Data-Driven Modal Decomposition Technique for Medical image analysis

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Nowadays, no one can deny the advances made by modal decomposition techniques. These methods, which are rooted in numerical linear algebra, can also be formulated as fully data-driven methods. This last allows us to discover and extract useful information from raw, complex data.
Generally, for data-driven methods, the data is arranged in large matrices as follows:

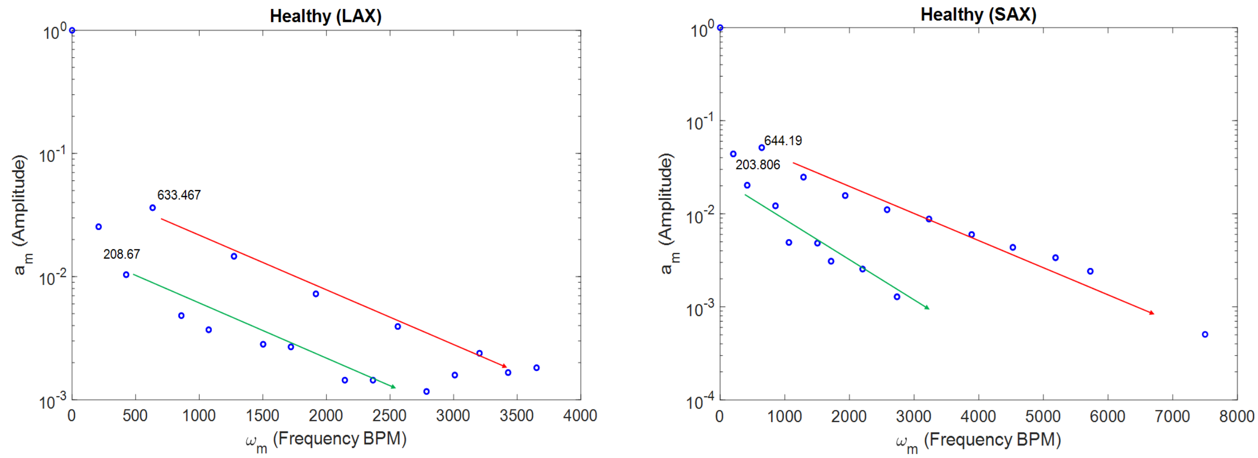
$$\boldsymbol{V}_1^K = [\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_k, \ldots, \boldsymbol{v}_K], \quad \text{with} \quad k = 1, \ldots, K, \tag{1}$$

where the column vectors $\boldsymbol{v}_1, \ldots, \boldsymbol{v}_k$ may include measurements obtained at different time instants, or frames (snapshots) of a video taken from a particular experiment.

In this work we present a data-driven, modal decomposition technique, capable of handling these type of data matrices. The technique, which is named the higher order dynamic mode decomposition (HODMD) [1], was originally introduced in the field of fluid mechanics for the analysis of complex data. This technique decomposes the spatio-temporal data $\boldsymbol{v}_k$ into an expansion of modes $\boldsymbol{u}_m$, where each mode has its own amplitude a_m, frequency ω_m and growth rate δ_m, as follows:

$$\boldsymbol{v}(t) \simeq \sum_{m=1}^{M} a_m \boldsymbol{u}_m e^{(\delta_m + i\omega_m)t_k} \quad \text{for} \quad k = 1, \ldots, K, \tag{2}$$

In this contribution we cover two main points: first, we elaborate on the two main steps of the HODMD technique. Second, we demonstrate the application of the HODMD algorithm on medical datasets, as we have recently introduced the HODMD technique to the medical field [2]. In particular, for the analysis of 2D echocardiography images. Hence, in this case $\boldsymbol{x} = (x_1, x_2)^T$, such that x_1 and x_2 are the horizontal and vertical coordinates of the image pixel, respectively.
The datasets presented in this document are taken from a mouse model in healthy conditions, and it encompasses two video loops taken from a long axis view (LAX) and a short axis view (SAX). Each dataset consist of the maximum number of 300 snapshots, covering at least three complete cardiac cycles.
In Figure (1), we present the results obtained from analyzing these two datasets using the HODMD algorithm. As we can observe, the HODMD was able to identify two signals, which can be seen divided into two different lines. The upper branch in both plots represents the heart rate, and the lower branch represent the respiratory rate. The dominant frequency for the LAX data is 633 beat per minute for the heart rate and 208 breath per minute for the respiratory rate. Similar results can be observed for the SAX data, as the dominant frequency is 644 beat per minute for the heart rate and 203 breath per minute for the respiratory rate.



(a) (b)

Figure 1: The frequencies captured from analyzing the data of the healthy heart (LAX on the left and SAX on the right)

Furthermore, as shown in table (1), and as anticipated, the two signals are periodic. Further details and results can be found in [2].

Frequencies		ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7	ω_8	ω_9	ω_{10}
Healthy	LAX	0	208.6	425.4	633.4	859.2	1074.2	1273.2	1502.4	1720.6	1916.9
	SAX	0	203.8	419.0	644.1	856.2	1063.9	1289.2	1505.0	1716.4	1934.4

Table 1: Frequency of the healthy dataset for both LAX and SAX.

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