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Towards automated interpretation of 12-Lead ECG image: Preliminary Experimental results on 2 Leads

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Abstract. A standard 12-Lead electrocardiogram (ECG) is one of the most commonly used cardiac diagnostic test. Each of the 12 ECG leads records the electrical activity of the heart from a different angle, and therefore align with different anatomical areas of the heart. This research analyzes multiple ECG leads for multiple anomaly detection and combines the results to produce higher accuracy and to interpret a wider range of cardiac events.

Keywords; ECG interpretation; ECG image; image to signal conversion; 12-Lead ECG

1. Introduction

Cardiovascular diseases are one of the most common diseases of the modern world. Cardiovascular disease (CVD) refers to any condition that affects the heart. Ischemic heart diseases alone are accountable for 13.2% or 11,310 of all deaths in Malaysia in 2016 [1]. The electrocardiogram (ECG) is one of the most common type of cardiac diagnostic test. It is a non-invasive test that is used to reflect underlying heart conditions by measuring the electrical activity of the heart. By positioning leads (electrical sensing devices) on the body in standardized locations, information about many heart conditions can be learned by looking for characteristic patterns on the ECG. In most hospitals ECG interpretation is done by a trained physician.

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Previous research conducted on ECG patterns mostly uses ECG raw signal as input and apply various signal analysis techniques to said signal [2][3][4][5][6][7][8][9] [10] [11] [12]. There are few studies done on ECG image analysis but most of these research focus on one lead of the ECG image (generally lead II) converting the ECG image to ECG signal and then apply signal analysis [13] [14] [15] [16] [17] [18] [19] [20] [21]. This process does not utilize all the available information on an ECG image which contains 12 leads and thus the image analysis is not optimized. Furthermore, different cardiac anomalies are more prominent on different lead signals. Only using one lead may overlook anomalies present on a different lead. Additionally, most ECG image to signal conversion is fully or partially manual process and loses some data during conversion and if the image resolution or Dots per inch (DPI) is not high the conversion and subsequently the analysis produces poor results.

Table 1: Some ECG anomalies detected on different Leads

ECG artefact Name	Display Lead
Normal sinus rhythm	I, II, III
Sinus bradycardia	I, II, III
Sinus tachycardia	I, II, III
Sinus arrhythmia	I, II, III
Atrial flutter	I, II, III
Atrial fibrillation	I, II, III
Junctional rhythm	I, II, III
Premature ventricular contraction	I, II, III
Ventricular tachycardia	I, II, III
Ventricular fibrillation	I, II, III
First-degree atrioventricular block	I, II, III
Second-degree atrioventricular block	I, II, III
Third-degree atrioventricular block	I, II, III
Right bundle-branch block	I, V5, V6
Left bundle-branch block	V1, V2, V5, V6
Right atrial hypertrophy	I, II, aVf
Left atrial hypertrophy	II, V1
Right ventricular hypertrophy	V1, V2, V5, V6
Left ventricular hypertrophy	V1, V2, V5, V6

2. Proposed Method

There are several standard format for digital ECG signal as well as several format for printed ECG. Different ECG machine may store or print the data in one of the available standardized version of ECG format. In all the available ECG format the lead title is constantly positioned. Location of the rest of the ECG can be determined by correctly computing the lead title position as the lead signal occupy a fixed area under the lead title location. To detect and separate the ECG signal from the ECG artefact (patient details, ECG legend, lead title) a technique to automatically detect and recognize text in natural images was used to detect the lead position [22] and then the calculated pixel position was used to extract ECG image portion with ECG signal (Fig. 2(a)). A simple rule-based approach was used to filter text and non-text regions based on geometric properties (Fig. 2(b)) [23] [24] with the intention of improving this technique later on with a combination of rule-based approach and machine learning approach to train a text vs. non-text classifier [25].

