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Automatic digitization of paper electrocardiograms – a systematic review

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Abstract

The digitization of electrocardiogram paper records is an essential step to preserve and analyze cardiac data. This digitization process is not flawless as it involves several challenges, such as skew correction, binarization, and signal extraction. Various approaches have been proposed to address these challenges and recent studies have introduced innovative solutions, such as deep learning models and automation processes. Although existing approaches have shown promising results, there is a lack of common databases and metrics where authors could evaluate and compare their methods. Furthermore, the limited accessibility of code or software hinders the comparison process. Overall, while digitization of paper ECG recordings is important in advancing cardiology research, additional efforts are needed to standardize the evaluation process while improving code accessibility. This article provides a systematic review of this process.

Key words: electrocardiogram, ECG, digitization

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Introduction

The electrocardiogram (ECG) is a widely used technology, developed to measure the electrical activity of the heart. ECGs have been recorded for more than a century, using a myriad of different devices in medical centers throughout the world. Current medical standards require triplicate 12-lead 10-second ECGs for pharmacological evaluation, but other types of ECGs, including long-recordings from Holter or other single lead devices can be used for monitoring.

However, the vast majority of these measures cannot be easily accessed nor used for automatic analyses, including application of modern machine learning (ML) techniques. One of the main reasons is related to the storage medium, which is very often a printer paper copy of an ECG, typically representing only a portion of the acquired signal. Although paper prints may have some advantages, they come with numerous drawbacks [1], including deterioration of the medium from ink evaporation, blurring, folding, overwriting, etc. They need significant human resources to be stored, accessed, queried, read and annotated. Furthermore, automatic machine learning (ML) algorithms require numerical vectors, the raw waveform signals, to detect patterns and learn from them.

Currently, only a small number of hospitals and medical centers in the world store ECG data as raw digital files (*i.e.*, XML, binary proprietary formats), while others, especially in developing countries, continue to use paper scanned image files (such as JPG, PNG or PDF). Handling the raw digital files requires additional expensive hardware (usually sold as add-ons with the ECG devices), or trained personnel and time to manually copy and store them in local IT systems.

Digital ECG files are valuable and allow clinicians and researchers to constitute larger datasets, which can be queried and automatically analyzed by modern algorithms, including powerful artificial intelligence (AI) models. Moreover, when coupled with other patient phenotype data, these datasets offer excellent opportunities for discovering and developing tools for predictive and personalized medicine. Unfortunately, many ECG datasets saved as paper prints or image scans, cannot be readily used in these types of analyses, although some authors have tried to use directly scanned ECGs for arrhythmia classification with limited results[2], [3]. There is a real need in the field for tools that digitize paper ECGs and convert them in high quality raw-equivalent signals for subsequent analyses and use, especially in the context of AI applications. In this article we review the state-of-the-art of such tools and compare different aspects including

methodology, performance and accessibility. A systematic literature search with the keywords “electrocardiogram” AND “paper” AND “digitization” performed on February 16, 2023, yielded 85 results on *Pubmed*, *ScienceDirect*, *Ieeexplore*, *ResearchGate* and *Google Scholar*.

Material and Methods

Systematic Literature Review

The systematic literature review method used here is composed of three different steps. The first step consists of identifying articles based on the search equation applied to articles’ abstracts and keywords. The second step is based in a novel approach, which computes similarities between papers based on co-citations and bibliographic coupling. This approach is implemented in a software called Connected Papers. We analyzed the inferred graph and applied a node connectivity filtering to remove weakly associated papers, while extending the selection of other relevant articles not detected by the first step. Finally, the third filtering step is based on expert evaluation with clear criteria of the different articles. Our systematic review approach is illustrated in **Figure 1**.

