Electrical Tomography Hardware Systems for Real-Time Applications: A Review

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ABSTRACT This paper presents a review of two-dimensional (2D) and three-dimensional (3D) electrical tomography (ET) hardware accelerators for real-time applications. While many recent review papers have discussed various algorithms for image reconstruction or acquisition systems, none of them has considered state-of-the-art hardware implementations of the associated image reconstruction algorithms to achieve real-time performance, especially for 3D ET where the computation requirement is excessively high. A 3D ET is useful in various applications such as robotics, autonomous vehicles, and process control, but it is computationally very expensive with respect to its 2D counterpart. Most implementations are based on single or multi-core CPUs and, to a lesser extent, on either graphics processing units (GPUs) or field programmable gate arrays (FPGAs). However, there is a clear gap between the currently available processors, whose computation power exceeds hundreds of teraflops per second (TOPS) at a reasonable low power consumption, and the ones recently used in ET systems. This gives great potential for next-generation ET systems to achieve real-time 2D and 3D ET reconstruction within a small form factor. The paper summarizes the most recent ET hardware systems with respect to their performance in terms of quality and processing frame rate, reconstruction methods, along with optimization and future directions.

INDEX TERMS Electrical impedance tomography, electrical capacitance tomography, image reconstruction, parallel computing platforms, sensor design.

I. INTRODUCTION

Electrical tomography (ET) provides a non-invasive way of measuring conductivity/resistivity or permittivity of a region using only boundary measurements. It has a wide range of applications in industrial, biomedical and geophysics domain [1], [2], [3]. ET systems can be divided into two categories: Electrical Impedance Tomography (EIT) and Electrical Capacitance Tomography (ECT). EIT measures the conductivity/resistivity of a region by using electrodes placed at the boundary of the target region, whereas ECT measures its dielectric value. There is a special case of EIT which measures the resistivity of a purely resistive domain and is known as Electrical Resistance Tomography (ERT) [4]. One major advantage of ET systems is that they do not have any ionizing effect on the target region and do not expose it to any hazardous radiations. In addition, they are much cheaper than other image modalities such as MRI, CT-scan, and Gamma-ray imaging techniques. This makes them suitable for many continuous monitoring applications. For instance, the recent world pandemic due to COVID-19 required continuous monitoring of lung aeration of critical patients [5], [6]. A portable, low-cost, and harmless EIT system was very much needed.

Nevertheless, a known limitation of ET systems is the fact that they yield low resolution images, which is mainly due to the high computation power that high resolution images may require [7]. Yet, many recent improvements to ET hardware accelerators have given rise to several real-time applications with additional combinations of other image modalities
such as ultrasonic or electromagnetic tomography in order to improve the image quality at a relatively low form factor [8]. In general, ET systems are not bulky with regards to capturing the data, but due to the nonlinear nature of the associated hardware algorithms, they usually require high-performance hardware platforms. This may include FPGA, GPU, System on Chip (SoC), and single or multi-core CPU-based hardware accelerators. In this paper, we review the most recent advancements in the field of embedded hardware accelerators targeting ET 2D and 3D image reconstruction algorithms. Both EIT and ECT have similar requirements for the data processing for the image reconstruction. Therefore, both of them are treated equally in this paper.

Although there have been several review articles on ET systems in the past, to the best of our knowledge, a detailed paper with discussion and review of hardware implementations of ET systems for real-time image reconstruction is still lacking. We conducted a search of available review articles using the Web of Science (WoS) and Google Scholar (GS) databases and found 27 closely related review articles since 2019. The search terms included “electrical”, “tomography”, “EIT”, “ECT”, “ERT”, and “review” in the title and topic in different combinations. The prime focus of these existing articles was majorly application-specific or related to reconstruction quality, with some discussing data acquisition techniques and their corresponding implementations. The review articles are summarized in Table 1. It is evident that there is a need for a review of recent developments towards portable real-time ET hardware systems for image reconstruction, which is the main focus of this paper. One of the major challenges in this area is that very limited work is observed with regards to hardware implementation of ET algorithms. Most of the work presented in the literature is limited to ET acquisition systems where the reconstruction is performed using a general-purpose computer, even many high-end commercial ET solutions use the same [29], [30]. However, we have extracted the most recent and relevant works available in the literature and presented them in this paper.

### A. ARTICLE SEARCH STRATEGY

A systematic article search strategy was adopted to find the most recent work on hardware systems for ET image reconstruction. Figure 1 shows the methodology adapted for the article search. At first, the keywords were identified, which can help in finding the most relevant articles. The keywords included “Electrical Tomography”, “EIT”, “ECT”, “ERT”, “Hardware”, “Embedded”, “Portable”, “Real Time”, “FPGA”, “GPU”, and “SOC” in different combinations in article title and topic/meta-data search along with their plurals or derivative forms such as “FPGAs”, “GPUs”, “Real-time”, “Field programmable gate array”, “System on chip”, etc. The search was conducted using the three major databases, i.e., WoS, GS, and IEEE. The most recent articles from 2017 onward were considered. While the title-based search is a good method to quickly find the relevant articles, given the limited amount of work done in the hardware systems for ET image reconstruction, we adopted a title and title + topic + metadata based search to collect a larger number of papers initially. For instance, a title-based search with the selected keywords yielded 80 articles in the WoS database, while a title + topic based search yielded 371 articles. Similarly, for the IEEE database, the title-based search resulted in 33 articles, while the title + metadata-based search resulted in 228 articles. While all the articles from the title-based search results were considered for further analysis, only the top 100 results from title + topic + metadata-based search results from both the databases were used. In the next step, the common articles were filtered and the results were

### TABLE 1. Summary of review articles.

| Type                      | Articles                                                                 |
|---------------------------|--------------------------------------------------------------------------|
| Applications              | construction [7], process [4], [9]–[13], material condition monitoring [14] |
| Biomedical                | lung [5], [15]–[18], demodulation [19], heart [8], cell culture [20]     |
| Geophysics                | [3]                                                                      |
| Reconstruction quality    | methods [21]–[24], Machine learning methods [25]                         |
| Signal processing         | demodulation [19], [26], preprocessing techniques [27]                  |
| Hardware implementation   | acquisition system [20], [28]                                            |

FIGURE 1. Article search strategy.
combined, which resulted in 223 unique articles. These articles were again filtered by reading their titles and abstracts, and this resulted in 75 articles, which were reviewed in detail, including their cited research, to find the most relevant articles for discussion in this paper. The final number of articles was 21, which was further categorized into 2D and 3D ET systems and are discussed in this paper in their respective sections.

