Multi-step Approach for the Extraction of RR Intervals from Scanned Paper ECGs

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Abstract

Even with modern ML/AI technology, re-digitizing scanned paper ECGs often fails due to significant artifacts introduced during printing, editing and scanning. In addition, available software lacks control for image distortion and inconsistent scanning speeds.

In a retrospective analysis, clinical paper ECGs from patients with amyotrophic lateral sclerosis (ALS) and cerebral amyloid angiopathy (CAA) were reexamined to compare heart rate variability. Here, we propose a multi-step MATLAB-based approach to extract accurate RR intervals. Image rotation was verified using Radon transform. Three regions of interest were selected from the scanned RGB image: a) the ECG standard grid was subjected to Gaussian filtering and converted to a 1D vector to determine the number of pixels per second, b) an ECG waveform was transformed using image erosion and dilation to mask the background color and suppress the grid lines to detect the R peak locations, c) verification of ECG duration. The mean RR intervals were compared with the device information on paper using Bland-Altman analysis.

The proposed approach was successfully tested on clinical paper ECGs from 48 ALS and 70 CAA patients. Validation with printed RR interval information based on the digital ECG shows high accuracy of the method (median difference: 2.6ms, quartile range: -0.6ms to 6.1ms).

1. Introduction

Often, in emergency departments, at wards, in land and air rescue services and at general practitioners electrocardiograms (ECGs) are still kept in paper form. These paper printouts are scanned into the digital patient file to enable appropriate documentation. This may be convenient at the individual level, but complicates further use, as reusing these ECGs in retrospective studies presents numerous computational challenges. Re-evaluation of parameters from scanned images usually requires a re-digitization process to utilize the same features as digital ECGs.

The re-digitization process is subject to significant artifacts and problems. These can be caused by the print itself (faded thermal print, missing ink at fast moving R spikes, labels printed above waveforms), by the further use as a work object (fingerprints, smudges, handwritten annotations), by manufacturer and configuration specifications (various ECG layouts, different ECG paper, different grid lines and properties), and by scanning problems when using a document feeder or flatbed device (low brightness/saturation, inclined/distorted scan, inconstant scan speed or document feed, vibration artifacts). The totality of the circumstances makes digitization more difficult or leads to a bias when comparing parameters extracted from digital with re-digitized ECGs. Therefore, in research studies the quality of the print and scan should be checked. This may include verifying the scanning speed and image rotation, as well as checking for artifacts.

Existing methods are based on image filters with edge/contour detection or use deep learning for the re-digitization of paper ECGs [1–5]. Background suppression is often used in combination with binarization to separate the ECG leads from background information. These approaches are also applied to camera-captured ECG images to enable fast automated diagnosis of ECG pathologies [6].

2. Methods

Clinical resting ECGs from patients with amyotrophic lateral sclerosis (ALS) and cerebral amyloid angiopathy (CAA) were reexamined in a retrospective study at the University Clinic of Neurology Magdeburg, Germany for the purpose of evaluating heart rate variability extracted