More specifically, in the first step we defined the following search equation: *ECG AND Paper AND Digitization* then applied it on abstract and keyword sections of articles from five different bibliographic databases: *PubMed*, *ScienceDirect*, *Ieeexplore*, *ResearchGate* and *Google Scholar*. The *PubMed* query returned 20 articles, while the *ScienceDirect* query returned 32 articles. For the *Ieeexplore* and *ResearchGate* databases, we used the search equation without restriction on the abstract and the title. This yielded 28 articles for *Ieeexplore* and 26 articles for *ResearchGate*. Finally, for *Google Scholar* we applied the search equation only on the title as the search filters on this platform are limited and obtained 28 articles. Overall, after discarding duplicates, we obtained a list of 85 different articles. A filtering step based on the keywords of all articles (when they were available) with the equation *Digitization OR Analog-to-Digital* allowed us to isolate 35 articles containing these keywords. This step was necessary to remove the false positive hits that were selected because the “digitization” keyword was only referred to, without being the real focus of the article.

The second step is based on the “Connected Papers” approach. We hypothesized that some relevant articles might have been missed during the first step, especially as the different datasets were searched with different resolutions (i.e., limited to the title, abstract or keywords). To make our review method more robust we

applied an approach, which focused on the similarity between papers. This is computed based on the concepts of co-citation and Bibliographic Coupling and is implemented in the Connected Papers platform, which uses the Semantic Scholar database covering more than 240 million papers. Each of the 35 articles identified above served as an anchor, allowing to identify similar articles and to infer an article similarity graph. We analyzed the 35 graphs and removed articles that displayed a connectivity smaller than 4, based on the observation that relevant articles were strongly connected while non-relevant articles were less connected. This approach would allow us to add relevant articles, resulting in a list of 44 articles.

Finally, the third and last step consisted of a manual curation and expert evaluation of the articles, through careful examination. We eliminated 12 articles; one was a review, one was a preprint, 2 were thesis dissertations and 8 did not deal with the subject. The final selection consisted of 32 articles, published from 1991 to 2022 and allowed us to compile a good overview of the different methods of digitization in ECG images.

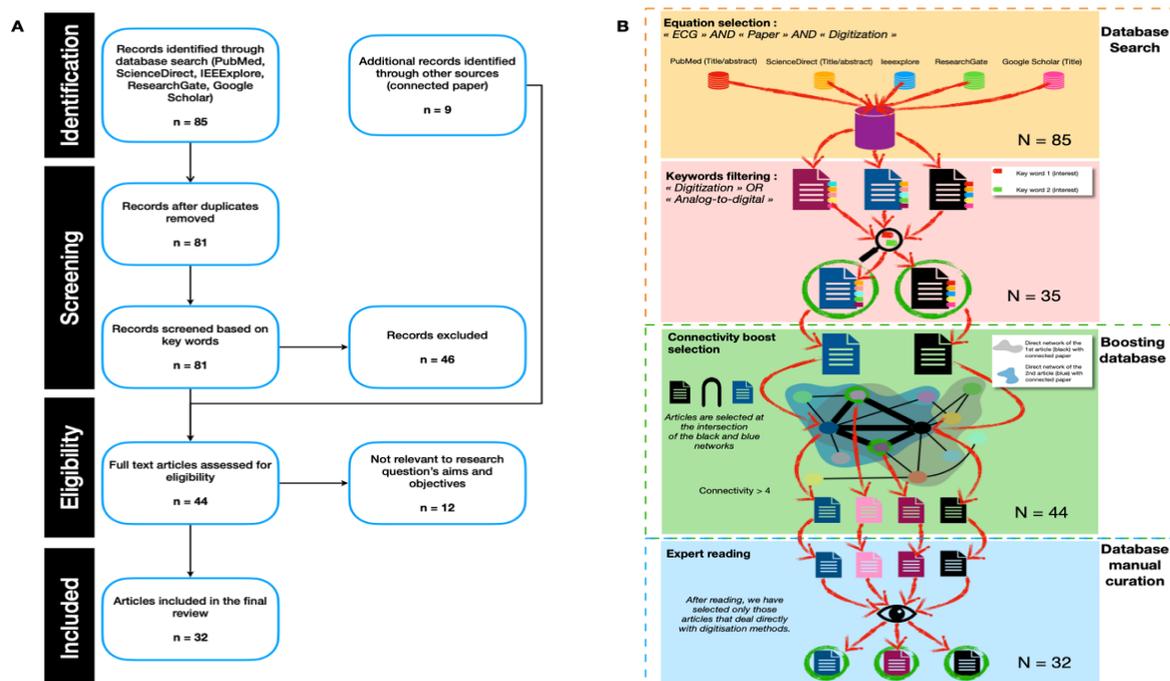


Figure 1: Systematic Literature Review approach as used in this article. A) The Prisma diagram showing the different stages of article selection B) The Detailed diagram of our article selection approach, including the Connected Papers step.