B. ORGANIZATION OF THE PAPER

The paper has been organized as follows: The next section provides the background on ET systems, which will be interesting for the new readers in the field to quickly understand the workings and requirements of an ET system. This is followed by sections with detailed reviews of the existing hardware systems for 2D and 3D ET systems, respectively. The details around the development of real-time ET systems are summarized from the existing literature since the year 2017. Discussion and detailed summary tables for both 2D and 3D systems are provided. The discussion is extended to consider future prospects, compute platforms, and use of machine learning and other techniques for designing portable and real-time ET hardware systems for image reconstruction.

II. BACKGROUND

An ET system consists of an array of electrodes, a data acquisition unit, a data processing unit, and a data visualization unit, as shown in Fig. 2. The electrodes are placed on the boundary/surface of the region for which the image is to be constructed. Figure 3 shows the block diagram of a general acquisition system. The electrodes are interfaced with the data acquisition system through multiplexers and demultiplexers. A high speed 12 to 16 bit analog to digital (ADC) is usually required to provide the digitized voltage reading of the output voltage of the selected pair of electrodes to the processing unit for the image reconstruction. A current or voltage source for an ECT or EIT system is connected to the multiplexer/demultiplexer together with the voltage reading unit. The measured data of a frame is then transferred to the data processing unit to reconstruct the corresponding 2D or 3D image. Figures 4 (a) and (b) show typical electrodes placement around the boundary of a region for 2D and 3D ET systems, respectively. In a 2D ET system, the electrodes are generally placed uniformly to cover a 2D cross section and the associated finite element model (FEM) is planar, whereas, in a 3D ET system, the electrodes are generally placed to cover a volume and, accordingly, the FEM is prepared for volumetric computation [31]. The reconstruction of the image is carried out using the measured signal and a forward model. As the number of boundary measurements is going to be much smaller than the number of conductivities/permeabilities to be solved, the problem is ill-posed. Transforming it into a well-posed problem requires some prior information using a regularization technique.

A. FORWARD MODEL

This is a model that can estimate the spatial electric field and obtain voltage measurements at boundaries by stimulating a current/voltage in a known conductivity/permeability distribution space [32]. The final image is obtained by repeatedly running this forward model with an inverse solver
Matrices are expressed in their normalized form as follows:

\[ V_i = S \sigma \]  

(1)

where \( V_i \) is the measured potential, \( S \) is the sensitivity matrix and \( \sigma \) is the conductivity distribution. The size of these matrices are \( Mx1 \), \( MxN \) and \( Nx1 \) respectively.

### B. MEASUREMENT PROCEDURE

Measurements are conducted using a data acquisition system as shown in Fig. 3. The current/voltage stimulation patterns are given to a single/pair of electrodes, and the corresponding voltage is measured from the other remaining electrodes. This process is generally repeated in different combinations for all the electrodes to collect the measured data corresponding to a single frame. The commonly used current/voltage injection patterns are adjacent, cross, opposite, and sinusoidal. For instance, for an EIT system, in the adjacent pattern, electrode \( j \) is given a positive current, and electrode \( j+1 \) is given a negative current of the same magnitude. This is repeated for each electrode, \( j = 1, 2, ..., E \), placed in numbered order around the boundary. In a cross injection pattern, electrode \( j \) is given positive and electrode \( j+k+1 \) is given negative, where \( k \) is the number of electrodes to skip in between [32]. Usually an AC current/voltage signal with a frequency range from 1 to 100 kHz is applied, depending on the application requirement where high frequency usually provides more details but at the expense of penetration depth. Multifrequency excitation is also suggested in some ET systems in order to reduce the data acquisition time [38], [39].

Thus, the choice of the measurement pattern is application dependent and defines the total number of measurements per frame, which in turn determines the size of the Jacobian matrix. High computation latency caused by the high dimension of the Jacobian matrix and the number of measurements to be performed for each single frame requires dedicated hardware to achieve real-time performance for an embedded and portable system.

### C. SENSOR PLACEMENT

The placement of the electrodes is important in ET systems as it defines the sensitivity distribution in the region which determines the quality of the reconstructed image. For 2D ET systems, the electrodes are generally placed uniformly around the boundary of the region to be imaged. But, in some applications more sensitivity is required within a known sub-region of the region, non-uniform placement can be observed with more electrodes placed closer to the region of interest [40]. Similarly, for 3D ET systems, the electrodes are usually uniformly distributed around the region/volume of interest. For instance, in [41], a special ECT sensor with a double helical electrode arrangement in a co-axial pipe for 3D volume imaging of two-phase annular flow was designed and assessed. It consisted of four electrodes placed on the inner pipe and eight electrodes placed on the surface of the outer pipe. It was observed that the reconstruction quality was better than the conventional ring placement. But, these types of custom sensors are only suitable for limited applications where it is possible to install them. Therefore, authors in [31], suggested different electrode placements for multi-phase flow through a single pipe in a non-invasive way for 3D ET. This includes double concave, multiple concave, double helix, staggered concave, multiple helix, two semi-cylinders, and a ring. It was concluded that while one type
of placement is suitable for a particular flow, it may not be suitable for others. However, a twin ring configuration around the volume is very common for 3D ET.

**D. INVERSE PROBLEM**

The inverse problem is to determine the conductivity/permeability distribution in the region by using the measured data. This is an ill-conditioned problem where any small variation in the measured data can cause a huge variation in the reconstructed image. Many linear or non-linear methods have been introduced in the literature to solve this non-linear problem, which can be either single or multiple iteration-based. In general, it is observed that the iterative methods tend to yield better image quality with an increasing number of iterations. Figure 5 shows the process of image reconstruction using iterative methods.

The solution of the inverse problem in its simplest form can be given as follows:

\[ \sigma = S^{-1} V_i \]  

(2)

It is worth noting that since the number of measurements is always less than the number of pixels in the image the inverse of matrix \( S \) does not exist. Linear back projection (LBP) is one of the simplest methods, which was used initially to get an approximate solution. It assumes a linear mapping between the conductivity distribution and the sensitivity matrix and is solved using the following equation:

\[ \sigma = S^T V_i \]  

(3)

The reconstruction is simple and fast as it removes the requirement for inverse matrix calculation. However, the reconstructed image quality is poor and might be suitable only for applications where a low resolution image at a high frame rate is acceptable [42]. This image is also sometimes used by many iterative methods as an initial solution.

Another way to solve the inverse problem is to modify equation (1) as:

\[ S^T V_i = S^T S \sigma \]  

(4)

so that, if the inverse of \( S^T S \) exists then,

\[ \sigma = (S^T S)^{-1} S^T V_i \]  

(5)

Mostly, the inverse does not exist because \( N \gg M \). Therefore, a regularization term is added to \( S^T S \) so that,

\[ \sigma = (S^T S + \lambda I)^{-1} S^T V_i \]  

(6)

where, \( \lambda \) is a scalar hyperparameter and \( I \) is the identity matrix. This is also known as Tikhonov regularization method. Another similar method which is widely used is one-step Gauss Newton (GN) for difference imaging and is given as:

\[ \sigma = (S^T W S + \lambda^2 R)^{-1} S^T W Y \]  

(7)

where, \( W \) is the inverse of the measurement covariance, and considering the measurements to be independent, it is a sparse diagonal matrix of dimension \( M \times M \). \( R \) is the sparse regularization matrix with dimension of \( N \times N \), and \( Y \) is the difference of measured potential with a reference signal. Equations (6) and (7) show the requirements of matrix inversion and several matrix multiplications, which are rather time-consuming and thus require dedicated hardware accelerators.