Once all the lead location is determined in ECG image all of the 12 leads can be separated and extracted from the ECG image (Fig. 3). Once one lead portion of the ECG image is chosen, then that image is converted into greyscale (Fig. 4). The resolution of an image is of upmost importance in any image processing techniques. Its truer in ECG image processing. The quality of the image has a big impact in the overall result of ECG image processing. The relation between ECG image pixel and voltage. The data must be converted from pixels coordinates to time and voltage levels using pixel scaling technique. The pixel scaling technique depends on the relationship between pixels and actual time-voltage values which is given in all ECG printouts, that is, 10 mm/mV and 25.0 mm/sec. Therefore, identifying the pixel equivalent of 10mm/mV and 25.0 mm/sec provides the relationship between pixels and time-voltage values. A method was designed to not to restrict the image size and quality and to make the image to signal conversion process automatic. A method to use pixel darkness to automatically detect the gridlines was used. Once the gridlines were detected the pixel distance between were calculated. As the distance between two gridlines are 5mm, they represent 0.2 second. So to obtain the relationship between the ECG pixel and ECG time-voltage value the following equation was used –

1 pixel = 0.2/GD second and ………………………………… (1)

1 pixel = 0.5/GD mV ………………………………………… (2)

where GD represent the gridline distance in pixels.

After the greyscale conversion the gridlines are removed by pixel thresholding method (Fig. 5). A grayscale level is selected as threshold to distinguish between the trace of interest and the surrounding noise such as the gridlines. The implementation of image thresholding results in the ECG waveform to be black and the surrounding medium to be white. Hence the ECG can be extracted easily from the thresholded image. After some trial and error with multiple ECG image with different dimensions and quality it was concluded that 85% darkness of the darkest pixel in ECG image is the best overall choice for pixel thresholding. After the removal of the gridline from the ECG image a median filter was used to remove various types of noise from the digital image

(Fig. 6). Using thresholding to convert ECG image to signal may generate some extreme value points (called outliers). Median filtering is better able to remove these outliers without reducing the sharpness of the image. After the noise removal the ECG pixel points are smoothed out (Fig. 7) and any missing date points can be interpolated using linear interpolation (Fig. 8) which is a method of curve fitting using linear polynomials to construct new data points within the range of a discrete set of known data points. After adding missing pixel points, the ECG image is converted into time-voltage signal using the previously derived pixel to mV and pixel to second equations (Fig. 9).

After converting the image into a digital signal, it can be analyzed with Matlab's Signal Processing Toolbox. Using this toolbox Peak Analysis can be performed in the ECG signal to find the locations and the value of the peaks. The ECG signal consists of the P wave, the QRS-complex which can be broken down into three major components: Q-wave, R-wave, S-wave and the T wave successively. The Matlab toolbox can be used on all 12 leads signal with different rules based on the lead signals characteristics. Once the complete P-QRS-T segment of the ECG is located on all the leads (Fig. 10) (Fig. 11), this information can be used to determine most prominent anomalies in ECG with high accuracy as shown in table 1.

3. Simulation and Results

The aforementioned combination of the methods showed promising results in preliminary experiments.

