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Sensor selection for tidal volume determination via regression – proof of methodology

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Abstract: Measurement of respiratory volumes based on breath-related upper body movements continues to be a subject of interest in science and research. In general, smart garments are becoming more common in medical diagnostics and therapy monitoring, and improved, miniaturized and more accurate sensors are opening up new opportunities. A crucial issue in the development of smart clothing is how many sensors to use and where to place them in the clothes. Using data from a motion capture system, two different regression methods (Lasso and Ridge) were evaluated that can be used to select appropriate sensor subsets. The performance of the subsets, obtained by the regression methods, were compared with the best set of sensors obtained by analysing all possible subsets. The Lasso method showed clear performance advantages over Ridge regression in this field of application, but both methods can be employed as they significantly reduce time and computational effort.

I. Introduction

Spirometry [1] and body plethysmography [2] are gold standards in pulmonary diagnosis. Both methods are based on airflow measurement through the mouth and nose. For decades, scientists and researchers have been working on an alternative measurement method to determine tidal volumes via breath-induced movement of the upper body surface. The potential benefits of an alternative to flow measurement have been known for a long time. Recently, new sensors and sensor technologies opened up new possibilities and new applications. Therefore, smart clothing is increasingly used in medical diagnostics and therapy monitoring [3]. Regarding the field of pulmonary diagnostics, a number of studies have already attempted to determine respiratory volume using different types of sensors. There were approaches via inertial measurement units (IMUs) [4], strain gauges [5], or via optical encoders [6]. However, a breakthrough approach has not yet been found.

In the development of smart shirts, minimizing the number of sensors is a very important aspect, as it reduces both complexity and cost. Based on the data of a motion capture system (MoCap) for measuring respiration-induced upper body movements, the results of two regression methods for sensor selection were compared with the optimal sensor set, obtained by analysing all possible combinations.

II. Methods

A motion capture system (MoCap) was used in this study as an optoelectronic plethysmograph to obtain respiratory movements of the upper body. The MoCap (Bonita, VICON, Denver, CO) used nine infrared cameras (VICON Bonita B10, firmware version 404) to record movements of 102 reflective motion capture markers, which were attached to a tight fit compression shirt (Fig. 1).

Figure 1: Sketch of the MoCap system and compression shirt.

The MoCap markers were placed evenly distributed in 7 different heights to the shirt. The VICON Nexus software (version 1.8.5.6 1009h, Vicon Motion Systems Ltd.) was used to process the MoCap raw data and to transfer them to MATLAB (R2021a, The MathWorks, Natick, USA) for further numerical analysis. Simultaneously, a spirometer (SpiroScout with LFX Software 1.8, Ganshorn Medizin Electronic GmbH, Niederlauer, Germany) measured respiratory volumes $\mathbf{v}_{Spiro}$ as a reference.

Five lung-healthy subjects (3 men and 2 women) attended the study. The subjects' average weight, age, and height were 66.2 ± 4.5 kg, 22.2 ± 2.5 years, and 1.75 ± 0.04 m, respectively. Between phases of normal spontaneous breathing, the subjects were instructed to perform shallow breaths, medium breaths and maximum breaths for about one minute.

Therefore, according to Laufer et al. [7] the movement of each MoCap marker was referred to its main movement axis. The resulting position changes of all MoCap markers were arranged in matrix form ($\mathbf{A_L}$) and a regression analysis was performed to solve $\mathbf{A_L x} = \mathbf{v}_{Spiro}$.

Based on the MoCap data during the measurement, two different regression methods that allow the selection of a sensor subset were compared with the optimal sensor subset, obtained by analysing all possible combinations. But this process is very computationally intensive, and therefore alternative methods were required - for larger subsets it is usually not feasible to analyse all combinations. A subset of 4 of 102 sensors yields to $4.2\cdot10^6$ combinations, a subset of 5 of 102 sensors to $83\cdot10^6$ and a subset of 6 of 102 sensors to $1.3\cdot10^9$ possible combinations.