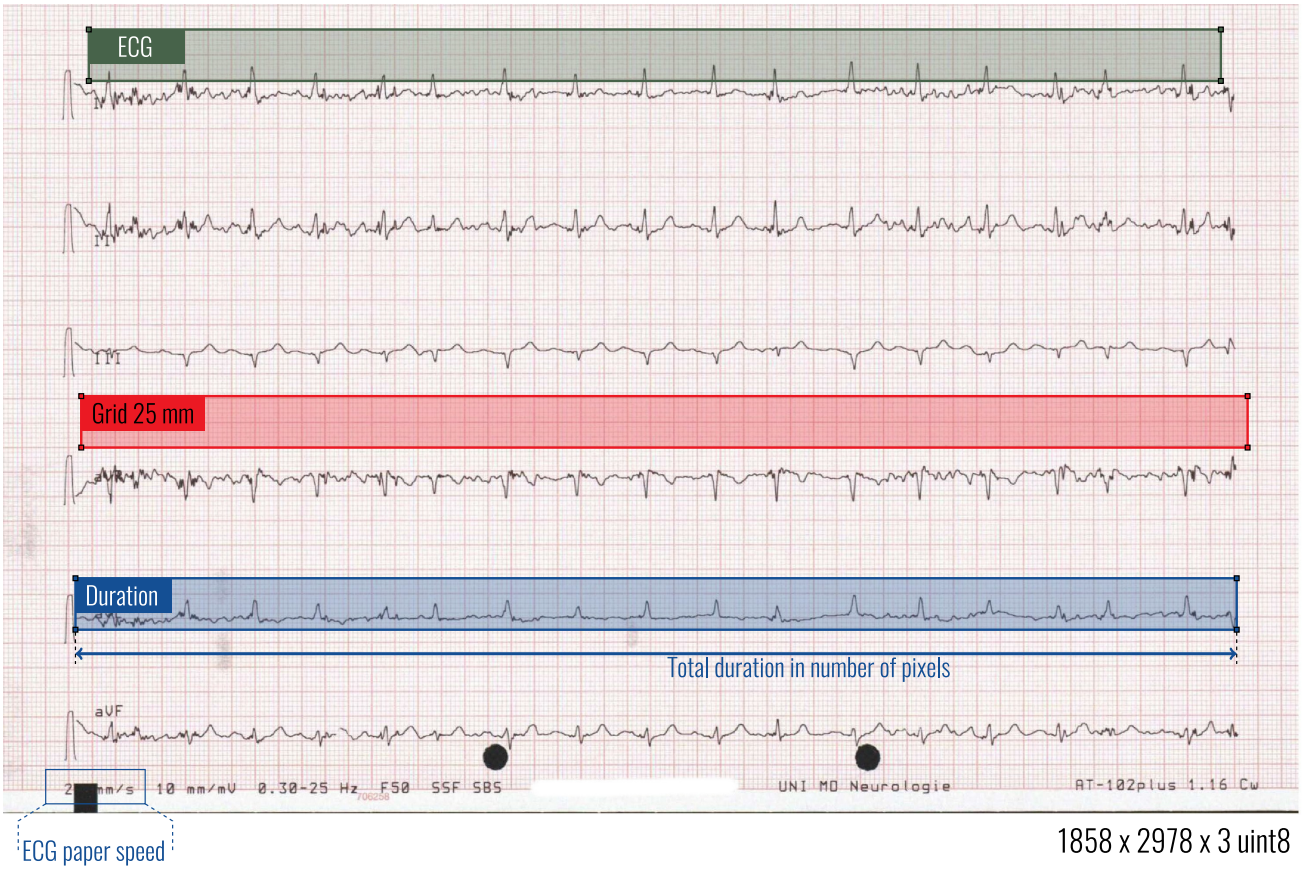

Figure 1. Clean scan of an example paper ECG with regions of interest to be set interactively in Matlab.

from paper ECGs. Average RR intervals printed on the paper served as ground truth reference for the comparison of re-digitized estimation of average RR intervals using Bland-Altman analysis in R. Header information were cropped from the scans for anonymization. Two digitization tools has been tested and evaluated beforehand: The ECG Digitization Tool [4] and PaperECG [7]. Due to poor quality and many failed conversions, an own processing pipeline was developed which was implemented as a semi-automated MATLAB-based program. Details on the processing steps are described in the following:

Three regions of interest (ROI) were selected via a graphical user interface from the scanned RGB image, see Figure 1: a) processing the ECG paper grid (red); b) processing an ECG waveform (green); c) checking the ECG duration (blue). The ECG paper speed that is printed on the paper was requested by direct keyboard input.

Radon transform Radon transform [8] was used to capture directional information of the whole image. If the grid was correctly printed on the paper and if the paper was straightly scanned, we expect clearly visible minima at $0\,^\circ$ when applying Radon transform (Matlab function `radon`). These minima results from the space between vertical grid lines (any style: solid or dotted) while the horizontal grid colors were cumulated evenly. In the same way we would expect emerging minima at a rotation angle of $\theta = 90°$. The standard deviation (SD) across θ values were used to quantify how pronounced the grid spacing is visible, which allows the rotation angle of the image to be accurately estimated from finding the maximum SD (see also [8]). Unbiased RR intervals from skewed images can be calculated in the following using trigonometry. The corrected RR interval would be $\mathrm{RR} \cdot \tan\theta$. Alternatively, a rotation matrix can be applied to the image, with the disadvantage that pixels must be interpolated.