Comparative methodology attributes

Comparing the different approaches was not straightforward as they covered different technologies, tasks and spanned over a large period of time when technology evolved quickly. However, we proposed a number of criteria that we believe are useful to the reader **Table 1**. One important consideration is the code or

software accessibility. Another attribute is the capability of the digitization approaches to handle poor quality images. Only articles where this was specifically mentioned are tagged as “True”. Another important consideration is how automated these approaches were and whether they required human intervention. Automation consisted mainly of detecting leads and three different scenarios were retained: (i) the article mentioned human intervention, (ii) the article did not mention anything and (iii) the article specifically mentioned that the lead detection was made automatically.

Finally, the last attributes of **Table 1** concern the signal extraction approaches. Three main steps were considered for the digitization process: (i) the deskewing method, (ii) the binarization method and (iii) the signal extraction method. The first step involved correcting or rotating the image, which may have been necessary due to the scanning process. The second step included the use of a binarization approach and the grid line removal to isolate the ECG waveforms in the image. Finally, the third step considered how the waveform was converted from a 2D image to a 1D signal after it was isolated from the image. **Figure 2** illustrates the different steps of the digitization process.

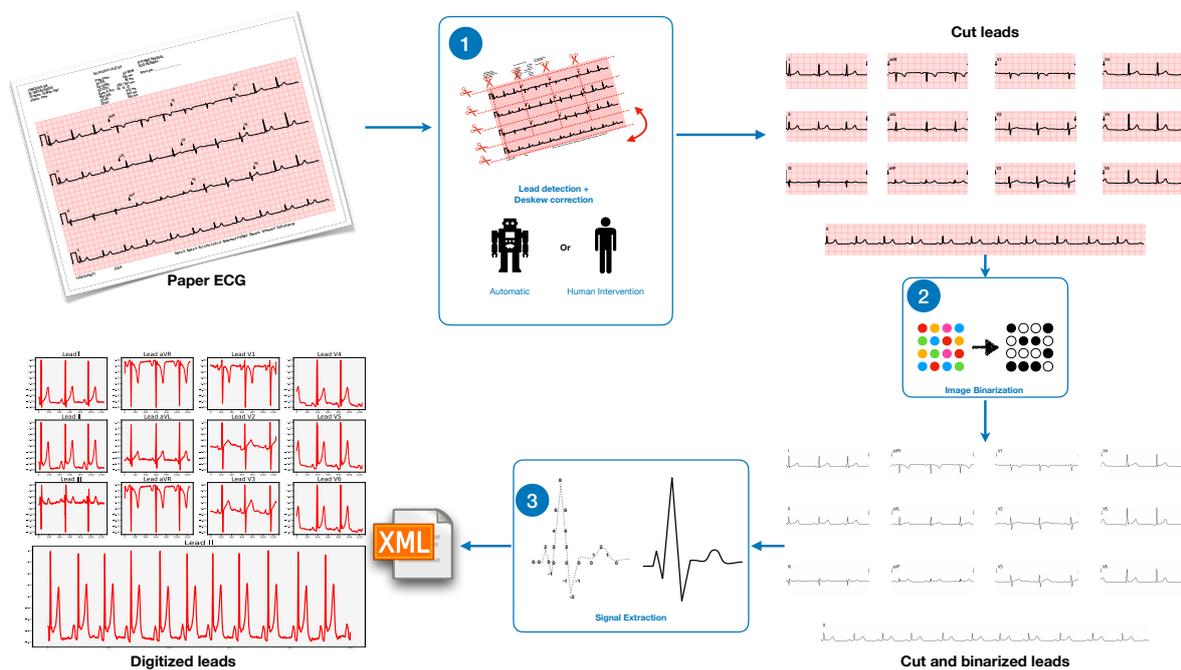


Figure 2: Schematic of the digitization process. The digitization process is composed of three main steps, which include, deskewing, binarizing the image and extracting the signal.

