Unsupervised vector quantization for robust lung state estimation of an EIT image sequence

Philipp Hörler, Guido Schuster and Reto Bonderer
Department of Electrical Engineering, HSR University of Applied Sciences, Rapperswil, Switzerland
{philipp.hoerler, guido.schuster, reto.bonderer}@hsr.ch

***Abstract*—Every year, several ten thousand patients die on mechanical ventilation. This happens because the lungs can currently not be monitored adequately in real-time, and thus suboptimal ventilator settings can cause severe lung tissue damage. Electrical Impedance Tomography (EIT) produces a real-time image sequence of the breathing lungs. So far, no automatic method has been available to detect the physiological regional lung states. We propose an algorithm that clusters the raw pixel-based data of the EIT image sequence into clinically relevant regions with similar physiological behavior. Our implementation is very robust regarding bad signal quality due to low signal to noise ratio (SNR). It is also highly efficient in terms of computational complexity by considering additional physiological knowledge. The functionality of the algorithm has been verified using EIT data of a human subject with acute lung failure at various Positive End-Expiratory Pressure (PEEP) levels. The results are in agreement with the study protocol. This method brings EIT treatment one step closer towards protective ventilation therapy.**

***Index Terms*—Computer Aided Diagnostics, EIT, Vector Quantization, Dynamic Programming, Lung Imaging**

I. INTRODUCTION

Mechanical ventilation therapy is the mainstay of treating patients with acute lung injury (ALI) or its more severe form, the acute respiratory distress syndrome (ARDS). However, the lung can only be treated optimally if the ventilation parameters are adjusted for an individual patient's need. Because to date, only the state of the global but not the regional condition of the lung can be monitored in real-time, the tidal volume or the airway pressure level (PEEP) of the ventilator is often not optimally set. Thus, already strained lung tissue can be further distended or even destroyed (ventilator-induced lung injury [1], [2]).

The physiological behavior of the breathing lung can be monitored by utilizing Electrical Impedance Tomography (EIT) [3], [4]. While changes in regional compliance have been used to set the mechanical ventilator, no automated method is available to extract the different regional lung states from the EIT images. The proposed method interprets raw EIT data into a physiologically meaningful color-coded lung image.

II. IMAGE CLUSTERING PROCESS

We use *vector quantization* [5] which is highly robust regarding bad signal quality due to low signal to noise ratio (SNR). Vector quantization is widely used in many popular applications, e.g. in speech recognition.

In our approach, the vector quantizer finds the most likely lung state of each pixel of the incoming EIT images. We consider five clinically relevant lung states in our model: *static over-distention*, *dynamic over-distention*, *healthy*, *dynamic collapse* and *static collapse*. Hence, the task is to find a maximum of five clusters, each containig pixels with similar characteristic temporal signals for that particular physiological lung state.

An image buffer, shown in Fig. 1a, stores the current and the N recent images to provide temporal information out of the EIT snapshots. It is sufficient to cluster the image column-wise because the clusters are contiguous and in sequence along the gravity vector [6]. Figure 1b depicts the input vectors of a selected column.

The measured EIT signals are different with each patient. An unsupervised vector quantization is required because no a priori knowledge of the cluster representatives is available. The representative signal of a cluster is defined as its ensemble average signal. The vector quantizer assigns every pixel to the cluster that results in the highest similarity. This means that a pixel is very similar to the other pixels in its cluster but very different to pixels in other clusters. The quantization algorithm varies the cluster boundaries until the optimal cluster distribution produces the lowest possible global distortion value, i. e. the sum of each cluster's distortion. The distortion value is the measure of similarity and defines and controls the decision base of the quantizer. It can easily be adapted to changing application requirements. The resulting clustering for one column is depicted in Fig. 1c. After a column has been processed by the algorithm, the next column is selected and processed the same way.

As soon as the last column has been processed, a color-coded image is available according to the cluster distribution (Fig. 1d). Each color corresponds to the physiological lung state of that specific voxel within the human thorax.