Grid spacing To calculate the number of pixels per second of recording, the horizontal locations of minor and major grid lines has been identified from the respective ROI. The negative image was Gauss-filtered with a standard deviation of 2 (`imgaussfilt`) to reduce compression artifacts from the image (Figure 2A). The image was then transformed to a 1D continuous vector by cumulating the pixel brightness across the columns. Peaks were identified by a noise tolerant peak finding algorithm [9] (Fig-

ure 2B). The differences of peak locations were screened for outliers that deviate more than 20% from the median. The 10%-trimmed mean of the outlier-free spacings was then used to determine the number of pixels between the grid lines (pixels per millimeter – PPM). The resulting average PPM printed as blue line in Figure 2C was also used to screen for systematic biases in order to verify the constant scanning speed.

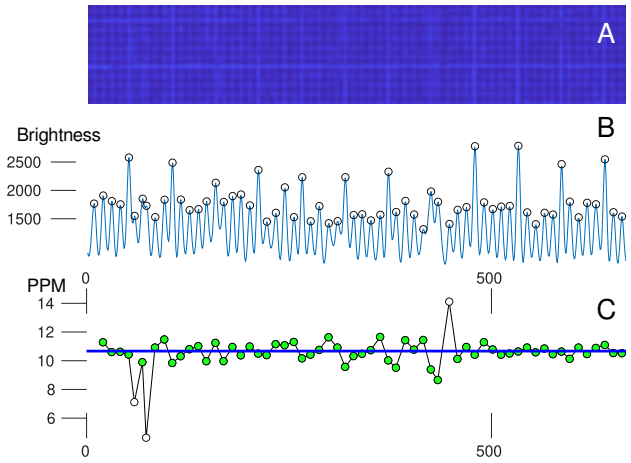

Figure 2. Grid space intervals: A) Negative source image, B) Cumulative column sum, C) Difference of identified peaks in pixels per millimeter (PPM).

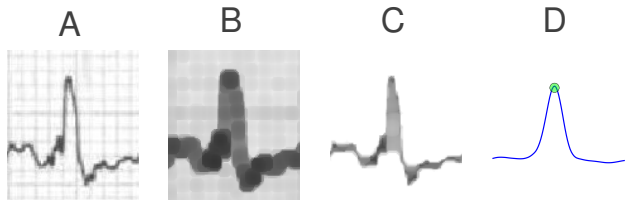

Figure 3. ECG image processing steps: A) Original, B) Erosion, C) Dilation and masking, D) Gauss-filter and weighted cumulative sum.

Image processing for R Peak identification Image filters were used to transform the ROI ECG image into a 1D-vector, see Figure 3: Image erosion (`imerode`) with ball-shaped structure (5 pixels radius); Weighted sum of RGB bits ($\omega = 0.45$ each) to mask background color; Image dilation (`imdilate`) with ball-shaped structure; Gauss-filter of negative image (`imgaussfilt`); Weighted cumulative sum of the intensity of blackness with a linearly increasing weighting from the lowest row to highest row to capture the R peak robustly (irrespective of thickness and blackness of the ECG baseline). The noise tolerant fast peak finding algorithm Peakfinder [9] was subsequently used to capture possible R peak locations. Results were screened by the GUI and thresholding or manual choice was applied by keyboard input.

RR intervals were computed from the successive differences. The calculation of the intervals from pixel scale to time scale (seconds) was done as follows:

$$\text{Interval [s]} = \frac{\text{Interval [px]}}{\text{Paper speed [mm/s]} \cdot \text{PPM [px/mm]}} \quad (1)$$

3. Results & Conclusion

The proposed approach has been implemented in Matlab R2024a and successfully tested on clinical paper ECGs from 48 ALS and 70 CAA patients. Identified image rotation angles and Bland-Altman-Analysis were carried out with R v4.4.1.

The ECG recordings were either 5 or 10 s long and of different quality and lead layouts. Most of the ECGs were written with Schiller CARDIOVIT AT-102, AT-102 plus, or AT-102 G2. Three recordings were written with GE Healthcare MAC 1200, 17 with GE MAC 5500 HD, and one with Stryker LIFEPAK 15. The semi-manual work for defining the ROI and reviewing results took less than two hours.