Reference	Dataset: Origin / Numbers of lead	Code or software accessibility	Noisy image Treatment	Human intervention	Deskew approach	Binarization approach	Signal Extraction
(Widman and Hines 1991) [1]	NA / 21 leads	False	NA	User intervention	NA	NA	Line finding algorithm
(Lawson et al. 1995) [4]	NA / 84 leads	False	NA	User intervention	NA	NA	Skelotization
(J.T Wang and Mital 1996) [5]	NA	False	NA	User intervention	NA	Iterative Mask	Thinning Algorithm
(Mitra, Mitra and Chaudhuri 2004) [6]	NA	False	NA	User intervention	NA	User defined threshold	Pixel vertical extraction
(Badilini et al. 2005) [7]	University of Rochester Heart Research Follow-Up Program / 720 leads	False/True	NA	User intervention	NA	NA	Active Contour
(Chebil, Al-Nabulsi, and Al-Maitah 2008) [8]	NA / NA	False	NA	NA	NA	NA	Pixel vertical extraction
(Swamy, Jayaraman, and Chandra 2010) [9]	NA / 120 leads	False	NA	NA	Radon Transform	Otsu	Pixel vertical extraction
(Shi, Zheng and Dai 2011) [10]	NA / NA	False	NA	NA	NA	Sobel	Pixel k-mean clustering
(Sanromán-Junquera et al. 2012) [11]	Hospital General Gregorio Maranon AND Hospital Universitario Virgen de la Arrixaca de Murcia / NA	False	NA	NA	Hough transform	NA	Pixel vertical extraction
(Kumar et al. 2012) [12]	MIT-BIH / NA	False	NA	User intervention	NA	User defined threshold	Pixel vertical extraction
(Jayaraman et al. 2012) [13]	NA / 300 leads	False	NA	NA	Radon transform	Otsu	Pixel vertical extraction
(Garg et al. 2012) [14]	NA / 240 leads	False	NA	NA	Hough transform	Color segmentation	Pixel vertical extraction
(Ravichandran et al. 2013) [15]	Emory Vietnam Twins Study / 638 leads	False	NA	User intervention	- User intervention	Otsu	Pixel vertical extraction
(Mallawaarachchi Perera and Nanayakkara 2014) [16]	NA / 216	False	NA	User intervention	- Radon Transform	Otsu	Pixel vertical extraction
(Patil and Karandikar 2015) [17]	NA / NA	False	NA	User intervention	NA	User defined threshold	Pixel vertical extraction
(Attin et al. 2016) [18]	NA / NA	False	NA	NA	NA	NA	Shortest Path