If we include the eventual errors, \( e \), which may occur during the measurements, then the equation (1) can be written as:

\[ V_i = S \sigma + e \]  

(8)

Thus, the approach to find the solution can be modified as a minimization problem,

\[ \hat{\sigma} = \arg\min_{\sigma} (\| S \sigma - V_i \|^2) \]  

(9)

where \( \hat{\sigma} \) is the conductivity/dielectric distribution for which the error is minimum. The solution in this form is generally done iteratively. One of most widely used method is Landweber method which is given by,

\[ \sigma_{k+1} = \sigma_k - \alpha S^T (S \sigma_k - V_i) \]  

(10)

where \( \alpha \) is a relaxation factor, which determines the rate of convergence, \( (S \sigma_k - V_i) \) is the voltage difference in the measured and the estimated value from the forward model during the \( k^{th} \) iteration. Another approach is the iterative Tikhonov which is formulated as follows:

\[ \sigma_{k+1} = \sigma_k - (S^T S + \lambda I)^{-1} S^T (S \sigma_k - V_i) \]  

(11)

Several other methods have been developed in the recent past to improve the image quality while achieving real-time performance, which is challenging and requires careful hardware-software co-design methodology.
E. COMPUTE PLATFORMS

Most of the early works in the ET system utilized general purpose CPU based computers (PC) to execute the image reconstruction algorithm. It usually operates at a high clock frequency, holding data within a multilevel memory structure hierarchy and eventually using single or double precision data types. However, this solution is mainly quasi-sequential in nature and does not explore the high parallelism that is intrinsically found in matrix multiplications and addition arithmetic as it is exhibited in ET equations (2)-(11). The hyper-threading concept available in recent modern CPUs can be explored, but it still yields only coarse-level parallelism. A faster execution of such ET algorithms is possible if the associated equations (2)-(11) are broken into several smaller computation tasks which can run in parallel. While modern-day CPUs offer multiple cores and multi-threading, which can be utilized to parallelize the calculations, they are still limited in number compared to some other dedicated platforms such as GPUs. For example, a 12ᵗʰ generation Intel Core i9-12900KS processor chip launched in 2022 has 16 cores (8 performance-cores and 8 efficient-cores) with 24 threads which can run simultaneously on performance-cores [43] and AMD’s Ryzen Threadripper PRO 5995WX processor launched in 2022, which consists of 64 cores supporting 128 simultaneous threads [44].

Graphics Processing Unit (GPU) processors on the other hand possess a large number of cores and are specially designed for parallel computations. For instance, Nvidea’s Jetson Xavier NX, launched in March 2020 for embedded platforms, has 384 cores [45] and some desktop-grade GPUs offer even 10000+ cores (GeForce RTX 3090 [46]). The high number of cores with a very low power consumption down to 1W/TOPS (Tera Operations Per Second) makes the GPU-based system more capable of computing high-end parallel tasks such as ET algorithms. However, compared to multi-core CPUs, GPUs typically run at a lower clock frequency. For instance, the Intel Core i9-12900KS works at a base clock frequency of 3.4 GHz, while the GeForce RTX 3090 works at only 1.395 GHz. Due to this, frequent memory access for data fetching or writing is also slower in the case of GPUs. Therefore, the computations that have to be carried out on a GPU need to be optimized for parallel execution by minimizing the frequent memory accesses.

FPGAs are other hardware platforms that can be potentially used for parallel computing. They have the advantage of offering a flexible hardware structure that can be programmed. FPGAs typically comprise reconfigurable control logic blocks (CLBs), digital signal processor (DSP) blocks, and re-programmable interconnects, which can be used to build customized hardware. An FPGA based system may not suffer from frequent data read/write because the memory units can be designed to be very close to the data processing unit. However, the number of CLBs and DSP blocks is relatively limited, which hinders their usage to host complex hardware algorithms. Due to the complex hardware structure to support their reprogrammability, the overall system clock speed is usually slower than the one available for the GPU and CPU processors [47].

While any of the multi-core CPU, GPU, or FPGA based platforms can be utilized to develop efficient ET accelerator hardware systems, multi-CPU cores using personal computers (PCs) have been the most frequently used without actually exploring the hyper-threading feature. FPGA based
ET systems have been extensively explored in the recent past, but mainly for implementing the sequencer of the data acquisition module and capturing the measurement data into local memory rather than accelerating the image reconstruction algorithm. In the next section, we will discuss some of the recent works which were done for the design of real-time portable and embedded 2D/3D ET hardware accelerators.

F. PERFORMANCE METRIC FOR ET HARDWARE ACCELERATORS

The performance of ET hardware accelerators is determined by the quality of image reconstruction and the corresponding execution time (e.g., number of frames per second-fps), which may include both the acquisition and processing times. Some of the commonly used metrics for the assessment of image quality are:

1) IMAGE CORRELATION COEFFICIENT (ICC)

It is used to measure the correlation between the actual conductivity/dielectric values and the reconstructed values, it is given as:

\[ ICC = \frac{\sum_{i=1}^{N}(\sigma_i - \bar{\sigma})(\epsilon_i - \bar{\epsilon})}{\sqrt{\sum_{i=1}^{N}(\sigma_i - \bar{\sigma})^2 \sum_{i=1}^{N}(\epsilon_i - \bar{\epsilon})^2}} \]  

where, \( \epsilon \) is the ground truth distribution and \( \sigma \) is the final calculated distribution values obtained after reconstruction. A value close to 0 shows no correlation and a value close to 1 shows a high correlation. Naturally, a value close to 1 is desirable for good reconstruction quality.

2) RELATIVE ERROR (RE)

The relative error, or the relative reconstruction error (RRE) is used to measure the relative error between the actual conductivity/dielectric values and the reconstructed values and is given as:

\[ RE = \frac{\|\sigma - \epsilon\|_2}{\|\epsilon\|_2} \]  

a value close to 0 is desirable for high quality reconstruction.

3) MEAN SQUARED ERROR (MSE)

It is used to measure the mean squared error between the actual conductivity/dielectric values and the reconstructed values and is given as:

\[ E = \frac{\sum_{i=1}^{N}(\sigma_i - \epsilon_i)^2}{N} \]  

a value closer to 0 represent better quality of reconstruction.