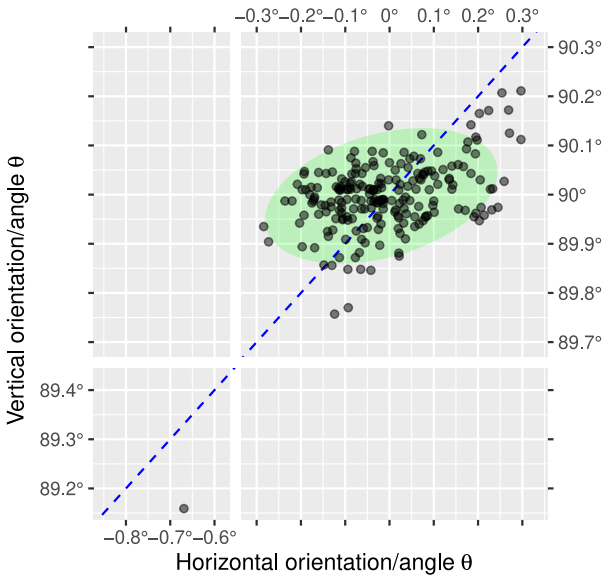

Figure 4. Image skew determined by Radon transform. The scatter plot shows the optimal rotation angles so that the grid lines are straight in the vertical or horizontal direction.

The rotation angles identified through Radon transform was negligible small, see Figure 4. As the rotation-adjusted RR intervals ($\text{RR} \cdot \tan\theta$) divided by the rotation-adjusted mean grid spacing (PPM), would result in the same RR intervals on time scale and as grid lines were

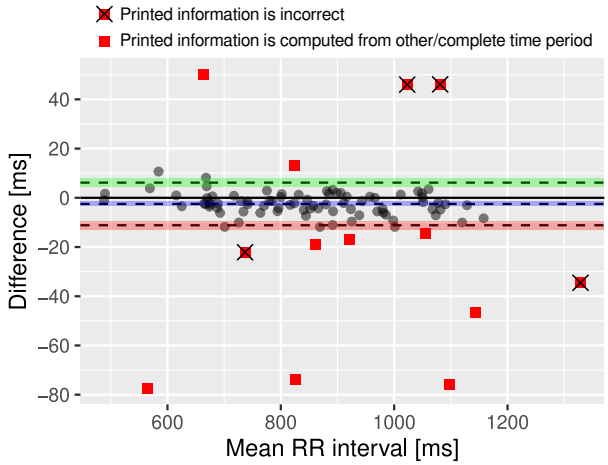

Figure 5. Bland-Altman plot with levels of agreement after exclusion of red-marked values, which can be attributed to wrong values printed on the ECG paper, or average intervals printed from a different/complete recording period.

successfully identified, correction of image rotation was not performed.

Bland-Altman-Analysis included 93 recordings with available reference values. A high level of accuracy can be observed from pairwise comparisons, see Figure 5. Large outliers were checked manually. For 8 of the 13 ECGs with the highest disagreement, the printed ECG only contains 5 seconds of recording, while the printed average RR interval may have been calculated from a non-printed/complete recording period. In four ECGs, the identified R peaks, ECG duration and quality were checked, providing evidence that the printed RR interval information was incorrect. In one ECG, the QRS cycle was not completely printed on the paper at the end of the recording, so the R peak can only be interpolated from the beginning of the R peak slope. Inclusion of this extrapolated RR interval would result in a difference within the limits of agreement. Removing these incorrect reference values and unfair comparisons, the limits of agreement are such as printed in Figure 5 with 95% confidence intervals. The median difference of re-digitized average RR interval is $2.6\,\mathrm{ms}$, the quartile range is $-0.6\,\mathrm{ms}$ to $6.1\,\mathrm{ms}$.

Conclusion Since there are not enough publicly available paper ECGs, AI methods may fail in the inference step as they do not generalize sufficiently due to a variety of problems/issues as described in the introduction. In the proposed extraction process, several image processing methods were used with manual control of quality and results. Although the extracted intervals cannot be verified in this study, we observe a strong agreement with the manufacturer's printed average RR intervals, making the re-digitized RR intervals plausible. This way, even incorrect manufacturer values can be found. Due to the interactivity of this multi-step approach, a high level of confidence in the scanning and extraction quality can be established. We believe that in this way we enable a reliable comparison of heart rate variability between different patient groups.

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