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Conference Paper · September 2018

DOI: 10.1109/ICITACEE.2018.8576915

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Compressive Sensing Approach with Double Layer Soft Threshold for ECVT Static Imaging

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***Abstract*— Electrical Capacitance Volume Tomography (ECVT) is a capacitance based tomography technology which is developed since its advantages on non-invasive properties, low energy, and portability. One of the challenge on developing this tomography technology is on its imaging algorithm. Naturally the imaging method forms under-determined linear system which is indicated by dimension of the measurement is much smaller compared to the projected value dimension. Mathematically it implies ill-posed inverse problem. Therefore Compressive Sensing framework is used to solve the corresponding inverse problem. To improve the accuracy of the predicted image reconstruction, new threshold approach, Double Layer Soft Threshold, is proposed and attached to the proposed Compressive Sensing based ECVT imaging method. The simulations results show that the proposed method is able to improve the conventional ECVT imaging method, Iterative Linear Back Projection (ILBP), by significantly eliminating the elongation error.**

Keywords*— *Compressive Sensing, Electrical Capacitance Volume Tomography, Imaging method, Double Layer Soft Threshold

I. INTRODUCTION

ECVT is capacitance based tomography which is rapidly developed since its advantages on non-invasive, low energy and portability properties. The capacitance is measured around the boundary of the sensor to identify the perturbation inside the sensing domain. It is further development of ECT which has its novel on reconstruction method. It utilizes fringing effect of capacitance based measurement to directly observe three dimensional objects more precisely in real time observation [1].

To support better performance and utility of ECVT imaging, the technology have been developed from several aspects. The sensor technology including the data acquisition technique [2-5] , the imaging method development [1, 6-8], and the application of ECVT especially on medical purposes [2, 9, 10] , is the research area of ECVT. This paper elaborates one of the purposed method to improve ECVT performance from the imaging method.

Some ECVT imaging technique such as NN-MOIRT [1], Combined Feed Forward NN [6], Compressive sensing based [7, 8] and ILBP [1] have been published. NN-MOIRT reported performs very powerful especially for dynamic imaging. However, due to simplicity and computation issue, ILBP is still practically used.

The challenging issue on ECVT imaging is the ill-posed inverse problem property which is difficult to solve. The dimension of the capacitance measurement values which is much smaller compared to dimension of the predicted permittivity value, forms under-determined linear system. Therefore, Compressive Sensing approach is used to solve the corresponding inverse problem

First CS framework for ECVT Static imaging has been proposed [7]. The proposed algorithm succeed to reconstruct the detected object in the ECVT domain but produce artefact at the edge of the sensor and the reconstructed image is overestimate the real object in terms of size. The further development proposed on [8] succeeds to eliminate the artefact but remain the overestimate problem.

This paper proposes a new post reconstruction approach which is named as Double Layer Soft Threshold technique to handle the overestimate issue. The elaboration will discuss the crucial part on modelling compressive sensing for ECVT imaging and present the ECVT imaging simulations for static object. The simulations showed that the proposed post reconstruction method is able to reduce the overestimate problem by giving more accurate imaging. In addition, it is also outperform the existing ECVT imaging method, ILBP, by significantly reduce the elongation error.

II. ECVT (ELECTRICL CAPACITANCE VOLUME TOMOGRAPHY)

ECVT is as sensor technology which has ability to reconstruct simultaneously a volume image of a region inside the sensing domain by utilizing the capacitance measurement [1]. It is non-invasive since the electrodes are attached on the wall out of the vessel to measure the capacitance. The simultaneous observation is smoother compared to the previous sensor technology, ECT (Electrical Capacitance Volume Tomography), since the Fringing effect is utilized [1],[11] . The volumetric imaging by ECVT makes 3D imaging for real time observation is more reliable compared to conventional 3D imaging by ECT [1].