(Lozano-Fernandez et al. 2016) [19]	NA / NA	False	True	User intervention	Perspective distortion correction	Color filtering	NA
(Math and Akkasaligar 2017) [20]	NA / NA	False	NA	User intervention	Hough Transform	User defined threshold	Pixel vertical extraction
(Rajiv Gandhi Institute of Technology, Mumbai, India et al. 2017) [21]	Saikripa Hospital, Mulund / 100032 leads	False	True	NA	NA	NA	Pixel vertical extraction
(Patil and Karandikar 2018) [22]	NA / 1512 leads	False/False	True	User intervention	NA	EBPS	Pixel vertical extraction
(Sun et al. 2019) [23]	NA / 1548 leads	False/False	NA	No user intervention	Hough transform	Scan line seed filing	Pixel vertical extraction
(Baydoun et al. 2019) [24]	Physionet / 360 leads	False/False	NA	No user intervention	Hough transform	Otsu	Connectivity algorithm
(Patil and Karandikar 2019) [25]	Gautama Hospital / 972-1298 leads	False/False	NA	NA	NA	Sauvola	Pixel vertical extraction
(Jalgaon, INDIA et al. 2019) [26]	NA / NA	False/False	NA	No user intervention	NA	NA	Dijkstraws shortest path
(Gupta and Sachan 2020) [27]	NA / NA	False/False	NA	No user intervention	Hough Transform	NA	pixel vertical extraction
(Li et al. 2020) [28]	Department of Medical Record Management / 1140 leads	True/True	True	NA	NA	Deep learning	Connectivity algorithm
(Tabassum and Ahmad 2020) [29]	MIT-BIH / 16265 leads	False	NA	NA	NA	HSV	Pixel vertical extraction
(Mishra et al. 2021) [30]	Saidhan Hospital AND STEMI Global / 38400 leads	True	True	User intervention	NA	Deep learning	Pixel vertical extraction
(Ganesh et al. 2021) [31]	NA / NA	True	NA	User intervention	Hough Transform	NA	Pixel vertical extraction
(Fortune et al. 2021) [32]	Oregon Health & Science University / 2760 leads	True	NA	User intervention	-User intervention	Otsu	Viterbi Dynamic programming
(Randazzo et al. 2022) [33]	Own / 192 leads	False/False	NA	User intervention	NA	Binary Mask	Pixel vertical extraction
(Wu et al. 2022) [34]	Imperial College London NHS Trust AND BIDMC / NA	True/True	NA	No user intervention	NA	Threshold	Pixel vertical extraction

Table 1: Articles considered for this review. After identifying selecting and discarding inadequate papers, we obtained a final list of 32 articles, which are described as a function of different methodological attributes.

Results

Deskewing The Image

The image obtained after the scanning process may be skewed and this can make it difficult to extract the signals. Therefore, rotation or straightening is required so that the contents are aligned horizontally or vertically. Two main deskewing approaches were observed in the reviewed articles. The first involved a manual correction of the skewness by selecting a rotation angle to deskew the image [15]. The second used automated algorithms to automatically deskew the image [20], [32]. The two main algorithms used were the Hough Transform and the Radon Transform. While the Radon Transform is slightly more precise, it is also slower than the Hough Transform [35].

Grid Removal

When digitizing paper ECGs, it is crucial to remove the gridline, which poses a challenge for algorithms because it introduces artefacts and noise in the image. For this, the image is binarized, converting each pixel to a black or white pixel level value based on its intensity. The first step is to convert the RGB pixel values to grayscale and determine the light intensity for each pixel. The threshold for distinguishing ECG lines and background pixels is critical; if the threshold is too low, it will generate noise, and if it is too high, information will be lost. Global thresholding was used by some articles [6], [12], [34], while others used specific algorithms to find the optimal threshold.

The most used algorithms for determining the optimal binarization threshold were Otsu [36] and Sauvola [37]. The Otsu algorithm is efficient for low noise images and proposes to maximize the inter-class and minimize the intra-class variation of the image pixels from the greys diagram. The Sauvola's algorithm uses patches to locally binarize the image and has the advantage of being robust to noisy images. The method proposed by Randazzo et al [33] is partly based on the idea of binarizing the image from a threshold. However, they proposed to convert the image to HSV (Hue, Saturation, Value) and define thresholds for each channel to extract only the signal.

There are several other specific methods available to remove the gridline in an ECG image. For example, the Scan-line-polygon-filing method which involves filling the inside of a polygon whose

edge is detected using connect region analysis (CRA). Once the edge is identified, the pixels that form the polygon are set to 1, and the other pixels are set to 0, effectively removing the gridline [23].

Another method is the iterative mask approach, which is similar to the Sauvola method. It involves binarizing the image by region using two masks, one horizontal and another vertical. The masks browse the image in the top-to-bottom and left-to-right directions. If two white pixels are in the extrema of the mask, every pixel in the mask is converted to white. Conversely, if only one pixel in the extrema is black, then the pixels in the mask remain the same [5].

Finally, a last method is based on color segmentation and is applied by column, where pixels from the grid line are usually lighter than pixels from the ECG waveform. Therefore, the darkest pixels are assigned the value 1, while the other pixels are set to 0, resulting in a binarized image [14]. An alternative approach is to convert the image into HSV format, where the grid line will have a higher value than the ECG waveform. With this representation, binarization is easier, especially for poor quality images [29].

