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Characterisation of Arteriovenous Fistula's Sound Recordings using Principal Component Analysis

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***Abstract*— In this study, a signal analysis framework based on the Karhunen-Loève expansion and *k*-means clustering algorithm is proposed for the characterisation of arteriovenous (AV) fistula's sound recordings. The Karhunen-Loève (KL) coefficients corresponding to the directions of maximum variance were used as classification features, which were clustered applying *k*-means algorithm. The results showed that one natural cluster was found for similar AV fistula's state recordings. On the other hand, when stenotic and non-stenotic AV fistula's recordings were processed together, the two most significant KL coefficients contain important information that can be used for classification or discrimination between these AV fistula's states.**

I. INTRODUCTION

Arteriovenous (AV) fistula is a vascular access used for cannulation in hemodialysis treatment. A surgeon creates an AV fistula by connecting an artery directly to a vein. The connection point is referred as *anastomosis* and it is commonly located near the patients wrist or elbow.

The most common fistula failure is venous stenosis [1]. Stenosis is an abnormal narrowing in a blood vessel or other tubular organ or structure. When blood is ejected through narrow vessels or arteries, the blood flow becomes turbulent. These turbulences generate measurable sounds "murmurs" that can be used for early and non-invasive diagnosis of stenosis [2].

In coronary artery diseases, murmurs have been associated with more spectral energy in the higher frequency bands. In [3], it is shown that the frequency bands where this extra spectral energy is located depend on the applied spectral analysis method e.g. eigenvector method. In a comparative study of diseased and normal patients, it was found that the extra spectral energy in the band between 300 and 800 Hz was significally reduced in normal patients [4]. *In vivo* studies have also been conducted [5], [6]. In [5], the wavelet transform was used to characterise turbulent sounds caused by a controlled occlusion in the femoral artery of dogs. The results showed that in the time domain, the turbulent sounds occurred at the peak of the blow flow and that the heart sounds contained more energy in the band between 200 and 1000 Hz.

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Even though phonoangiography has been used extensively in coronary artery diseases, few studies have been carried out in venous stenosis. In [7], it is shown that normal fistulas have highest signal amplitude close to the anastomosis and it declines when you move downstream. Moreover, it was found that in the time domain the systolic peak of stenotic segments is higher and narrower compared to non-stenotic segments.

The purpose of the present paper is to identify features of the AV fistula's sound recordings that can be utilised for characterising the state of the fistula. The signal analysis framework combines Karhunen-Loève expansion and *k*-means algorithm. The idea is to evaluate if the directions of maximum variance can contain good feature for classification or discrimination of AV fistula's state. This paper is organised as follows. Section 2 presents a description of the dataset and the methods used to characterise the recordings. The results are described in section 3 and finally the conclusions and future works are presented in section 4.

II. METHODOLOGY

In this section, the dataset used in the present study and the proposed signal analysis framework are described. The signal analysis framework is comprised of three stages. At the pre-processing stage, the envelope of the fistula's sound recording is computed and segmented, i.e. the timing of the maximum peaks are determined. Then, the mean correlation matrix $\overline{\mathbf{R}}_x$ is estimated and the Karhunen-Loève expansion is used to compute and determine the most significant basis functions. Finally, the classification of the principal components is carried out by *k*-means clustering algorithm.

A. Dataset

The recordings were made in end-stage renal failure patients. These patients underwent hemodialysis treatment three times a week. Six patients were selected from the dataset available in [7]. The first five patient were selected according to the following criteria: 1) No history of the stenosis at the anastomosis and 2) at least 40 seconds recordings. One extra patient was selected because underwent angioplasty during the measurement campaign and it provides a valuable before and after case. For the latter patient, recordings at the site of the lesion were made before and after angioplasty. Table 1 summarises the details of the dataset.