A. The ECVT Component

The ECVT consists of hardware and software component. They are assembled to produce imaging that represents the perturbation inside the sensing domain. There are three mains parts of ECVT [1]: Sensor device, data acquisition device and computer system as figured on Figure 1.

On the sensor device, some electrodes are attached on the outer side of the sensor's wall. The number of the attached electrodes determines the capacitance measurement's dimension. For N attached electrodes, there is C_2^N number of capacitance measurement [1]. The resulted capacitance will be processed by data acquisition system to make it feasible for computerized processing. The capacitance measurement is utilized to predict the permittivity distribution which represent the perturbation inside the sensing domain. The perturbation in the sensing domain will be predicted by the imaging algorithm installed in the computerized reconstruction control

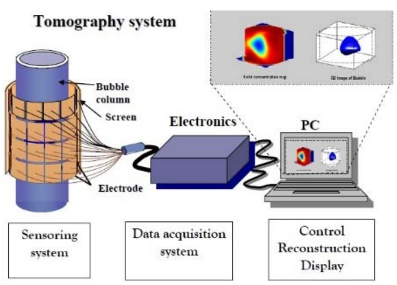


Fig 1. ECVT Hardware component [12] *CtechLab*

B. *The Mathematical Model*

The mathematical model behind the ECVT tomography system consists of forward problem and inverse problem. The forward problem determines the mathematical model to calculate the capacitance around the sensor boundary. While the inverse problem determines the mathematical model to predict the permittivity distribution by utilizing the measuring capacitance.

Forward Problem

Perturbation inside the sensing domain is the phenomena that will be predicted by the imaging algorithm. It is represented by Poisson equation as stated in (1) below [1]:

$$\nabla\epsilon(x,y,z)\nabla^2\emptyset(x,y,z) = -\rho(x,y,z) \qquad (1)$$

where $\nabla\epsilon(x,y,z)$ represents the permittivity distribution, $\nabla^2\emptyset(x,y,z)$ represents the potential distribution of the electrical field and $\rho(x,y,z)$ represents the charge density.

By assuming no charge inside the sensor, (1) can be represented as (2) below [1]:

$$\nabla\epsilon(x,y,z)\nabla^2\emptyset(x,y,z) = 0 \qquad (2)$$

By using FEM (Finite Element Method) the potential can be calculated, hence the relation between capacitance measurement and permitivitty value can be represented as (3) below [1]:

$$C_i = -\frac{1}{\Delta V_i}\oint_{A_i} \epsilon(x,y,z)\nabla\emptyset(x,y,z)dA \qquad (3)$$

where ΔV_i is the voltage difference between the electrodes pair and A_i is the surface area enclosing the detector's electrode.

Equation (2) relates the perturbation inside the sensing domain which is represented by dielectric constant (permittivity) $\epsilon(x,y,z)$, into the measured capacitance C_i.

To solve (3) analytically or numerically may give more precise solution. However it will be much more complicated and computationally cost due to its complexity. One of possible solution is by approximating the relation between measurement capacitance and predicted permittivity by linear mapping, Sensitivity Model. It is taken due to its simplicity. The given formula (4) below is the linearization of (3)

$$\begin{bmatrix} C_1 \\ C_2 \\ \cdot \\ \cdot \\ \cdot \\ C_M \end{bmatrix}_{M\times 1} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdot & \cdot & S_{1N} \\ S_{21} & S_{22} & S_{23} & & & S_{2N} \\ & & \cdot & & & \\ & & \cdot & & & \\ S_{M1} & S_{M2} & S_{M3} & & & S_{MN} \end{bmatrix}_{M\times N} * \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \cdot \\ \cdot \\ \cdot \\ \epsilon_{N-2} \\ \epsilon_{N-1} \\ \epsilon_N \end{bmatrix}_{N\times 1} \qquad (4)$$