4) AREA RATIO (AR)

It is defined as the ratio of the area of the target object \( (A_t) \) present in a ground truth image to the area of the target object \( (A_r) \) identified in the reconstructed image.

\[ AR = \frac{A_t}{A_r} \]  

AR value close to 1 represents better reconstruction.

5) POSITIONAL ERROR (PE)

It measures the reconstruction accuracy with respect to target position and is calculated as:

\[ PE = p_t - p_r \]  

where \( p_t \) is the target position in the ground truth image and \( p_r \) is the estimated target position from the reconstructed image. The smaller the value of PE higher is the positional accuracy.

III. 2D ELECTRICAL TOMOGRAPHY HARDWARE ACCELERATORS SYSTEMS

Developing accurate, high-speed, and portable 2D ET systems has been an active area of research. In this section we review some of the latest works which were conducted in this area since year 2017. As was mentioned in the introduction section, we used the WoS and GS databases to find all the relevant articles. Table 2 summarizes the findings of some of the most relevant work.

A. RECENT REVIEW

In [48], a 2D PC-based 16 electrode ECT based airflow injection system for industrial process control was presented. The ECT system consists of one upstream and one downstream ring to capture the 2D particle distribution inside the pipe. The upstream electrodes, along with the airflow injection system, were used to control the downstream particle distribution in real-time. The acquisition rate of the system was up to 100 fps and the ECT reconstruction throughput was 67 fps for an image size of 64 × 64 pixels with 835 outer pixels in the cross section using the LBP algorithm.

Authors in [49], designed a real-time compact EIT system with a PCI platform (cPCI-S-2501) using FPGA (XC6SLX100) based board for data acquisition and CPU (Intel core i7, 4GB, @2.2GHz) for image reconstruction as shown in Fig. 9. The acquisition system supported a frame rate of 120 and the complete reconstruction was carried out @32 fps with 1024 mesh elements. The system used Split augmented Lagrangian shrinkage algorithm (SALSA), which transforms an unconstrained optimization EIT inverse problem into an equivalent constrained optimization problem. The algorithm was implemented using EIDORS library and was compared with two-step iterative Shrinkage/Thresholding (TwIST), sparse reconstruction by separable approximation algorithm (SpaRSA) and one-step GN. For a mesh count of 6400 elements, the time required by SALSA was 0.1782s which was only 10.3% of SpaRSA, 3.8% of TwIST and 2.3% of GN. The experiments showed that SALSA significantly improves the computation time compared to other methods but is still dependent on the number of mesh elements and achieves a throughput of 5 fps for 6400 pixels/frame. This is still not suitable for real-time applications where larger mesh size with higher frame rate are much needed.

Researchers in [50], designed a portable 8-electrodes EIT system with a client server architecture. The server consists of a Red Pitaya board (Fig. 10), which comprises a Xilinx's
ZYNQ7010 FPGA chip with a built-in dual-core ARM Cortex A9 microprocessor (Fig. 11) to run Red Pitaya Operating System (OS), a customized operating system based on Linux. A general purpose PC was used as a client, which initiates the request to fetch the sensor data. The server conducts the data acquisition task at the rate of 50 fps and provide the acquired data to the client, which proceeds with image reconstruction at a throughput of up to 40 fps (for 942 pixels/frame) using Generalized Vector Sampled Pattern Matching (GVSPM) algorithm. The reconstruction image error measured as the average error in the length and width of the target object was 8.07% with ICC of 0.65 when the electrode size was 10 mm (diameter), and was 1.49% with ICC of 0.75 when the size was 30 mm (diameter). Increasing the number of electrodes or optimizing the size of the electrodes may be required to further improve the image quality. Also, an equivalent frame rate with much higher number of mesh elements is generally required for many applications.

In [53] a wearable and portable 16-electrode belt was designed. Similar to [50], the processing was done using a general-purpose IBM-compatible PC while the data was acquired using an Avnet Zedboard with Zynq 7000 (SOC module) at a rate of up to 30 fps. Another wearable EIT-belt was designed in [54]. But, in this implementation, the captured data was continuously sent to the Azure cloud through a secure shell (SSH) for 2D image reconstruction. The cloud compute engine consisted of NV24s series virtual machines with 24 cores hyper-threading processor and 224GB of RAM. A parallel cluster based method was employed for Jacobian matrix computation of the flexible belt boundary. The hyper-threading technique allowed the OS to address two virtual cores per physical core. A significant speed-up of 20.17 times was obtained using the parallel approach compared to the sequential method. The optimum performance \((op)\) defined as:

\[
op = sp - sp_{ref}
\]

where, \(sp\) is the speed-up and \(sp_{ref}\) is the speed-up reference based on Amdahl's law [55] and is given as:

\[
sp_{ref} = \frac{1}{(1-f) + \left(\frac{f}{P}\right)}
\]

where, \(f\) is the proportion of time affected by applying the parallel approach and \(P\) is the number of processors, was evaluated over the number of processors. It was observed that \(op\)
increases with increase in number of physical processors and then decreases when virtual processors are used. This shows that actual physical cores are more important in improving the performance.

With regards to portable ET systems, authors in [56] proposed a low-cost EIT system using a multicore CPU based on the Raspberry Pi4/PC for image reconstruction using the GN algorithm and an Arduino Mega-based board for data acquisition. The reconstruction time for an image of 576 mesh elements was 5.7735s, which was 2.95 times more than the PC (Intel core i5, 16GB, @2.3 GHz) but approximately 4 times cheaper. Hence, this system is portable and low-cost but may not be useful for real-time imaging. The reconstruction was carried out using EIDORS and Octave without any optimization.

Similarly, authors in [57], designed a portable wearable belt to measure multiple body parameters. It uses 16 electrodes for EIT and Electrocardiogram (ECG) data acquisition, in addition to an accelerometer, pressure sensor, gyroscope, magnetometer, microphone, and finger sensors for measuring other body parameters (body position, respiratory effort, snoring sound, SPO2, etc.). The system consisted of a multi-parameter module which was mounted on the chest belt and was connected to the main body module. FPGA (EP3C10F256C8N) was used as the communication bridge for data acquisition using a customized serial communication protocol @11.25 Mbps. The image reconstruction and signal processing tasks were performed on the Raspberry Pi 3 using embedded software developed with the QT library (a toolkit for graphical user interface design). It used Fidelity-embedded regularization (FER) algorithm with the subspace-based motion artifact rejection for image reconstruction. A throughput of 25 fps was achieved but with low image resolution, which is only suitable for air flow approximation for breathing pattern detection.

While the embedded software helped in reducing the image reconstruction time, the Raspberry Pi3, containing a quad-core ARM Cortex A53 with 1GB LPDDR2, and even the Raspberry Pi4 microprocessor, are not powerful computing platforms. On the other hand, the use of GPU based high compute platforms with parallelized operations is a promising solution. For instance, in [58], it was demonstrated that a speed-up of approximately 20 times could be achieved using a GPU (NVIDIA GTX 970, @1.215GHz, 4GB DDR5) over a CPU (Intel core i5-4460, 4 cores, 8GB, @3.2GHz). The iterative GN algorithm with 150 iterations for a Jacobian matrix of size 240 × 300 was considered in this implementation.