B. Pre-processing

Before computing the envelope of the signal, distorting components, e.g. baseline wander, and sounds not originating

TABLE I

MEASUREMENT POINT AND DURATION OF THE FISTULA'S SOUND RECORDINGS

Patient	Recording Site	Duration	Heart rate
P1	Anastomosis session 1	30 Sec	66 bpm
	Anastomosis session 2	15 Sec	68 bpm
P2	Anastomosis session 1	30 Sec	66 bpm
	Anastomosis session 2	15 Sec	67 bpm
P3	Anastomosis session 1	30 Sec	74 bpm
	Anastomosis session 2	15 Sec	75 bpm
P6	Anastomosis session 1	30 Sec	74 bpm
	Anastomosis session 2	10 Sec	78 bpm
P7	Anastomosis session 1	30 Sec	73 bpm
	Anastomosis session 2	30 Sec	72 bpm
K2	Before angioplasty	40 Sec	93 bpm
	After angioplasty	20 Sec	95 bpm

from the fistula were removed by feeding the signal to a 50 Hz high-pass filter.

The envelope of the signal $s(n)$ was calculated utilising the method described in [8], where the envelope is expressed as

$$x(n) = \sqrt{s^2(n) + \check{s}^2(n)}, \quad (1)$$

and $\check{s}^2(n)$ is the Hilbert transform of $s(n)$. Then, the envelope was filtered with a 10 Hz low-pass filter and the index of the maximum peak was determined for every pulse interval present in the envelope. Since the detected segments were not equally long, the segments were aligned to the maximum peak and a fixed duration, around it, was used for all the segments. This fixed duration was based on the heart rate of the patient at the moment of recording. Subsequently, each detected segment was normalised in amplitude as follows

$$\mathbf{x}_i = \frac{\mathbf{x}_i^*}{max(\mathbf{x}_i^*)}, \quad (2)$$

where $\mathbf{x}_i^*$ is the i^{th} unnormalised detected segment. When fistula's sound recordings of different patients were combined and processed together, each segment was considered as a zero mean process, i.e. the mean of the segment was subtracted from it. However, when recordings of the same patient were processed, the mean was kept because this procedure would discard important information [9]. Fig. 1 shows an example of the sound signal $s(n)$, envelope $x(n)$ and filtered envelope.

C. Karhunen-Loève Expansion

A normalised detected segment can be represented by a linear combination of basis functions $\boldsymbol{\varphi}_k$:

$$\mathbf{x}_i = \sum_{k=1}^{N} w_{i,k}\boldsymbol{\varphi}_k. \quad (3)$$

The KL basis functions were obtained as the most significant eigenvectors of the mean correlation matrix $\overline{\mathbf{R}}_x$ that results from the normalised detected segments in the signal's envelope.

Once the eigenvectors and eigenvalues of $\overline{\mathbf{R}}_x$ were calculated, the cumulative energy index described in [8] was used to determine the energy content in each basis function. This index is expressed as

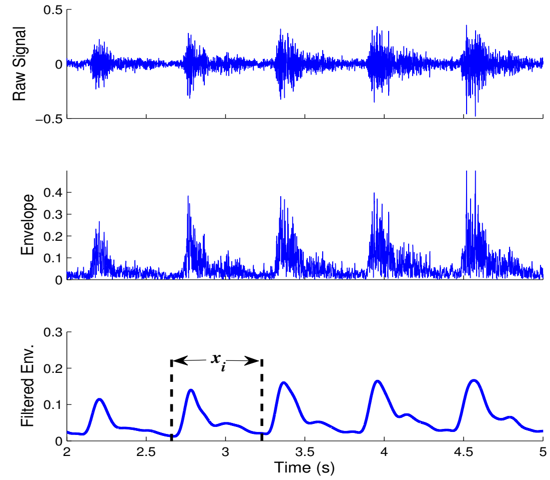

Fig. 1. Three seconds example of the sound signal, envelope and filtered envelope

$$R_K = \frac{\sum_{k=1}^{K}\lambda_k}{\sum_{k=1}^{L}\lambda_k}. \quad (4)$$

The KL basis functions which contain the 95% of the total energy were considered as the most significant. Subsequently, each KL coefficient vector $\mathbf{w}_{K,i}$ was calculated as follows

$$\mathbf{w}_{K,i} = \mathbf{\Phi}^T\mathbf{x}_i \quad and \quad \mathbf{\Phi} = [\boldsymbol{\varphi}_1 \quad \boldsymbol{\varphi}_2 \quad \cdots \quad \boldsymbol{\varphi}_K], \quad (5)$$

where K denotes the number of most significant basis functions.