Capacitance measurement is represented *M*-dimension of vector *C*, while the permittivity distribution is represented by *N*-dimension of vector ϵ . The linear mapping function approximation is represented by *M*×*N* dimension of sensitivity matrix *S*. The sensitivity matrix will be used as the projection matrix as expressed in (5) [1]

$$S_{ij} \cong V_{0j}\frac{E_{si}(x,y,z).E_{di}(x,y,z)}{V_{si}V_{di}} \qquad (5)$$

where $E_{si}(= -\nabla\phi)$ is the electrical field distribution vector when the source electrode in the *i*th pair is activated with voltage V_{si} while the rest of the electrodes are grounded. E_{di} is the electrical field distribution vector when the detector electrode in the *i*th pair is activated with voltage V_{di} while the rest of the electrodes are grounded. V_{0j} is the volume of the *j*th voxel.

Inverse Problem

Inverse Problem is process to predict the permittivity distribution ϵ by utilizing capacitance measurement C. Given the inverse problem as (6) below:

$$\begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \cdot \\ \cdot \\ \cdot \\ \epsilon_{N-2} \\ \epsilon_{N-1} \\ \epsilon_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdot & \cdot & S_{1N} \\ S_{21} & S_{22} & S_{23} & & & S_{2N} \\ & & \cdot & & & \\ & & \cdot & & & \\ S_{M1} & S_{M2} & \Phi_{M3} & & & S_{MN} \end{bmatrix}_{M\times N}^{-1} * \begin{bmatrix} C_1 \\ C_2 \\ \cdot \\ \cdot \\ \cdot \\ C_M \end{bmatrix}_{M\times 1} \qquad (6)$$

Equation (6) represents the imaging mathematical model which appears as simple inverse problem. Nevertheless, it becomes complicated since the S matrix is ill posed. The ill-posed condition is occurred since the dimension of the predicted permittivity distribution (N) is normally much higher compared to the dimension of the measured capacitance (M). In linear Algebra it relates to the number of variables is less than the number of the equations. Thus it leads to the under-determined linear system which cannot guarantee the unique solution.

III. ECVT Imaging Based On Compressive Sensing Framework

Compressive sensing is a framework that enable signal recovery with less data sampling compared to Shannon-Nyquist Theorem [11-13]. Mathematically, it is promising for the ECVT imaging system since the dimension of measurement data is much smaller compared to the dimension of the projected data. This section discusses our proposed algorithm for ECVT imaging based on compressive sensing framework.

A. Compressive Sensing Framework

CS framework is said to be enable to reconstruct a certain naturally sparse or transformed sparse signal by utilizing less number of sampling data compared to the Shannon-Nyquist theorem [13-15]. In linearization point of view, it is enable to solve an under-determined system [16]. To do so, sparsity and incoherence between measurement matrix and the dictionary should be satisfied.

The Mathematical Model

Given a discrete-time signal $\alpha \epsilon R^N$ and consider a measurement system that acquires M-dimension of measurement value, then the linear measurement can be represented as (7) [15].

$$y = \Phi\alpha \qquad (7)$$

The sensing matrix is represented by MxN matrix Φ while the capacitance measurement is represented by M dimensional vector y. Φ. M is typically is much smaller compared to N. $\alpha \epsilon R^N$ is a coefficient vector which normally has only $K \ll N$ non-zero coefficient [15, 16]. α is needed to be reformulated to ensure that it will adapt with the CS framework [14]. The original signal α is often reformulated as a linear combination of a small number of signals taken from a "resource database" determined as dictionary $\psi \epsilon R^{NxL}$ and has the formulation as expressed in (8).

$$\alpha = \psi s \qquad (8)$$

On this state, α is considered as sparse signal in base ψ with K-degree of sparse. Hence, the Eq. (6) can be represented as:

$$y = \Phi\,\psi s \qquad (9)$$

The main idea of CS system is projection of α to a low dimensional measurement vector y by measurement matrixΦ.