III. IMPLEMENTATION

A trivial, exhaustive approach evaluates all combinations iteratively in order to find the optimal cluster distribution producing the smallest global distortion. The global distortion is calculated at each iteration step and compared against

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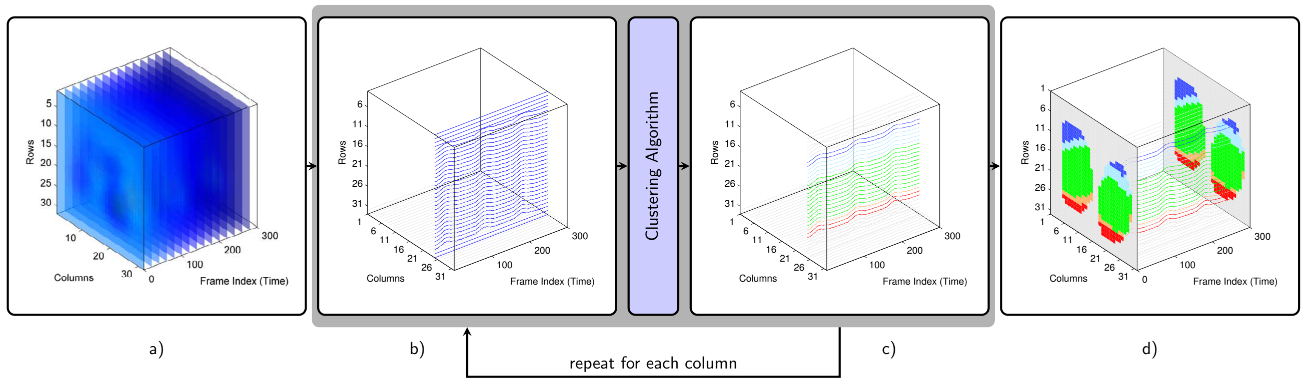

Fig. 1. Image clustering process: a) incoming EIT image sequence, b) extracted input vectors of one column, c) clustered output vectors and d) estimated lung state after all columns have been processed.

the previous best stored match. If the new distribution is closer to the optimum, then the best match is replaced by the current global distortion and the present distribution. An iterative implementation like this is very expensive in terms of computational complexity. It is $O(R^W)$, where R is the number of rows and W is the number of clusters. These algorithms demand a lot of computation power and therefore require expensive hardware.

Dynamic programming is a much more efficient approach. The lung state estimation problem can be broken down into one simpler sub-problem for each cluster. The optimal structure property exists since over-distended, healthy and collapsed lung states appear contiguous and in sequence along the gravity vector [6]. By utilizing a trellis graph, the clustering can be postponed until we can look at a sequence of decisions. The drawback of postponing a decision is that the number of choices increases exponentially with each sample. We use dynamic programming to keep this explosive growth of choices under control. The dynamic program is implemented as a *Viterbi algorithm* adapted from [5].

The dynamically programmed algorithm is $O(R^2W)$, i.e. it only increases linearly with the number of clusters.

IV. Conclusions and Future Work

We have developed a highly efficient vector quantization algorithm to cluster temporal EIT data according to the physiological state of the lungs. The performance of the algorithm has been determined using EIT data recorded during a progressive lung recruitment maneuver [7].

Due to gravity, the sequence of collapsed lung states along the columns (which are collinear with the gravity vector) is not arbitrary, but structured in a way that suggests a dynamic programming solution. The computational complexity is reduced this way from $O(R^W)$ to $O(R^2W)$. This massive optimization allows the algorithm to run even on low power and low-cost embedded computer systems.

Using the EIT image sequences of [7], we confirmed that our algorithm is able to estimate the physiological lung states of individual regions. The algorithm and particularly the structure of the distortion function must be optimized and verified within a comprehensive test series. Of major importance is a corresponding ground truth for the test series data. This is required to validate the algorithm against the correct clinically relevant lung states.

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