Signal Detection / Extraction

The most straightforward approach to extract the waveform data from the image is to examine each column pixel, identify the pixels that correspond to the waveform, and associate each of them with a numerical value on the vertical axis. Many studies have used this method, including those referenced by the articles [6], [8], [9], [11]–[16], [21]–[23], [25], [27], [29]–[31]. The algorithm scans each column of the image, identifies the pixels corresponding to the ECG waveform, and records their coordinates. The index in the rows represents the amplitude value, while the index in the columns represents the time value.

Other approaches propose, in their own way, to extract the signal from the image. There are clustering-based approaches, such as the Connectivity[24], [28] and K-mean[10] algorithms. The idea is to group pixels according to their spatial proximity, their mathematical similarity or their brightness.

Finally, we can also mention algorithms based on the minimization of mathematical functions. The Active Contour algorithm [7] for instance proposes 3 functions (path length, path continuity and signal

fidelity) updated for each pixel of the image. The idea behind this is to minimize the path length and maximize the signal fidelity and path continuity. The Viterbi dynamic programming [32] proposes the same thing but reduced to a single function to be minimized. The Dijkstra's algorithm [18], [26] applies weights to each pixel of the image and then seeks to find the shortest path minimizing the weights to reconstruct the signal.

Robustness To Noise

The concept of robustness to noise is complex because of its broad definition. To focus on poor-quality images, we reviewed articles that explicitly address this issue and found four that fit our criteria. Two of the articles proposed mathematical solutions, while the other two proposed using deep neural networks. The first article used an anti-aliasing algorithm and a K-Fill filter to smooth the line and reduce noise [21]. The second article used bit plane slicing. Each color was defined on 8 bits, for example 0 was defined as 00000000 and 255 was defined as 11111111. The idea of bit plane slicing is to consider only the 7th and 8th bits (the leftmost numbers) because these are the bits that carry the most information. Next, the authors propose to compute the maximum entropy on the 7th and 8th level (bit) to transform the image into grey scale [22]. The third article presents a neural network trained to binarize the image based on the U-net architecture [28], while the fourth article introduced a method, which finds the optimal binarization threshold with the help of a neural network based on a pixel intensity distribution [30].

Human Intervention

Automating ECG analysis is crucial as it reduces the amount of time and effort needed for analysis by humans and improves reproducibility. The detection of the regions of interest (ROI) is the most critical aspect of automation in ECG image processing.

Only a group of the articles selected in this review can be considered fully automatic in terms of ROI detection [23], [24], [34]. The horizontal projection-based approach was used in these studies where the intensity level [23], [34] or the variance [24] is computed horizontally to obtain a vector of the variance or intensity level on the ordinate of the image. These vectors display peaks that correspond to the leads' position. Subsequently, the image is cropped between these peaks to isolate the leads. The level of

human intervention must be kept to a minimum to ensure reproducibility, as different users may select the ROI differently, which can lead to variations in results.

Performance Evaluation

A wide range of techniques have been employed in the literature to improve the binarization, signal detection/extraction, or to deskew the image and it is important to evaluate these techniques and determine their performance and usability.

As illustrated in **Table 1**, there is a lack of uniformity in the databases used, which makes the comparison of the methods quite challenging. For instance, certain articles attempted to digitize poor quality images, so one can expect fewer good results than articles that digitize high-quality ECG images. Out of the 32 articles considered here, only 13 (41%) provide the origin of the databases, and unfortunately none of them are in common.