B. Proposed Algorithm for Static ECVT Imaging

An ECVT imaging method based on Compressive Sensing Framework is proposed. The new threshold method, Double Layer Soft Threshold, is attached on the post reconstruction step to improve the predicted image accuracy.

Given the linearization of ECVT forward problem as stated in Eq. (4), the permittivity is reformulated as Eq. (10) to guarantee the adaptable into the CS framework. The permittivity g is represented into another sparse signal representation using DCT dictionary as expressed in Eq. (10).

$$g = \psi * \theta \qquad (10)$$

where g is N×1 array of permittivity value, ψ is N×k matrix of dictionary that fulfill the DCT requirement expressed in Eq. (11).

$$\psi(p,q) = \sqrt{\frac{2}{N}}\left[c(p)\cos\frac{(2q-1)(q-1)}{2N}\right] \qquad (11)$$

where

$$p,q = 1,2,..,N, c(p) = \begin{cases} \dfrac{1}{\sqrt{2}}, p = 1 \\ 1, p = 2,3,\ldots,N \end{cases}$$

and α is N×1 array of the sparse representation signal.

Using Eq. (9), the ECVT imaging forward problem stated in Eq. (4) can be reformulated into Eq. (12).

$$C = S\,\psi\theta \qquad (17)$$

The inverse problem stated in Eq. (6) becomes Eq. (13).

$$\theta = (S\psi)^{-1}C \qquad (13)$$

The overall proposed method is presented on the block diagram on the Figure 2 below

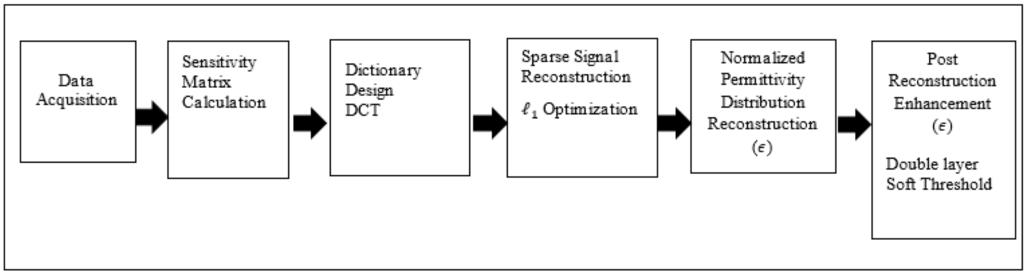


Fig 2. Enriched Compressive Sensing Based Method for ECVT Static Imaging

Figure 2 presents the proposed method to do ECVT imaging. Sensitivity matrix which is formulized on Eq 5 is used as the projection matrix while DCT (Discrete Cosine Transform) and l1 optimization is used as the dictionary and sparse recovery algorithm correspondingly. The proposed new double layer soft threshold is attach as the post reconstruction method.

The idea of the proposed double layer soft threshold is based on Chebychef Theorem and Empirical Rule which are talking about the concentration of data distribution. In simple way, the two theorems said that the data distribution will be located in around 1 up to 3 standard deviation from the mean. Based on the theorems, the proposed double layer soft threshold is presented as on (14), (15) and (16) below:

Layer 1 (14)

$$\epsilon_1 = \begin{cases} 0, & \epsilon_0 \leq \delta \\ sign(x) * (x - \delta), \epsilon_0 > \delta \end{cases},$$

Layer 2

$$\epsilon = \begin{cases} 0, & \epsilon_1 = 0 \\ \epsilon_1, 0 < \epsilon_1 \leq \delta_1 \\ 1, \epsilon_1 > \delta_1 \end{cases}$$

Which

$$\delta = range(\bar{x} + 1.\alpha : \bar{x} - 1.\alpha) \quad (15)$$

$$\delta_1 = mode(\epsilon_1) \quad (16)$$

The post reconstruction enhancement is proposed additional procedure to increase the reconstructed image resulted by the Compressive Sensing based imaging algorithm. Simple Threshold based method is proposed on the post reconstruction enhancement to maintain the algorithm complexity.