In another application of EIT, the authors in [60] designed a square 20 × 20 cm² EIT-based tactile sensor. They used 16 electrodes, with one additional internal electrode at the center of the area, which was used to inject electrical current into the internal field to improve the reconstruction quality. This yields 256 measurements per frame with 576 mesh elements per frame. A synthetic dataset was prepared containing 228072 training samples which mapped the voltage measurements to the mesh conductivities. They proposed a neural network based method for reconstruction (EIT-NN) with “spatial sensitivity aware mean-squared error” (SSA-MSE) as the loss function for image reconstruction. The voltage measurements were the input to the model, and the mesh conductivities were imposed as model output. The training of the model was conducted using a GPU (NVIDIA, Titan X, 11 GB), but the image reconstruction task was carried out using a general-purpose PC. The authors claim that the EIT-NN with SSA-MSE showed a better quality reconstruction compared to the conventional one-step GN, iterative GN, primal-dual interior-point method (PDIPM) and SA-SBL with a computation time of 0.0640 seconds. The achieved frame rate of around 15 fps may be suitable for many applications, but the image size of only 576 pixels is considered low for many of them. A Deep D-bar method for real-time image reconstruction was also suggested in [66]. The regularized D-bar method, which uses a non-linear Fourier transform, tailor-made for the EIT problem, suffers from blurring due to low-pass filtering of scattering data [67]. This was improved by using an additional Convolutional Neural Network (CNN) to remove the blur and to identify sharp boundaries. The model was trained without using any experimental data but with simulated data only, yet it was able to enhance the image contrast. Methods like this one, where the dependency on experimental training data is not required, deserve to be explored further.

A GPU-based parallel computation method for 2D EIT absolute image reconstruction with 32 electrodes was discussed in [61]. It used a simulated annealing (SA) approach to solve the inverse problem in which a conjugate gradient (CG) algorithm was used for the forward problem [68], with 32 instances corresponding to 32 independent current injections. The solution utilized CPU and GPU data processing with workload distribution as shown in Fig. 13. The authors showed that an efficient GPU based hardware algorithm does not exhibit divergence and that it allows to avoid random memory access. A contiguous access of memory in a sequence is preferred for faster execution. In their parallel hardware implementation, the colored padded jagged diagonal storage (pJDS) matrix format was considered for the entire parallel implementation of the conjugate gradient (CG) algorithm. The computation involved matrix-vector multiplication, the inner product of two vectors, and a triangular solver, which was implemented using a parallel approach with the pJDS matrix format. Whereas the serial implementation of the same suffered from the increasing size of the matrix, the parallel implementation showed significant speedups with increasing size, even including the data transfer time. For instance, matrix-vector multiplication for the size of 1046 mesh elements required 23.3 ms using the serial approach but only 14.9 ms using the parallel approach. For the size of 9500 mesh elements, 211.4 ms and 43.6 ms were needed for the serial and parallel approaches, respectively. The GPU-based parallel implementation exhibited higher processing time gains with the increasing size of the matrix, but this gain is limited by the number of cores and...
TABLE 2. Summary of recent work in 2D electrical tomography.

| Ref.  | Application                          | Algorithm       | Electrodes | Frame rate          | Mesh count          | Performance metric                                                                 | Hardware platform                                                                 |
|-------|--------------------------------------|-----------------|------------|---------------------|---------------------|------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| [48]  | Multiple phase flow (ECT)            | LBP, Landweber  | 16         | Acquisition: @100 fps Processing: @67 fps | Image 64x64         | Visual qualitative, particle distribution                                          | PC Based                                                                          |
| [59]  | Biomedical, Thorax (EIT)             | SALSA, SpaRSA, TwIST, GN | 16         | Acquisition: @120 fps Processing: @32 fps | 1024 elements       | PE, RES, SD, RNG                                                                  | Xilinx Spartan-6, XC6SLX100, for acquisition and PC (Intel core i7, 4GB, @2.2GHz) for reconstruction |
| [50]  | Biomedical, Thrombus Detection (EIT) | GVSPM           | 8          | Processing @40 fps  | 942 triangular units | Image correlation, Area ratio                                                      | ZYNQ7010 FPGA SoC for acquisition and PC for reconstruction                       |
| [54]  | Wearable belt (EIT)                  | Iterative with regularization and hyperparameter with initial estimate using LBP | 16         | -                   | Flexible boundary          | Plot for speed up for Jacobian computation                                           | Azure cloud (NV24s, 24 core, 224GB RAM) for reconstruction                        |
| [56]  | General (EIT)                        | GN              | 16         | PC: 6.39009s per frame RPi4: 27.8069s per frame | 576 elements (c2c2) | Visual qualitative                                                                | Arduino Mega for Acquisition, RPi4 (ARM v8, 4GB DDR4, @1.5GHz) or PC (Intel core i5, 16GB, @2.3 GHz) for reconstruction |
| [57]  | Biomedical, EIT multi-parameter      | PER with subspace motion artifact rejection | 16         | Processing: @25 fps  | Low                  | Visual qualitative                                                                | FPGA (EP3C10F256C8N) for acquisition and RPi3() for reconstruction             |
| [58]  | General (EIT)                        | Iterative GN with Tikhonov | 16         | Jacobian computation in 0.25ms | 300 elements    | Computation time                                                                  | NVIDIA GTX 970, @1.21GHz, 4GB DDR5                                             |
| [60]  | Robotics, Tactile Sensing (EIT)      | EIT-NN, GN one step, GN iterative, SA SBL, PDIPM | 16         | Processing: @ up to 15 fps | 576 elements | Confusion matrix, TPD metric                                                      | Single GPU, NVIDIA Titan X, 11-GB RAM for Training and PC for reconstruction (unspecified specs) |
| [61]  | Biomedical, Lung aeration (EIT)      | Conjugate gradient | 32         | Processing: 162.56 ms (evaluation of one objective function) | up to 20.700 elements | Speed up plot                                                                    | GTX 980 GPU and Xeon ES645                                                        |
| [62]  | Two phase Flow (ECT)                 | LBP             | 8          | Processing: @3233 fps | Image 64x64         | Mean Error                                                                       | Stratix V FPGA, 305K LUTs                                                        |
| [63]  | Two phase Flow (ECT)                 | Interframe correlation, GN, iterative Landweber | 8          | Acquisition: @63 fps Processing: @560 fps (520 boundary pixels) | Image 64x64         | Image correlation, error in %                                                    | Stratix 10 FPGA @ 400-MHz                                                        |
| [64]  | Process (ECT)                        | Iterative LBP   | 6          | -                   | 16x16 (image region), 720 elements (Forward model) | Visual qualitative                                                            | FPGA Cyclone V, Acquisition and processing                                      |
| [65]  | Process (ECT)                        | LBP, Iterative LBP | 8          | Processing: @12000+ fps | 16x16 (image region), 720 elements (Forward model) | Image Error, Plot of resource utilization, plot of frame rate | FPGA SoC Cyclone V, Acquisition and processing                                 |
memory available on the hardware platform. NVIDIA’s GeForce GTX980 GPU with 4GB RAM and 2048 CUDA cores and Intel’s Xeon ES6452.4GHz with 32 GB RAM, running Windows 7, were used in this implementation. It was concluded by the authors that the speed-up saturated with a gain of 5 times over the serial approach with around 7000 mesh elements. A more powerful GPU with a higher number of cores and higher data transfer speeds could further increase the saturation limit.