Similarly, the lack of uniformity in the measured elements and metrics presented in **Table 2** was also observed. It is essential to note that 9 articles out of 32 (28%) are not presented in **Table 2**. One of them measured a specific EGM (electrogram) classification, while another used a pre-trained model to classify the digitized ECGs. Finally, 7 other articles did not provide performance metrics of their digitization. Thus, only 23 articles were retained and analyzed in **Table 2**. What stands out from these results is the variety of the measured elements (21 elements: P wave amplitude, P wave duration, etc.) and the variety of the ways to evaluate performance (13 metrics: T-test, RMS, etc.). We have also noted the number of different articles that used these metrics or measured a particular element. Most of the articles presented the measurements either on the RR distance or on the overall signal. The measurement on the RR distance was found in 62% of the articles and the measurement on the signal as a whole in 62% of the articles. To effectively compare the different methods featured by papers, it is crucial to have common ground metrics on which they could be evaluate

Reference	P amplitude	P duration	Q amplitude	Q duration	R amplitude	R duration	S amplitude	S duration	T amplitude	T duration	PQRS amplitude	Heart rate	QT	RR interval	PR interval	RS duration	QT interval	Signal	QRS duration	ST interval	HRV	QRS amplitude	RR amplitude
(Widman and Hines 1991)[1]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr	NA	NA	NA	NA	Corr	NA	NA	Mean Δ / RMSE	Mean Δ / RMSE
(Lawson et al. 1995)[4]	T-Test	T-Test	T-Test	T-Test	T-Test	T-Test	T-Test	T-Test	T-Test	T-Test	NA	T-Test	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Mitra, Mitra and Chaudhuri 2004)[6]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	T-Test on the Fourier Transform	NA	NA	NA	NA	NA
(Badilini et al. 2005)[7]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	RMSE / Mean Δ / Median Δ	NA	Mean Δ	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Chebil, Al-Nabulsi, and Al-Maitah 2008)[8]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Relative Error	NA	NA	Relative Error	NA	Relative Error	RMSE	Relative Error	NA	NA	NA	NA
(Swamy, Jayaraman, and Chandra 2010)[9]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Acc	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Shi, Zheng and Dai 2011)[10]	Absolute Error	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Acc	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Kumar et al. 2012)[12]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Relative Error	NA	Relative Error	Relative Error	Relative Error	Relative Error	Corr	NA	NA	NA	NA	NA
(Jayaraman et al. 2012)[13]	Acc / Slope	Acc / Slope	NA	NA	Acc / Slope	NA	NA	NA	Acc / Slope	Acc / Slope	NA	Acc / Slope	NA	Acc	Acc/Slope	NA	Acc / Slope	DTW_classifier / Adaboost classifier	Slope	Acc / Slope	NA	NA	NA
(Garg et al. 2012)[14]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Acc	NA	NA	NA	NA	Accuracy	NA	NA	NA	NA
(Ravichandran et al. 2013)[15]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr_Intra / Corr_Inter	Corr_Intra / Corr_Inter	NA	Corr_Intra / Corr_Inter	Corr	Corr_Intra / Corr_Inter	NA	NA	NA	NA
(Mallawaarachchi Perera and Nanavakkara 2014)[16]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Acc	NA	NA	NA	NA	NA
(Attin et al. 2016)[18]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	RMSE	NA	NA	NA	RMSE/Corr	NA	NA	NA	NA	NA
(Rajiv Gandhi Institute of Technology, Mumbai, India et al. 2017)[21]	NA	NA	NA	NA	Acc	NA	Acc	NA	NA	NA	NA	Acc	NA	Acc	NA	NA	NA	PSCM	NA	NA	NA	NA	NA
(Patil and Karandikar 2018)[22]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	RMSE / Acc / Corr	NA	NA	NA	NA	NA
(Sun et al. 2019)[23]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	RMSE / PRD	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Baydoun et al. 2019)[24]	Corr	NA	Corr	NA	Corr	NA	Corr	NA	Corr	NA	NA	NA	NA	Corr	Corr	NA	Corr	Corr	NA	NA	NA	NA	NA
(Patil and Karandikar 2019)[25]	NA	NA	NA	NA	Acc / Absolute Error	NA	Acc / Absolute Error	NA	NA	NA	NA	Acc / Absolute Error	NA	Acc / Absolute Error	NA	NA	NA	NA	NA	NA	NA	NA	NA
(Li et al. 2020)[28]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr	Corr	NA	NA	Corr	Corr	NA	Corr	NA	NA
(Tabassum and Ahmad 2020)[29]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr	NA	NA	NA	NA	NA
(Ganesh et al. 2021)[31]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr_Intra / Corr_Inter	Corr_Intra / Corr_Inter	NA	Corr_Intra / Corr_Inter	RMSE / Acc	Corr_Intra / Corr_Inter	NA	NA	NA	NA
(Randazzo et al. 2022)[33]	NA	Mean Δ	NA	NA	NA	NA	NA	NA	NA	NA	NA	Mean Δ	NA	Mean Δ	NA	NA	Mean Δ	Corr	Mean Δ	NA	NA	NA	NA
(Wu et al. 2022)[34]	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Corr/RMSE	NA	NA	NA	NA	NA