A KL coefficient vector, $\mathbf{w}_{K,i}$ was considered as outlier if

$$\mathbf{w}_{K,i} < q_1 - 1.5H \quad or \quad \mathbf{w}_{K,i} > f_3 = q_3 + 1.5H, \quad (6)$$

where q_1, q_3 and H are the first quartile, third quartile, and interquartile range respectively [10].

D. K-means Algorithm

K-means is an unsupervised learning algorithm that solve the well known clustering problem. The algorithm is composed of the following steps [11]:

1) Select the number of clusters: c and the initial centroids: $\mu_1, ..., \mu_c$.
2) Classify samples according to nearest μ_i.
3) Recompute μ_i.
4) Repeat steps 2 and 3 until μ_i no longer move.
5) Return the centroids: $\mu_1, \ldots, \mu_c$.

The selection of the initial centroids was carried out in two steps: 1) the centroids were selected randomly from a 10% KL coefficients subset, then k-means algorithm was applied to the subset. 2) The resulting centroids were used to initialise the k-means algorithm, but this time applied to all the KL coefficients.

A square Euclidean distance metric was used to classify the KL coefficients,

$$D = \sum_{i=1}^{K} (w_i - v_i)^2, \tag{7}$$

where w_i and v_i have K coordinates corresponding to the most significant basis functions.

III. RESULTS

A. Basis Functions

The cumulative energy index, R_K, was calculated for all the recordings. In all cases, the two most significant KL basis functions accounted together for at least 95% of the total energy.

The ten recordings at the anastomosis were processed together and the two most significant basis functions are shown in Fig. 2. These two functions may be interpreted as follows: the most significant basis function reflects the average shape of the pulse waveform. Meanwhile, the second basis function reflects delayed contributions to the pulse waveform. If the anastomosis's recordings are processed by patient, the energy increases to 99% and the basis functions are very similar to the shown ones in Fig. 2.

For the case of before and after angioplasty (patient K2), the recordings were combined and the most significant basis functions are shown in Fig. 3. Both basis functions are similar to the obtained ones for the anastomosis's recordings (see Fig. 2) and the change in the sign of the second basis functions can be given to numerical issues.

B. Clustering

For every segment $\mathbf{x}_i$, the KL coefficients corresponding to the most significant basis functions were computed using (5) and clustered with k-means algorithm.