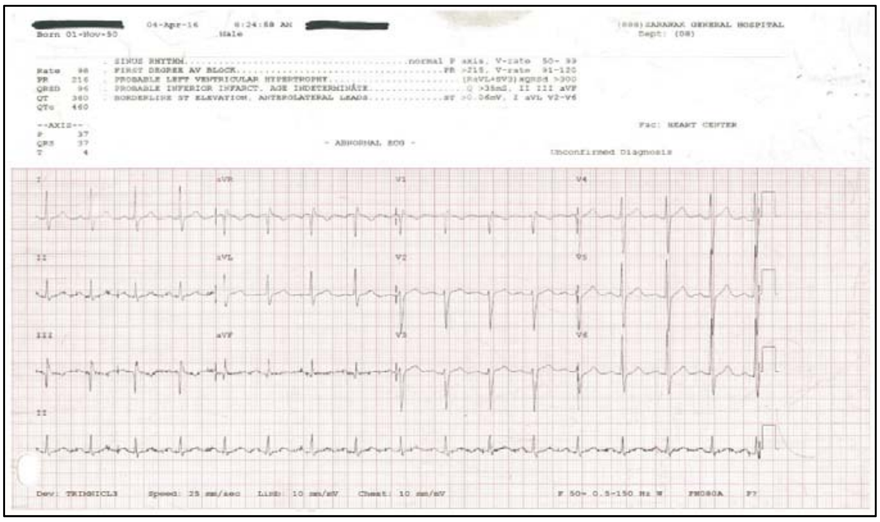

Fig 1(a). ECG image 1

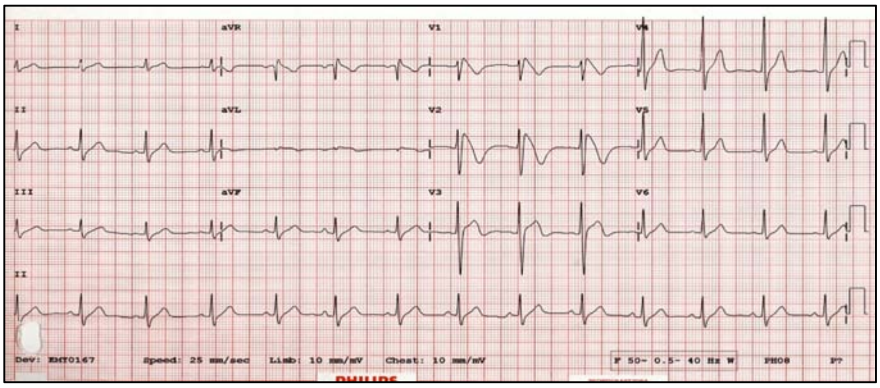

Fig 1(b). ECG image 2

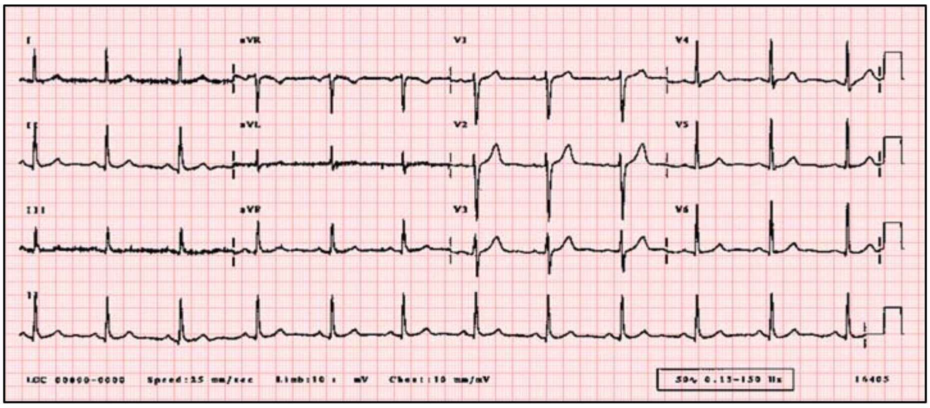

Fig 1(c). ECG image 3

Fig 2(a). Detection of ECG Lead title

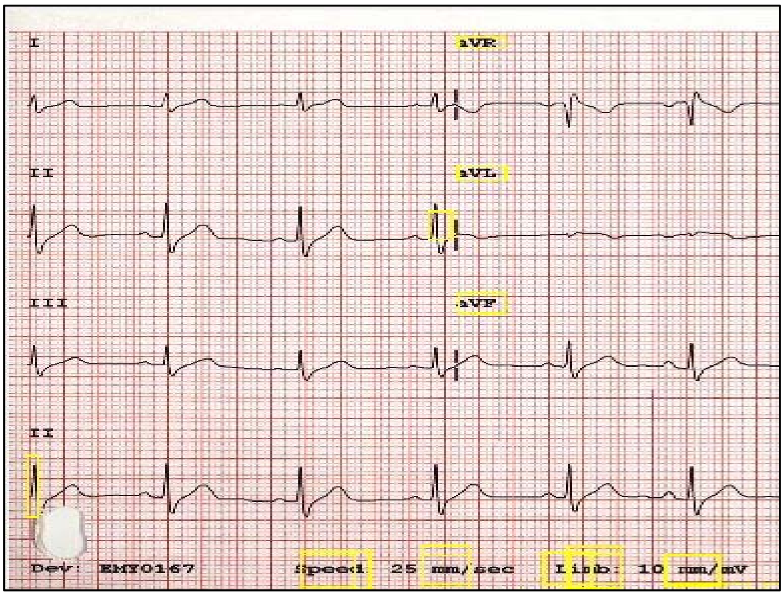

Fig 2(b). Detection of ECG Lead title

Fig 3. Separation of one Lead of the ECG image (Lead II)