C. Simulation Set Up

A simulation is set up to evaluate the performance of the proposed ECVT imaging algorithm. A cylindrical geometry sensor with 8 attached square electrodes is built to imitate the ECVT sensor as illustrated in Figure 3. Objects that has significant dielectric contrast to the environment is located in the middle of the sensor domain with various dielectric contrast. The imaging algorithm should detects the existence of the object.

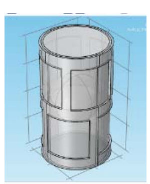


Fig 3. Cylindrical Sensor with 8 electrodes, *d*=10 cm, *h*=20 cm, *Source* [12] *CTech Lab*

Table I describes the properties of the simulation apparatus including the sensor geometry, property of detected object, contrast dielectric, and performance measurement. Coefficient of correlation (R) and algorithm complexity $o(n)$ are the quantitative measurements for evaluating the imaging algorithm performance. The evaluation is also supported by qualitative assessment by observing the resulted image.

TABLE I. PROPERTIES OF SIMULATION

Simulation Parameter	Specification
Sensor Geometry	Cylindrical Sensor with 8 electrodes attached
Objects	One sphere on the center of the sensor
Contrast Dielectric	1:3; 1:6; 1:70
Performance Evaluation	Qualitative measurement, R, $o(n)$

IV. RESULT AND DISCUSSION

To show the impact of the additional post reconstruction enhancement into the proposed compressive sensing based imaging algorithm on static ECVT Imaging, the simulation results with and without the assignment of the post reconstruction enhancement are presented. The performance's comparison with the conventional ECVT Imaging, ILBP is following.

A. Analysis on Additional Post Reconstruction Enhancement

The additional post reconstruction enhancement by proposed double layer soft threshold is assigned after observing that the compressive sensing based imaging algorithm succeeds to reconstruct the perturbation inside the ECVT sensor but resulting disturbing noise at the same time. The proposed simple double layer soft threshold succeeds to eliminate the disturbing noise as presented on Figure 5 up to Figure 8.

To enrich the analysis, the conventional hard threshold is also simulated and compared to the proposed threshold method. The accuracy is measured by using Coefficient of correlation (R) as presented on Table II below

TABLE II. THE IMPACT OF THRESHOLD INTO ECVT IMAGING BY CS IN R (COEFFICIENTT OF CORRELATION)

Contrast Dielectric	Without Threshold	Hard Threshold	Double Layer Soft Threshold
1:3	0.6934	0.7331	0.8269
1:6	0.7019	0.7409	0.8454
1:70	0.7732	0.8464	0.8678

Based on the accuracy presented on Table II, it can be seen roughly that post reconstruction enhancement by threshold both conventional hard threshold and proposed double layer soft threshold is able to increase the imaging performance not only in low contrast dielectric but also in high contrast dielectric. The conventional hard threshold is able to increase the performance up to 7% in average while the proposed double layer soft threshold performs much better by increasing the performance up to 17% in average. It means, the proposed threshold formula succeed to elevate the CS-based ECVT imaging method by 10% in average. It seems shallow but so much improvement as shown on the supported qualitative analysis which is figured on Figure 5 up to Figure 8.

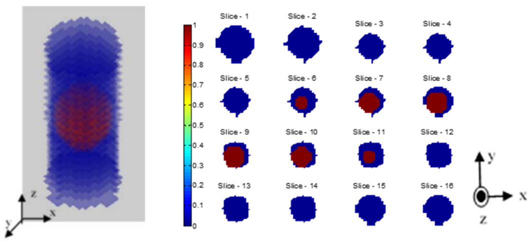


Fig 4. The Reference Image

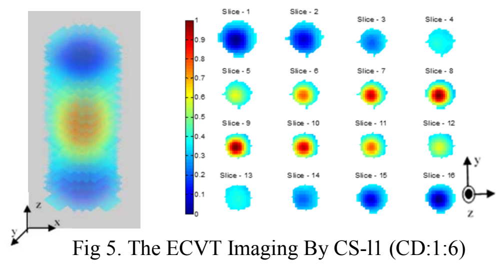


Fig 5. The ECVT Imaging By CS-l1 (CD:1:6)

