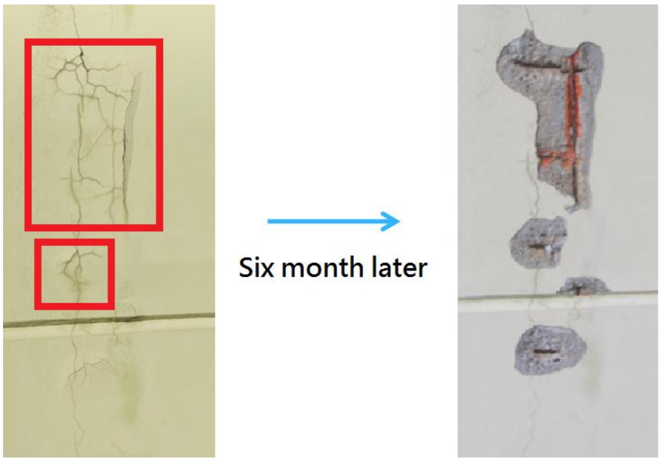


Fig. 7. Left: the original inspection results, note, red boxes show the most significant damage that can be visually seen. Right: Damage area after 6 month; note that damaged area is larger than expected.

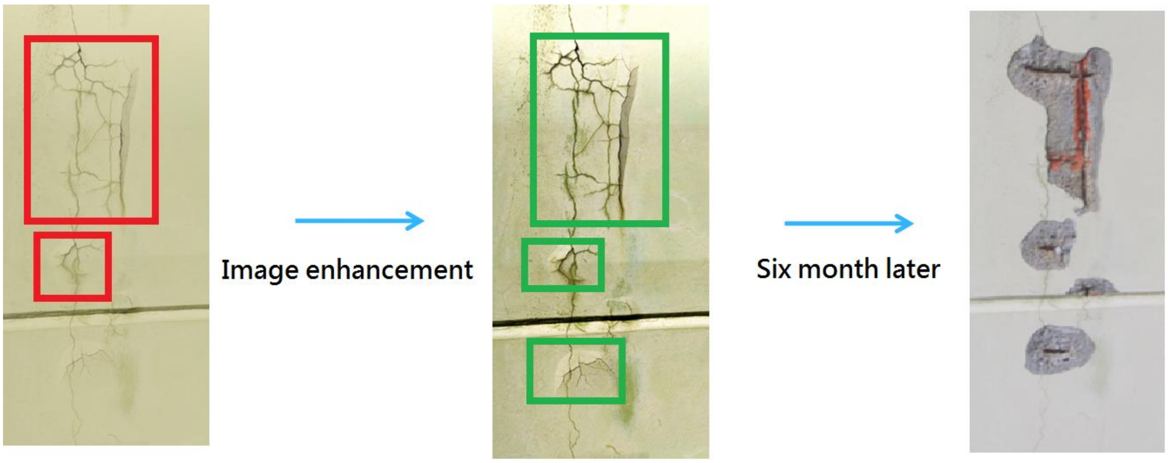


Fig. 8. Left: original picture. Middle: after image enhancement, note, the green boxes shows the significant damage area done visually. Right: results of 6 month after initial inspection, note that the green boxes area shows good match with final results.

6. Conclusion

This paper has described both benefits and challenges of using flying robot for the visual inspection of the bridges or other infrastructures. Further developments of the image enhancement were implemented and presented in this paper. A UAV equipped with a camera was built for the collection of high-resolution images. The Fuzzy Automatic Contrast Enhancement (FACE) method was utilized to reveal features and hidden patterns of structure damages from the images that were captured on the UAV. Real tests of structure inspections were performed using the proposed methodologies and technologies. The results show that the automatically enhanced UAV images not only show the details of the structure cracks but also help predict the locations of the potential damages. Significant damages were found at the said locations as predicted by the enhanced images.

Acknowledgments

This paper is supported by Ministry of Science and Technology, Taiwan (grant numbers MOST 105-2221-E-033-025 and MOST 105-2119-M-033-001) and the Center for Robotics Research, and Environmental Control and Hazard Mitigation

AME0016

Technology Center at Chung Yuan Christian University, Taiwan.

References

[1] Golabi, K., Thompson, P., and Hyman, W., 1993, "Pontis: a network optimization system for bridge improvements and maintenance". *Technical Manual FHWA-SA-94*, **31**.

[2] Brecher, A., 1995, "Infrastructure: a national priority". *Soc Women Eng*, **4**(16), pp. 14-16.