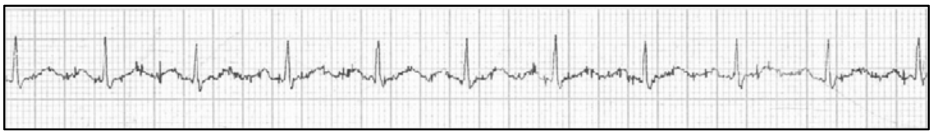

Fig 4. Converted greyscale image

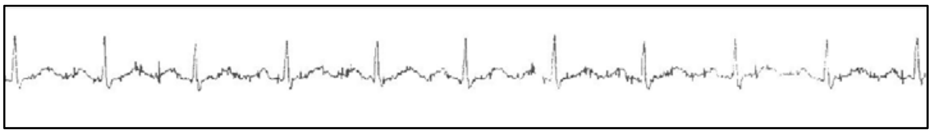

Fig 5. ECG image with gridline removed

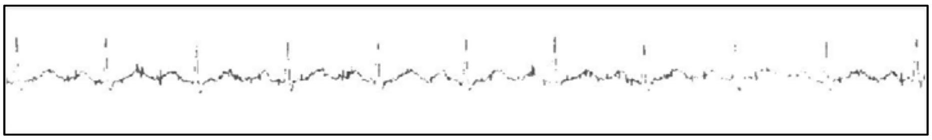

Fig 6.Signal image with Median filtering to reduce noise

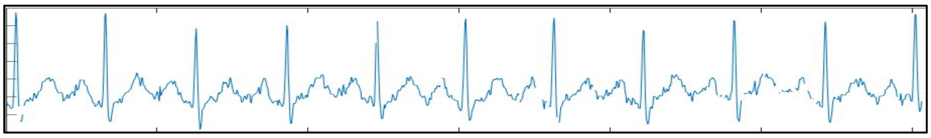

Fig 7. Image to pixel point signal conversion

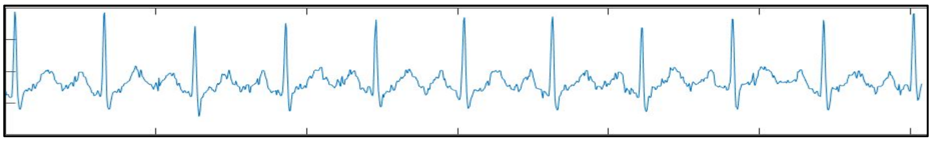

Fig 8. Interpolated pixel point signal

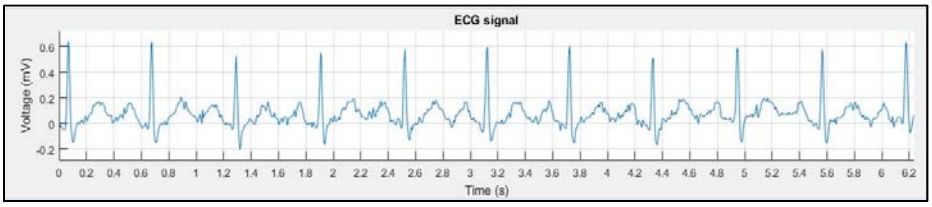

Fig 9. Pixel point signal to ECG time-voltage signal

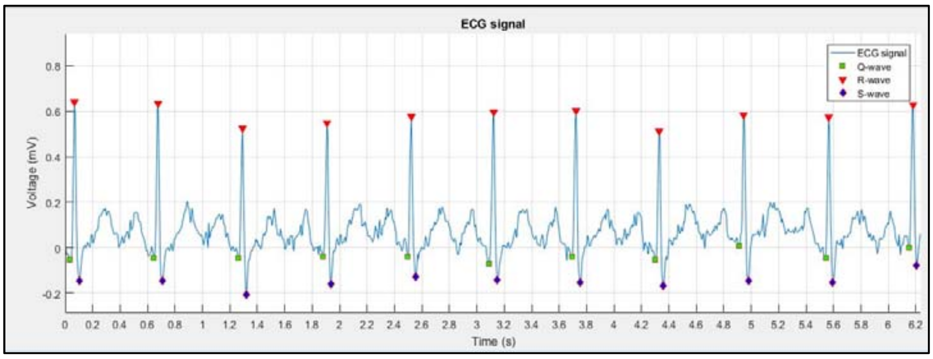

Fig 10. QRS complex detection

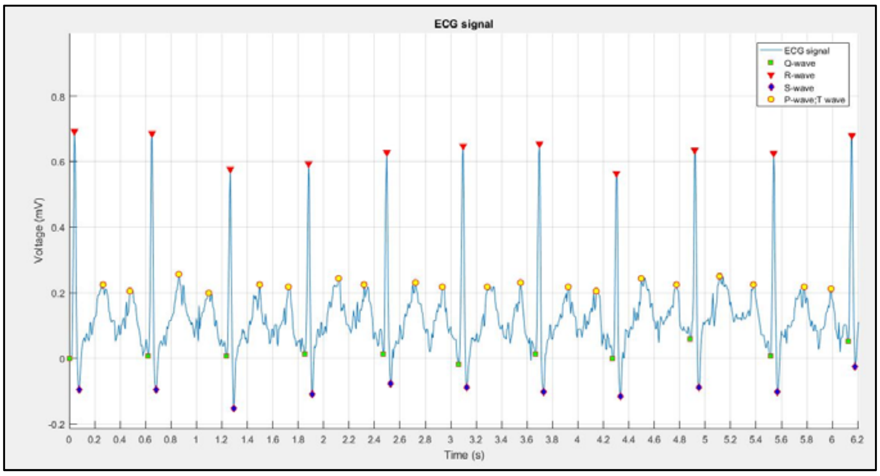

Fig 11. P-T wave detection

Table 2: Accuracy of calculated Heartrate

ECG Image	ECG Lead	DPI	Derived Heartrate	Actual Heartrate	Accuracy
Image 1	I and II	200	98	98	100%
Image 2	I and II	150	80	80	100%
Image 3	I and II	120	61	61	100%

4. Future Work

A better method of detecting text on ECG needs to be worked on. Currently only two leads were converted from image to signal, all 12 leads have to be converted and incorporated with the technique in the future. While multiple anomalies can be calculated from the derived information from all 12 leads, for preliminary experiments only the heartrate was determined from 2 leads (lead I and lead II). Additional work has to be done to successfully determine most of the ECG anomalies.

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References

[1] DEPARTMENT OF STATISTICS MALAYSIA (2017). PRESS RELEASE STATISTICS ON CAUSES OF DEATH, MALAYSIA, 2017. [online] Available at: https://www.dosm.gov.my/v1/index.php?r=column/pdfPrev&id=Y3psYUI2VjU0ZzRhZU1kcVFMMThGUT09 [Accessed 1 Dec. 2017].