Table 2: Performance evaluation metrics used by the different articles described in this review.
(Corr: Correlation, Acc: Accuracy, RMSE: Root Mean Square Error)

Code accessibility

When lacking standardized datasets and metrics, another way to effectively compare the performance of the methods described in the different articles would be to execute their code. Code accessibility is in this case a crucial factor. However, despite thorough investigation on various platforms such as "*GitHub*" and "*paperwithcode*", as well as other resources including *ResearchGate*, *ScienceDirect*, *Google Scholar*, *PubMed*, and *Ieeexplore*, only 6/32 (19%) of the articles were identified with available code.

ECGscan [7] provided a demo software that allows users to only view the digitization process of the provided ECG. However, we noticed that the demo was not accessible anymore as of from March 2023. Personal ECG digitization requires paid professional services and the software is not provided. Another article [34] offers a free web application that can import and digitize paper ECGs. Few other articles provide access to their code for testing purposes. Some offer GitHub access [31], [32] and the code is written either in Python or MATLAB. Another article provided a complete data bundle, including documentation, test images, a neural network model, and code to perform the digitization [28]. One of the articles only described the pseudocode, requiring language specific implementation to be able to use [30]. Nevertheless, despite the limited accessibility of code, these articles provided valuable insight into the techniques used for ECG digitization.

Discussion

The process of comparing digitization approaches for paper ECGs is not a simple task. A major challenge in this area of research is the lack of standardization in metrics and the absence of benchmark datasets. Only 15/23 (65%) of the articles provide common measurement elements, including the RR interval and the whole signal length. Moreover, the metrics of measuring these elements (RMSE, correlation, DTW, etc.) vary greatly across articles, which makes it difficult to compare results.

The variability of the databases used to evaluate the methods, further compounds the challenge of comparing results even with identical metrics. The quality of paper ECGs must also consider their ability of dealing with noise.

In addition, code accessibility is a major issue as only 6/32 (19%) of the articles shared their code or a usable software. This lack of accessibility makes it difficult to evaluate the efficiency of the different

approaches and limits the development of new techniques. The few articles that do present their code often make them available through paid licensed software, bundled black boxes or professional services. Opensource software that does not profit business corporates are expected to make significant advances in this domain.

Several articles presented techniques that aimed to overcome specific challenges in ECG digitization, including poor image quality or automation of the process. These techniques take advantage of the use of deep learning models, as well as more advanced binarization and signal extraction approaches. However, the performance of these techniques needs to be evaluated and compared.

Overall, ECG digitization is a complex process that requires careful consideration of several factors, including the quality of the paper ECGs, evaluation metrics, code accessibility, and potential information loss. Improvements in these areas would facilitate the development of new and more accurate techniques for ECG digitization and expand the potential uses of ECG data.

Conclusion

In conclusion, the digitization of ECG paper records has garnered significant interest in the medical community. However, the current state of the field poses several challenges to the adoption and efficient comparison of various approaches. The lack of standardization in metrics and databases, along with limited code accessibility, makes it challenging to assess and compare different methods' performance. Despite these obstacles, researchers have proposed various techniques for digitizing paper ECGs, which can be further improved by addressing issues such as poor image quality and automation. Overall, there is a need for increased standardization and accessibility in this field to enable more efficient comparison and adoption of digitization methods. A valuable contribution to this research topic would be the creation of international databases with data from multiple facilities as well as standardized metrics allowing for comparison and evaluation of ECG digitizing approaches.

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