Authors in [62] proposed an FPGA-based hardware accelerator to execute LBP-based ET image reconstruction for 64 × 64 pixels/frame using 8 electrodes. The application was a two-phase flow through pipes, where the cross-sectional image reconstruction task was carried out on the Altera Stratix V FPGA at 400 MHz, within which a total of 305K logic elements (LE) were utilized. A frame rate of 3233 fps was achieved, but the image resolution is still considered low for several real-time applications.

In another similar application of 2D ECT for two-phase flow, researchers suggested an inter-frame correlation based method to reduce the overall execution time [63]. The target region was divided into 64 × 64 mesh elements and the reconstruction procedure was carried out only for a specific region of interest identified from the consecutive frames. The measured voltage/capacitance and the conductivity/permittivity of interest identified from the consecutive frames. The measurement data was acquired wirelessly. The iterative LBP algorithm, was designed for imaging lost foam coating process. It used six wireless capacitive sensors, with each sensor being a pair of electrodes. The electrodes were placed around the rectangular foam pattern in the compressed sand. A reconfigurable, segmented, parallel inner product architecture for parallel matrix multiplication was implemented in the aforementioned FPGA platform, which doubled the processing throughput compared to the sequential PC-based implementation. The system utilized only 11% of logic gates and 15% of memory, which may make it adequate to host other more complex ET algorithms with a larger number of image pixels. In a similar extension of this work in [65], the complete image reconstruction was implemented on an FPGA (Cyclone-V) SoC platform, and the measurement data was acquired wirelessly. The iterative LBP method was used for reconstruction, and a segment-based matrix-vector architecture was proposed, where the large matrix multiplications were carried out in smaller parallel segments. MATLAB’s model-based design platform was used to design the system where the segment length worked only 11% of logic gates and 15% of memory, which may lead to a maximum power consumption of 32.6 W, which remains excessively high for embedded ET systems.

In [64], a complete standalone 2D ECT system (16 × 16 frame size) using FPGA (Cyclone-V) was suggested. The system, which hosts the LBP algorithm, was designed for imaging lost foam coating process. The segment length worked with a larger number of image pixels. In a similar extension of this work in [65], the complete image reconstruction was implemented on an FPGA (Cyclone-V) SoC platform, and the measurement data was acquired wirelessly. The iterative LBP method was used for reconstruction, and a segment-based matrix-vector architecture was proposed, where the large matrix multiplications were carried out in smaller parallel segments. MATLAB’s model-based design platform was used to design the system where the segment length worked as an input to the design flow and could be configured as per the requirements. A higher segment length enables faster computation, but at the cost of more resources. The authors claimed to have achieved a frame rate of over 12000 fps for a 16 × 16 image size with eight electrodes. While the frame rate is sufficient for several applications, the image resolution is very low. The performance of this approach for a higher number of electrodes and much higher resolution needs to be evaluated.

B. SUMMARY

It can be observed from Table 2, which summarizes the most recent 2D ET hardware accelerators, that the hardware computing platforms used for real-time 2D ET systems are

\[ \Delta \sigma = (S^T S_r + \lambda R^T R_r)^{-1} S^T \Delta V_i \] (21)

where \( S_r \) and \( \Delta \sigma_r \) are the smaller sub-matrices corresponding to the small region of change. This helped to significantly reduce the processing time as there were lesser pixels to compute and update every frame in the continuous flow. The reconstruction was performed by modifying equation (5) as:

\[ S \Delta \sigma = S_r \Delta \sigma_r \] (20)
mostly CPU-based general-purpose computers or embedded multi-core CPUs (e.g., Raspberry Pi) and relatively few of them consider using FPGA and GPU-based platforms for executing the image reconstruction algorithm. For 2D ET systems with relatively low image resolution, not exceeding $64 \times 64$ pixels/frame even PC-based sequential implementations are able to achieve a throughput of around 25 fps when running simple non-iterative algorithms such as LBP. However, these systems are not portable and can only be used for limited applications that can tolerate low image quality. Indeed, the design of the portable ET system was mainly focused on the design of the data acquisition module, and relatively less amount of work was done for the design of dedicated computing platforms, in spite of the substantial speed-up they can achieve. For instance, in [48], it was observed that the LBP method on a PC-based platform could be achieved at a throughput of 67 fps, whereas its implementation on an FPGA-based platform could yield a throughput of 3233 fps. This shows that the parallel compute enabled dedicated platforms can offer significant gain over sequential PC-based solutions and therefore further efforts are worth to be done for designing combined (acquisition + processing) real-time embedded ET systems.

IV. 3D ELECTRICAL TOMOGRAPHY HARDWARE ACCELERATORS SYSTEMS

3D ET systems, which are highly needed in applications where accuracy and/or volume imaging are desirable, feature much higher computation requirements than 2D ET systems. For instance, in [71], it was shown that 3D EIT systems can exhibit only $\pm 10\%$ image RE in percentage, which is much less than 2D EIT ($\pm 24\%$) and 2.5D EIT ($\pm 21\%$) while requiring a larger number of electrodes to cover the complete 3D volume of the region of interest and hence a high Jacobian matrix dimension.

A. RECENT REVIEW

Although 3D ET systems have been in use for a long time, the ones that are portable and can achieve real-time performance are relatively limited because of the heavy computation time they require. For instance, while mesh elements for 2D ET systems are typically in the 100–1000 range (refer to Table 2), they easily exceed 10,000 for a 3D ET system. Processing this much data in real-time is a challenging problem and needs continuous hardware and software research. To the best of our findings, the most recent and relevant real-time 3D ET systems present in the literature are summarized in Table 3.