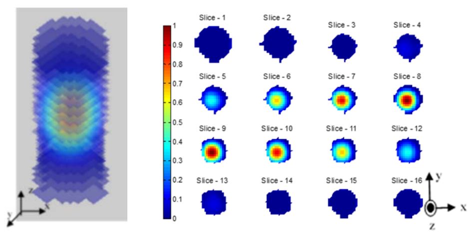


Fig 6. The ECVT Imaging By CS-l1-Hard Threshold (CD:1:6)

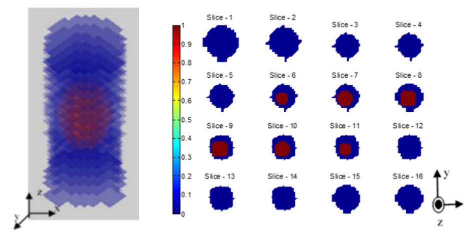


Fig 7. The ECVT Imaging By CS-l1-Double Layer Soft Threshold (CD:1:6)

Figure 4 is the reference image which represents the real perturbation inside the sensing domain. While, Figure 5 up to Figure 7 present the imaging results for static ECVT imaging by proposed algorithm on contrast dielectric 1:6. On Figure 7, the static ECVT imaging is reconstructed by CS based algorithm without employing any post reconstruction image enhancement. It can be seen that the algorithm is able to detect the perturbation inside the sensing domain. However, the reconstructed image is followed by quite high noise which will interfere interpretation.

The proposed simple post reconstruction image enhancement, both by simple hard threshold (CS-ℓ_1--Hard Threshold) and double layer soft threshold (CS-ℓ_1-Double Layer Soft Threshold), succeeds to improve the reconstructed image by giving more localized imaging. Moreover, the proposed double layers soft threshold presents better precision compared to hard threshold as also presented on quantitative measurement in Table II.

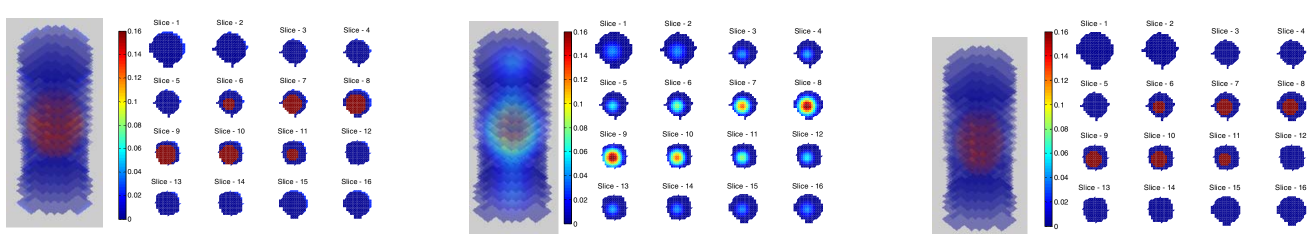
B. *Performance Comparison*

The best performance of the proposed compressive sensing based imaging method is compared to the conventional ECVT imaging method, ILBP). To evaluate the robustness subject to dielectric contrast, the ECVT imaging algorithms are simulated for various dielectric contrast which represent low and high dielectric contrast. Table III presents the accuracy of the proposed ECVT Imaging algorithm, CS-ℓ_1-Double Layer Soft Threshold, compared with the ECVT conventional imaging algorithm, ILPBP, in coefficient of correlation (R) parameter. It can be showed that the proposed method has significantly better accuracy compared with ILBP both in low or high dielectric contrast. In average the proposed ECVT Imaging algorithm is able to increase the accuracy up to 16.37%. The presented quantitative analysis is also supported by the qualitative measurements on high contrast dielectric as figured on Figure 8.