One of the regression methods used was Ridge regression [8]. Ridge regression solves:

$$\mathbf{x}_{opt} = [x_1, \dots x_n]^T_{opt} = \underset{\mathbf{x}}{\operatorname{argmin}}\left(\left\|\mathbf{A_L x} - \mathbf{v}_{spiro}\right\|_2 + \alpha\|\mathbf{x}\|_2\right)$$

where n is 102, the number of parameters / sensors and $\alpha\|\mathbf{x}\|_2$ is the Tikhonov regularization term using α as regularization factor.

To reduce the sensor set to k sensors, the sensors were selected to which the k highest absolute values of $\boldsymbol{x}_{opt}$ were assigned.

The other regression method used was the least absolute shrinkage and selection operator (Lasso) [9], which enabled a sparse solution for $\mathbf{x}$, solving:

$$\mathbf{x}_{opt} = [x_1, \dots x_m]^T_{opt} = \underset{\mathbf{x}}{\operatorname{argmin}}\left(\left\|\mathbf{A_L x} - \mathbf{v}_{spiro}\right\|_2 + \lambda\|\mathbf{x}\|_1\right)$$

where m is the number of chosen parameters and $\lambda\|\mathbf{x}\|_1$ the penalty term of the regularization with λ as regularization factor.

By a suitable selection of λ, the number of sensors could be reduced to k sensors. The Lasso method is robust to outliers, provides sparse solutions, and prevents overfitting. In particular, the Lasso property of providing sparse solutions is advantageous in the context of sensor selection. The Ridge regression does not offer sparse solutions, but compared to analysing all possible combinations, the time and computational cost for the Lasso and the Ridge methods are negligible. Thus, these two regression methods were compared to the truly best sensor set, obtained by analysing all sensor combinations - the one provided the lowest mean error was selected.

Since it is difficult to achieve a robust comparison of both methods based on 5 data sets only, a bootstrapping resampling procedure was used. From each of the 5 measurements, 100 random data segments (of random length) were selected on which the analysis was performed. The bootstrapping method, in contrast, allows a considerably more robust and meaningful comparison.

III. Results and discussion

Fig. 2 shows the direct comparison between the optimal combination, the Lasso technique and the Ridge regression. The mean errors of the two regression methods are almost the same, but are found to be higher than the mean errors of the optimal method. Compared to lasso and optimal method, ridge regression has higher peak errors. Therefore, the Lasso variant outperformed the Ridge regression. In addition, Lasso's tendency to sparse solutions can be used to minimize the number of sensors used for smart shirt development - thus reducing the cost and complexity of the shirt.

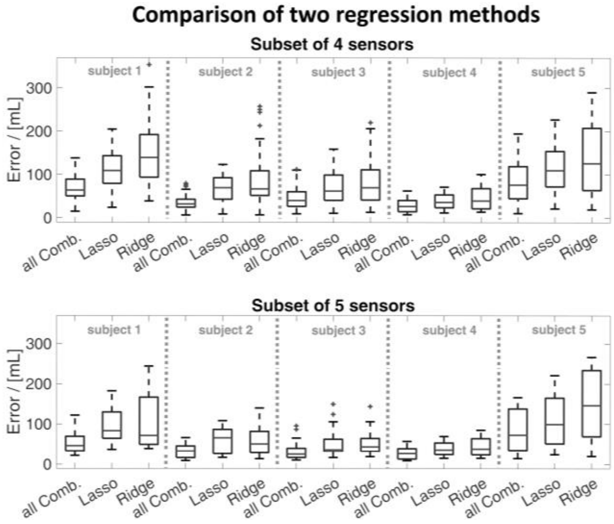

Figure 2: Errors of the different approaches, regarding subsets of 4 sensors (top) and subsets of 5 sensors (down)

IV. Conclusions

Both regression methods show that they are capable of defining subsets with low computational and time effort, but their performance is below the performance of the optimal subset. Lasso is preferable to Ridge regression.

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Author's statement

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