Authors in [69] used a twin plane electrode arrangement for 3D imaging and velocity measurement in a two-phase flow through pipes. The ECT system uses a total of 24 electrodes, with 12 in each plane. The 3D images were reconstructed using $21 \times 21 \times 29$ mesh elements. A dedicated data acquisition system was used with an acquisition rate of 241 fps for 276 independent measurements per frame. The reconstruction was carried out using LBP, Landweber, Tikhonov, and iterative Tikhonov on a PC. The reconstruction time using the Tikhonov method was 2.5 ms i.e., 400 fps, which is promising, but the image resolution, which consists of 12,789 pixels per frame was relatively low for several real-life 3D ET applications.

In [70], authors designed a 3D wireless ERT system (WERT) for determining in real-time the two-phase particles’ distribution of glass beads-NaCl solution within a rotating vessel. A total of 40 invasive electrodes were placed around a PVC cylindrical vessel in 5 layers, with 8 electrodes in each layer. The measurements were conducted using the adjacent method, yielding 40 measurements for each plane. The acquisition system was designed using an Arduino Uno microcontroller with a 10-bit ADC that supported a frame rate of 2 fps. The acquired data was transmitted to the host PC wirelessly through Bluetooth with a maximum transmission speed of about 921 kbits/s, which satisfied the requirements of the designed WERT system. As the vessel was rotating, the actual measurement data was collected and time-averaged over 5 seconds to allow the rotating field to stabilize. A single-step GN algorithm was used for image reconstruction using EIDORS on an IBM-compatible PC, and the reconstructed image was binarized as there were only two phases (liquid and solid particles). The actual measured and the numerically simulated analysis showed a deviation of only 7.21%. While 3D reconstruction provided encouraging results, the reconstruction was implemented using only sequential data processing. A dedicated hardware accelerator could have substantially increased the system throughput.

In another implementation, authors in [71], developed a wearable 3D real-time lung ventilation monitoring system. A total of 48 electrodes were placed in 3 planes, with 16 in each plane. A 48-channel active electrode SoC was placed on the belt using a flexible printed circuit board. Another Hub-SoC was used for data gathering and communication via Bluetooth @10 fps to a PC, which executes the iterative GN image reconstruction algorithm for an image size of 150,000 pixels. The reconstruction quality was compared with a 2D model using only one plane data and a 2.5D model using three planes of data without information exchange...
between planes. The 3D image reconstruction showed much better accuracy than the others, with a 3D volume reconstruction error of ±10%, much lower than that of 2.5D and 2D image reconstruction, which exhibited ±21% and ±24% error, respectively. Nevertheless, the reconstruction algorithm was also executed on a sequential PC-based platform. In a similar work on respiratory motion tracking in [72], authors used 80 electrodes in 5 layers (16 in each layer) for 3D image reconstruction. The image volume consisted of 113,664 mesh elements with 111 layers of 32 × 32 resolution each. The reconstruction was carried out using modified TV (MTV) and compared with the TV and traditional Tikhonov method, which showed an improvement in the image quality by 20% and 30% respectively in terms of lung regional ratio (LRR) defined as,

\[ LRR = \frac{VA}{VA + TA} \]  

(22)

where, VA is the lung ventilation area and TA is the thorax area apart from the lungs. The reconstruction time for the methods MTV, TV and Tikhonov was around 574ms (∼2 fps), 700ms (∼1.5 fps), and 323ms (∼3 fps) respectively, on a PC configured with 2.7GHz GPU, and 8GB RAM. The data acquisition and transfer to the PC for reconstruction took only 2.5ms. This shows that a parallel and optimized implementation of the algorithm on a high-performance computing platform is much needed to improve the frame rate of the system.

Recently, a 3D Micro EIT dedicated system for cell imaging was designed and accessed in [73]. A cylindrical container of 10 mm in height and 12 mm in diameter was prepared with 17 electrodes placed at the bottom of the plane as shown in Fig. 14. One reference electrode was placed at the center of the bottom plane. The other electrodes were placed in the form of two concentric circular rings, consisting of eight electrodes each. The FEM analysis was conducted using 235,000 mesh elements, which spanned the complete cylindrical volume to be imaged. Measurements were conducted using the multi-frequency EIT system [77], with a frame rate of 546 fps under serial mode and 1014 fps under semi-parallel mode. The basis pursuit denoising method was used for reconstruction using a Xeon X5650 CPU, 2 cores and 24 GB RAM as a compute platform. It took 5 seconds to complete the reconstruction of a single frame, which remains excessively high for efficient real-time applications.

Authors in [74] proposed a fast Barzilai-Borwein Gradient Projection for Sparse Reconstruction (GPSR-BB) that can resolve the inverse problem into bound-constrained quadratic
programming and achieve a gradient projection with line search. A projection method is combined with the GPSR-BB to reduce the computation time for higher mesh count. Simulation and experiments were carried out using 16 electrodes around a cylinder. 3D model was used for the forward problem with around 67,000 tetrahedral elements, and for the inverse problem, a cross section with 812 square elements was used. Six different methods that include Landweber, Tikhonov, TwIST, GPSR-BB, GPSR-BB based on truncated singular value decomposition (TGPSR-BB) and GPSR-BB based on Krylov subspace (KGPSR-BB) were used for reconstruction. The corresponding reconstruction time using these methods with simulated data with 3% noise was 0.22s, 9.13s, 0.080s, 1.65s, 1.38s, and 0.060s, respectively. A general purpose computer with an Intel Core i7 @2.7GHz was used. The results show a frame rate of around 16 fps for 812 pixels/image and around 10 fps for 2,472 pixels/image using KGPSR-BB algorithm. A higher frame rate with much higher number of elements is required for real-time systems.

In other work, authors in [75], proposed a hand gesture recognition system using EIT with 2D and 3D electrode placement. Eight different gestures were prepared, and machine-learning based methods were used to classify the gestures. The system consists of a 12-bit current-steering DAC, an acquisition module based on Xilinx Artix-7 FPGA (100/33 fps for 2D/3D acquisition) and a PC with Matlab for classification. There was no image reconstruction required and the classification of gestures was performed by using the measured signals only. Decision tree, Support Vector Machine (SVM) and Artificial Neural Network (ANN) were used for classification. The number of classes was limited to eight, but for developing a higher number of gestures, deep neural network based methods can be explored. Also, the classification of the measured signals avoids the requirement of solving the inverse problem directly.

A parallel multi-GPU multi-node approach in a heterogeneous distributed system was proposed in [76]. It used a distributed parallel computing approach to execute the image reconstruction algorithm to adequately cope with the large matrix sizes. A single CPU was only able to perform 10-15 iterations of Landweber for image reconstruction in one second, whereas the platform with two nodes and multiple GPUs was able to achieve a frame rate of up to 8 fps with 50 iterations. The largest image size which was tested corresponded to 672 KB, for which a throughput of 1 fps using 400 iterations could be achieved.