TABLE III. RECONSTRUCTION ACCURACY IN R FOR VARIOUS DIELECTRIC CONTRAST

Contrast Dielectric	CS-ℓ_1-Double Layer Soft Threshold	ILBP
1:3	0.8269	0.6957
1:6	0.8454	0.6981
1:70	0.8678	0.7889

Figure 8 consist of three ECVT imaging which is indexed by (a), (b), and (c). Point (a) represents the actual perturbation inside the sensing domain which is considered to be reference image. Point (b) is the static ECVT imaging by ILBP and point (c) by the proposed algorithm, CS-ℓ_1-Double Layer Soft Threshold.



(a) (b) (c)

Fig 8. ECVT Static Imaging on High Dielectric Contrast (1:70)
(a). ECVT Image Reference, (b). ECVT Imaging by ILBP, (c). ECVT Imaging by CS-ℓ_1-Double Layer Soft Threshold

The proposed ECVT imaging algorithm, CS-ℓ_1-Double Layer Soft Threshold, presents better image reconstruction as figured on Figure 8 (c). It no longer contains elongation error and give better precision.

Algorithm Complexity

Algorithm complexity is another thing besides accuracy that should be evaluated on discussing an algorithm's performance. As general, the proposed ECVT imaging method, CS-ℓ_1-Double Layer Soft Threshold, exceed the conventional ECVT imaging, ILBP, in terms of accuracy. Table IV presents and compared the algorithm complexity between ILBP and Compressive Sensing based ECVT imaging method.

TABLE IV. ALGORITHM COMPLEXITY

ECVT Imaging Method	**Algorithm Complexity *O*(n)**
ILBP	$O(7n+3)$
CS-l1-Hard Th	$O(n^{2.37}+ nlog(n)+4)$
CS-l1-Double Layer Soft Th	$O(n^{2.37}+ nlog(n)+10)$

As shown on Table IV, ILBP has much more better algorithm complexity since it is linear. It indicates that ILBP is easy to be implemented and low computational cost.

Compressive sensing based ECVT imaging as the proposed imaging method has polynomial algorithm complexity. Compared with ILBP, it is worse. The polynomial appears since there is multiplication between sensing matrix and dictionary process in compressive sensing based ECVT imaging method. However, it can be resolved by using computer hardware with higher memory storage.

If it is utilized for static imaging with 16 x 16 x 16 voxel dimension, the personal laptop with 8GB RAM, i7 processor still can handle it smoothly. The difference running time of the proposed method with the ILBP is only around 1 seconds (elapsed time). The higher RAM memory needed if the imaging is projected into 32 x 32 x 32 voxel and above dimension.

V. CONCLUSION

A Compressive Sensing based imaging method has been proposed for static ECVT imaging. It is enriched by post reconstruction image enhancement with proposed threshold method, double layers soft threshold, to increase the accuracy of the reconstructed image. The threshold procedure on the post reconstruction process succeeds to increase the imaging accuracy up to 17% on average.

In terms of accuracy the proposed ECVT imaging method, CS-ℓ_1-Double Layer Soft Threshold, exceeds the performance of the conventional ECVT imaging method, ILBP. The proposed method is able to elevate the reconstruction accuracy up to 16.7% on average. However, the tradeoff is on the algorithm complexity. In terms of algorithm complexity, the proposed algorithm has higher computational cost compared with ILBP. The limitation is still worth since the producing imaging improves the interpretation's accuracy. The complexity weakness can be resolved by using computer hardware with higher memory.

ACKNOWLEDGMENT

The authors would like to thank CTech Lab Edwar Technology for their supportive discussions and some research resources.

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