[2] Rabee, A. and Barhumi, I., 2012, July. ECG signal classification using support vector machine based on wavelet multiresolution analysis. In Information Science, Signal Processing and their Applications (ISSPA), 2012 11th International Conference on (pp. 1319-1323). IEEE

[3] Mai, V., Khalil, I. and Meli, C., 2011, August. ECG biometric using multilayer perceptron and radial basis function neural networks. In Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE (pp. 2745-2748). IEEE.

[4] Tashiro, F., Aoyama, T., Shimuta, T., Ishikawa, H., Shimatani, Y., Ishijima, M. and Kyoso, M., 2011, August. Individual identification with high frequency ECG: preprocessing and classification by neural network. In Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE (pp. 2749-2751). IEEE.

[5] Balasundaram, K., Masse, S., Nair, K., Farid, T., Nanthakumar, K. and Umapathy, K., 2011, August. Wavelet-based features for characterizing ventricular arrhythmias in optimizing treatment options. In Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE (pp. 969-972). IEEE.

[6] de Oliveira, L.S., Andreão, R.V. and Sarcinelli-Filho, M., 2011, August. Premature ventricular beat classification using a dynamic Bayesian network. In Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE (pp. 4984-4987). IEEE.

[7] Sayadi, O. and Shamsollahi, M.B., 2011. Life-threatening arrhythmia verification in ICU patients using the joint cardiovascular dynamical model and a Bayesian filter. IEEE Transactions on Biomedical Engineering, 58(10), pp.2748-2757.

[8] Vullings, R., De Vries, B. and Bergmans, J.W., 2011. An adaptive Kalman filter for ECG signal enhancement. IEEE transactions on biomedical engineering, 58(4), pp.1094-1103.