[3] Roberts, J., and Shepard, R., 2000, "Bridge management for the 21st century". *Transportation Research Record: Journal of the Transportation Research Board*,(1696), pp. 197-203.

[4] Oh, J.-K., Jang, G., Oh, S., Lee, J. H., Yi, B.-J., Moon, Y. S., Lee, J. S., and Choi, Y., 2009, "Bridge inspection robot system with machine vision". *Automation in Construction*, **18**(7), pp. 929-941.

[5] Federal Emergency Management Agency, *Structural Collapse Technician Course - Student Manual*. See also URL http://www.w1npp.org/ARES/BUILDI~1.PDF.

[6] Scanlon, R. F., 2009, "Routine Visual Bridge Inspection Guidelines (Level 1 Inspections) for Bridges". *Structures Engineering of Main Roads Western Australia*, Paper number 6706-02-2234.

[7] Manual, B. M. T., 1992, *US Federal Highway Administration*, Wilbur Smith Associates.

[8] Silano, L. G., 1993, *Bridge inspection and rehabilitation: a practical guide*, John Wiley & Sons.

[9] Aldunate, R., Ochoa, S. F., Peña-Mora, F., and Nussbaum, M., 2006, "Robust mobile ad hoc space for collaboration to support disaster relief efforts involving critical physical infrastructure". *Journal of Computing in Civil Engineering*, **20**(1), pp. 13-27.

[10] Kuo, C.-M., Kuo, C.-H., Lin, S.-P., Manuel, M. C. E., Lin, P. T., Hsieh, Y.-C., and Lu, W.-H., 2016, "Infrastructure Inspection Using An Unmanned Aerial System (UAS) with Metamodeling-Based Image Correction". ASME 2016 International Design and Engineering Technical Conferences & Computers and Information in Engineering Conference, IDETC/CIE 2016, Charlotte, NC, USA, Number IDETC2016-59193.

[11] Arici, T., Dikbas, S., and Altunbasak, Y., 2009, "A histogram modification framework and its application for image contrast enhancement". *IEEE Transactions on Image processing*, **18**(9), pp. 1921-1935.

[12] Demirel, H., Ozcinar, C., and Anbarjafari, G., 2010, "Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition". *Geoscience and Remote Sensing Letters, IEEE*, **7**(2), pp. 333-337.

[13] Lin, P. T., and Lin, B. R., 2016, "Fuzzy Automatic Contrast Enhancement Based on Fuzzy C-Means Clustering in CIELAB Color Space". The 12th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications, MESA 2016, Auckland, New Zealand, Number 92.

[14] Gupta, S. G., Ghonge, M. M., and Jawandhiya, P., 2013, "Review of unmanned aircraft system (UAS)". *Technology*, **2**(4).

[15] Jain, A. K., 2010, "Data clustering: 50 years beyond K-means". *Pattern recognition letters*, **31**(8), pp. 651-666.

[16] Wagstaff, K., Cardie, C., Rogers, S., and Schrödl, S., 2001, "Constrained k-means clustering with background knowledge". ICML '01 Proceedings of the Eighteenth International Conference on Machine Learning, Vol. **1**, pp. 577-584.

[17] Huang, Z., 1998, "Extensions to the k-means algorithm for clustering large data sets with categorical values". *Data mining and knowledge discovery*, **2**(3), pp. 283-304.

[18] Hartigan, J. A., and Wong, M. A., 1979, "Algorithm AS 136: A k-means clustering algorithm". *Applied statistics*, pp. 100-108.

[19] Bezdek, J. C., Ehrlich, R., and Full, W., 1984, "FCM: The fuzzy c-means clustering algorithm". *Computers & Geosciences*, **10**(2), pp. 191-203.

[20] Cannon, R. L., Dave, J. V., and Bezdek, J. C., 1986, "Efficient implementation of the fuzzy c-means clustering algorithms". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **2**, pp. 248-255.

[21] Pizer, S. M., Amburn, E. P., Austin, J. D., Cromartie, R., Geselowitz, A., Greer, T., Ter Haar Romeny, B., Zimmerman, J. B., and Zuiderveld, K., 1987, "Adaptive histogram equalization and its variations". *Computer vision, graphics, and image processing*, **39**(3), pp. 355-368.

[22] Ramesh, N., and Nityananda, R., 1986, "Maximum entropy image restoration in astronomy". *Annual review of astronomy and astrophysics*, **24**, pp. 127-170.