B. SUMMARY

It can be seen that the research work conducted so far for the design of a real-time 3D ET system is very limited compared to its 2D counterpart. The higher electrode count leads to more measurements, which increases the acquisition time. Furthermore, the larger mesh count exponentially increases the computation time, which is required for 3D image reconstruction. As discussed in section III some embedded 2D ET systems have used FPGA and GPU-based compute platforms, but their use for 3D ET systems remains very limited. Thus, most 3D ET image reconstruction tasks are carried out using high-end CPUs with a large amount of RAM. A distributed on-premise or cloud-based architecture can be a very useful approach for very large size matrices. However, dedicated parallel architecture on modern compute-intense embedded platforms is much needed for portal real-time ET systems.

V. DISCUSSION AND FUTURE PROSPECTS

A. COMPUTE PLATFORMS

The major challenge in the computation of the ET image reconstruction arises due to the increasing size of matrices that are necessary for capturing accurate volume information. A high quality image can be obtained if large-sized matrices are supported by the appropriate computing platform. As observed from sections III and IV, most of the research works which were conducted on ET systems mainly used Matlab/Octave on IBM-compatible computers. Table 4 shows various compute platforms which were discussed in this paper. Matlab/Octave uses mostly sequential computation processes using a general-purpose PC. The size of the matrix in this case is limited by the amount of the RAM capacity and its utilization. The lack of fine-grained parallel hardware implementation on PCs has consistently led to excessively high computation time to no match real-time constraint. Some works that have used FPGA platforms as hardware accelerators for ET reconstruction algorithms could show attractive results to handle in real-time even large matrix sizes. In addition, since many recent data acquisition systems are already using FPGA for implementing the sequencer of the data acquisition module [28], [57], [77], using them for image reconstruction as well seems to be a preferable choice.

TABLE 4. Compute platform used for 2D/3D reconstruction.

| Compute Platform      | 2D ET systems | 3D ET systems |
|-----------------------|---------------|---------------|
| CPU based             | RPi - [56], [57] | PC - [69]-[71], [73]-[75] |
| GPU based             | [58], [61]    | -             |
| FPGA based            | [62]-[64]     | [50]          |
| Cloud/Distributed     | [54]          | [76]          |
towards the design of a complete single-board embedded real-time ET system. Modern embedded FPGA platforms are now available with integrated dedicated high-performance processors of different types, which can simultaneously handle different tasks of the algorithms (Fig. 15). For instance, coarse grain parallelism corresponding to data acquisition and image display tasks on the DSP processor and fine-grained parallelism corresponding to matrix multiplication on the FPGA module.

GPUs, the performance of which was boosted by AI and machine learning algorithms demands is also another potential solution for next generation real-time 2D and even 3D ET systems. They also incorporate on-chip various processor technologies, which can be very beneficial for 2D and 3D ET algorithms (Fig. 16). For instance, in addition to the hundreds of GPU cores which can execute matrix arithmetic in a single thread multiple data (STMD) manner, a hardwired tensor core is used for high-speed matrix multiplication. Similar to the processor integrated FPGAs, the modern embedded GPU boards are also available with an integrated processor, as shown in Fig. 16. A GPU based data processing system will have the benefit of rapid development and support for dynamic matrix size. Hence, the high count of physical cores (e.g. Jetson AGX Orin 64GB has 2048 cores) [79], makes them suitable for highly parallelized implementation of the 2D/3D algorithms. Furthermore, due to availability and support of various libraries, machine learning based reconstruction algorithms will be more efficient on the GPUs with faster development time.

B. MACHINE LEARNING FOR ET APPLICATION
The use of Machine Learning (ML) for ET has seen a significant rise in recent years. The authors [25], provide a review of various ML techniques for solving the inverse problem. One of the major challenges with the use of ML is the availability of suitable and large database for training. Generally, synthetic data is generated and used, [80] has presented a standard database for training various ECT systems. [66] proposed DNN based deep D-bar reconstruction which showed some improvements over the basic D-bar method. An additional CNN was added to the D-bar method to improve the final reconstructed image. While continuous efforts in this direction can lead to higher accuracy, modern GPU processors, which were specifically designed for AI and machine learning algorithms, can be valuable to meet the real-time constraints of ET systems such as: Gesture recognition [75], where full image reconstruction is not required. Nevertheless, while implementing ML, special attention needs to be paid to the data precision of the underlined hardware platform. It was revealed in the literature that a ML/DNN based method may not require a full double-precision calculations and the use of even half-precision may not significantly reduce the accuracy of the system [81]. Many recent compute platforms and edge devices are now optimized for half-precision calculations, and this can significantly enhance the processing throughput of 2D and 3D ET systems.

Another advantage of the use of ML-based reconstruction methods is that there are some software tools available to easily optimize the implementations to some extent, especially on GPUs. For example, Python-based model quantization libraries are available in TensorFlow, which can be used to develop quantized models with lower bit precision and faster execution on the target hardware [82]. The supported target hardware includes multi-core CPUs, GPUs, or Tensor Core Units (TPUs). While this is a good starting point for
faster execution, a more parallelized implementation is also possible to further optimize the solution, but requires considerable effort. This is relatively difficult for FPGA-based implementations due to a lack of software tools. Although FINN is available from Xilinx for Python-based model quantization, development as well as deployment on some specific boards, it is still limited to an experimental stage [83], [84]. There is no standard tool available directly to implement the optimized models for parallelized inferencing on the FPGAs. For optimized models, custom implementations are required, which demands significant effort but holds the potential to provide promising results.

VI. CONCLUSION

The non-invasive and non-harmful features of ET systems have led to their widespread usage for several real-life applications. The major challenge remains the high computation requirement to yield high resolution images. The non-linear behavior and the ill-conditioned and ill-posed nature of the inverse problem have led to the emergence of various regularization-based ET algorithms, which involve various time-consuming matrix arithmetic operations such as multiplications and matrix inversions, which require dedicated hardware accelerators if real-time performance is sought. Although some attempts have been made to design real-time acquisition systems and algorithms that are better suited for real-time applications [66], [85], little effort has been made to design suitable hardware accelerators to perform the reconstruction. In this work, we reviewed recent articles related to the hardware platforms for embedded and real-time 2D/3D ET systems. Table 2 and Table 3 list the most significant platforms that have been revealed so far for 2D and 3D ET systems, respectively. Most of these systems utilized embedded acquisition systems and general-purpose PCs for tomographic image reconstruction, which limited their performance since no optimization or parallelism implementation was adopted. However, some systems, such as: [61], [63], [64] suggested using FPGA/GPU platforms for 2D ET, with which a significant speed-up could be achieved. Hardware accelerators targeting 3D ET systems are yet to be designed. This can be facilitated by the availability of very powerful GPU processors which can handle 100s of TOPs with only a few watts of power consumption at the edge using a small form factor. The recent acquisition of Xilinx by AMD can lead to even more attractive hybrid GPU-FPGA processors and platforms like this can help in building highly optimized real-time ET systems.

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