[9] Camm, A.J., Lip, G.Y., De Caterina, R., Savelieva, I., Atar, D., Hohnloser, S.H., Hindricks, G., Kirchhof, P., Bax, J.J., Baumgartner, H. and Ceconi, C., 2012. 2012 focused update of the ESC Guidelines for the management of atrial fibrillation: an update of the 2010 ESC guidelines for the management of atrial fibrillation developed with the special contribution of the European Heart Rhythm Association. European heart journal, 33(21), pp.2719-2747.

[10] Hakacova, N., Trägårdh-Johansson, E., Wagner, G.S., Maynard, C. and Pahlm, O., 2012. Computer-based rhythm diagnosis and its possible influence on nonexpert electrocardiogram readers. Journal of electrocardiology, 45(1), pp.18-22.

[11] Rhys, G.C., Azhar, M.F. and Foster, A., 2013. Screening for atrial fibrillation in patients aged 65 years or over attending annual flu vaccination clinics at a single general practice. Quality in primary care.

[12] Pathoumvanh, S., Hamamoto, K. and Indahak, P., 2014, March. Arrhythmias detection and classification base on single beat ECG analysis. In Information and Communication Technology, Electronic and Electrical Engineering (JICTEE), 2014 4th Joint International Conference on (pp. 1-4). IEEE.

[13] Chebil, J., Al-Nabulsi, J. and Al-Maitah, M., 2008, May. A novel method for digitizing standard ECG papers. In Computer and Communication Engineering, 2008. ICCCE 2008. International Conference on (pp. 1308-1312). IEEE.

[14] Swamy, P., Jayaraman, S. and Chandra, M.G., 2010, April. An improved method for digital time series signal generation from scanned ECG records. In Bioinformatics and Biomedical Technology (ICBBT), 2010 International Conference on (pp. 400-403). IEEE.

[15] Shrivastava, P.R., Panbude, S. and Narayanan, G., 2014. Digitization of ECG Paper Records using MATLAB. International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN, pp.2278-3075.

[16] Mohamed, B., Issam, A., Mohamed, A. and Abdellatif, B., 2015. ECG image classification in real time based on the haar-like features and artificial neural networks. procedia Computer Science, 73, pp.32-39.

[17] Wee, L.K. and Supriyanto, E., 2010, August. Electrocardiogram display data capturing and digitization based on image processing techniques. In Proceedings of the 10th WSEAS international conference on applied informatics and communications, and 3rd WSEAS international conference on Biomedical electronics and biomedical informatics (pp. 359-364). World Scientific and Engineering Academy and Society (WSEAS).

[18] Sahu, N.K., Ayub, S. and Saini, J.P., 2013. Detection of Normal ECG and Arrhythmia Using Adaptive Neuro-Fuzzy Interface System. International Journal, 3(11).

[19] Hsieh, J.C. and Lo, H.C., 2010. The clinical application of a PACS-dependent 12-lead ECG and image information system in E-medicine and telemedicine. Journal of digital imaging, 23(4), pp.501-513.

[20] Sharma, J., Kumar, V., Ayub, S. and Saini, J.P., 2012. Uniform sampling of ECG waveform of MIT-BIH normal sinus rhythm database at desired intervals. International Journal of Computer Applications, 50(15).

[21] Sansone, M., Fusco, R., Pepino, A. and Sansone, C., 2013. Electrocardiogram pattern recognition and analysis based on artificial neural networks and support vector machines: a review. Journal of healthcare engineering, 4(4), pp.465-504.

[22] Chen, H., Tsai, S.S., Schroth, G., Chen, D.M., Grzeszczuk, R. and Girod, B., 2011, September. Robust text detection in natural images with edge-enhanced maximally stable extremal regions. In Image Processing (ICIP), 2011 18th IEEE International Conference on (pp. 2609-2612). IEEE.

[23] Gonzalez, A., Bergasa, L.M., Yebes, J.J. and Bronte, S., 2012, November. Text location in complex images. In Pattern Recognition (ICPR), 2012 21st International Conference on(pp. 617-620). IEEE.

[24] Li, Y. and Lu, H., 2012, November. Scene text detection via stroke width. In Pattern Recognition (ICPR), 2012 21st International Conference on (pp. 681-684). IEEE.

[25] Neumann, L. and Matas, J., 2012, June. Real-time scene text localization and recognition. In Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on (pp. 3538-3545). IEEE.