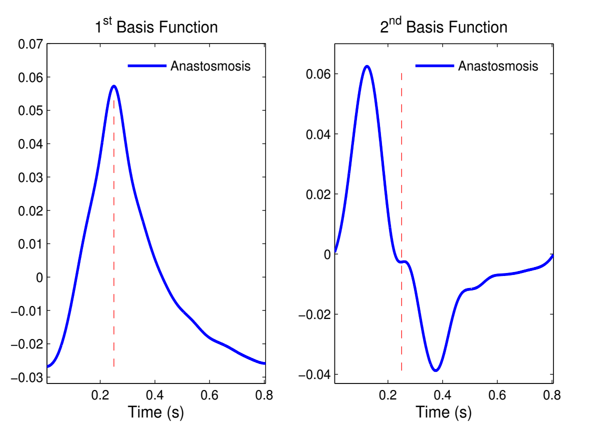

Fig. 2. The 2 most significant KL basis functions: anastomosis's recordings

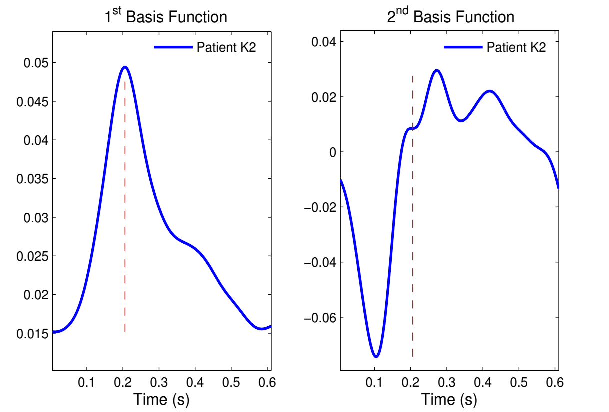

Fig. 3. The 2 most significant KL basis functions: patient K2

For the anastomosis recordings, an unknown number of classes were considered in the data. Therefore, the clustering problem was solved repeatedly for different number of clusters. The results suggest one natural cluster because independently of the number of clusters, the distribution of the coefficients tends to be equitable, i.e. similar amount of coefficients contributed by each patient to the same cluster. This can be explained by the fact that according to the clinic records, all AV fistulas were working properly, i.e. no stenosis at the anastomosis by the time the recordings were made [7]. Hence, the proposed signal analysis framework seems to be not affected by parameters that change from patient to patient such as vessel's diameter and blood flow velocity.

For patient K2, the number of classes were known: two. All the recordings of this patient were processed together and the two most significant basis functions were utilised to compute the KL coefficients. Since, the solution of k-means depends on the initial centroids, a local minimum can be reached. To overcome this problem, 10 replicates were carried out and the one with the lowest total sum of distances is shown in Fig. 4. The first cluster is mainly formed by coefficients coming from after angioplasty recordings 69.1%. Meanwhile, cluster 2 has 87.1% of the coefficients coming from before angioplasty recordings, see table 2. Since some factors as a variations of the heart rate (caused by the parasympathetic and sympathetic activity) can affect a detected segment and therefore the KL coefficients, the misclassification shown in table 2 was expected. Thus, the results of k-means should be analysed based on the dominant behaviour of a recording rather than by detected segments. However, a threshold cannot be defined in this study due to the lack of data.

In summary, the KL coefficients definitely contain information that can be used for classification or discrimination of AV fistula's states. However, the results are preliminary and need to be further confirm by applying the method to a wider dataset.

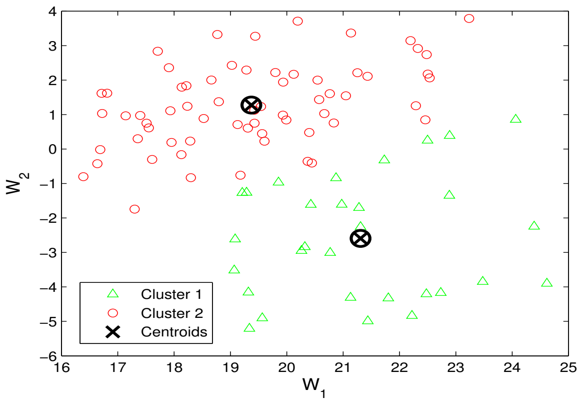

Fig. 4. Resulting clusters: before and after angioplasty

IV. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

A signal analysis framework for sound recordings of arteriovenous fistula based on principal component analysis and k-means algorithm is proposed. The results showed that the proposed signal analysis framework was consistent for similar AV fistula's state recordings for different patients. On the other hand, when stenotic recordings of AV fistulas were processed together with non-stenotic recordings, it was found that the KL coefficients corresponding to the most significant basis functions are potential features for classification or discrimination of AV fistula's states. However, the significance of these results need to be further established.

B. Future Works

The extension of the dataset is planned through data acquisition campaigns at Lund Hospital, Lund, Sweden and private hemodialysis clinics in Nicaragua to validate the results achieved with the proposed signal analysis framework.

V. ACKNOWLEDGEMENTS

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TABLE II

NUMBER OF COEFFICIENTS PER CLUSTER: BEFORE AND AFTER ANGIOPLASTY.

Recording Site	Cluster 1	Cluster 2	**Total**
Before Angioplasty	8	54	**62**
After Angioplasty	22	10	**32**
Total	**30**	**64**	**94**

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