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Monitoring and Analysis of Noise Levels in Intensive Care Units Using SSA Method

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ABSTRACT

Patients and staff in hospitals, including intensive care units (ICUs) can be exposed to high levels of acoustic noise. In many cases those levels can be significantly above the levels recommended by the World Health Organisation (WHO), affecting both patients and staff working on those units. A first step towards reducing the ICU noise is to monitor and analyse noise levels in the ICU. In most studies performed to date, the analysis of noise and noise levels has been done manually, via human interpretation of raw recorded results. This paper uses singular spectrum analysis (SSA) to process and analyse sound pressure levels (SPLs) recorded in ICUs in hospitals in Spain using a dedicated data logging system. SSA algorithm decomposes time-series, in this case SPL time-series measured over a period of time, into a number of components. Those components can then be analysed and interpreted individually or merged with some other components with similar characteristics to be analysed as a group. This approach reveals some interesting characteristics of the SPL time-series and could potentially help in predicting as well as preventing the high SPLs in the coming periods.

Keywords: Noise, Analysis, Decomposition
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1. BACKGROUND AND OBJECTIVES

Intensive care units (ICUs) are noisy and busy environments, with patients being subjected to disturbances throughout the day and night. The sources of noise in ICUs can range from the noise generated by the hospital staff on duty to noise generated by medical equipment, which generates both alarms to staff as well as operating noise. In many cases produced noise is important and necessary for the proper operation of the ICU. However, noise can induce significant changes in the depth and quality of sleep and negatively affect health and patient recovery in general. Furthermore, the physiological and psychological effects of poor sleep, including its association with delirium, has been recognised in recent studies. Delirium in critical care can be associated with a prolonged recovery, higher patient mortality and morbidity. Reduction of noise in ICUs would therefore be of significant benefit to both patients and staff in those units.

The World Health Organisation (WHO) recommendations for noise levels [1] suggest that hospitalised patients in observation or treatment areas should not be exposed to ambient sound levels greater than 35 dB, with a night-time peak noise level of 40 dB. A number of studies [2],[3] related to measurement, analysis and reduction of noise in ICUs have been reported in recent years. Many of those works have demonstrated the lack of compliance with these recommendations, with elevated sound levels being attributed to both equipment and human activity [4]. A number of reports also suggest that maintaining levels of ambient sound below the WHO recommendations is not achievable without a specific noise reduction management programme [5], [6].

Most of the studies performed in order to asses and analyse noise in ICUs are either focusing on standard measurement of noise levels in decibels in ICUs over a short period of time or, in addition to that provide some insight into the spectral nature of the noise [7]. The work reported in [3] analysed and compared levels of hospital noise through a number of years. Study has indicated that in approximately half century, since 1960 average daytime noise in hospitals increased from 57 dBA in 1960 to 72 dBA in 2005 while the average night time noise rose from 42 dBA to 60 dBA in the same period. This corresponds to linearly increasing trends of 0.38 dB/year during the day and 0.42 dB/year at night. The later works however, mainly focus on frequency analysis where the frequency of noise, in addition to noise amplitudes is calculated and provided. Very few studies focus on measurement and analysis of noise levels over longer periods of time. A study [8] conducted measurements of noise levels in ICUs and have reported levels as high as 79.7 dB during the night and 83.4 dB during the day. However, it might be of some interest and benefit to study and analyse the noise variation not only during a single day or night period but to conduct the study over a longer period of time - several days, weeks or even months.

The purpose of this paper is to help understand and interpret SPL time series measured over long periods of time in ICUs. For doing this, various time-series analysis and processing methods can be used. In this work a well-known singular spectrum analysis (SSA) algorithm has been applied to decompose the measured time-series into its oscillatory components for easier interpretation of measured SPL data. This allows gaining a better insight into variation of SPLs in ICUs over long time periods and may improve the ability to pinpoint, and perhaps even predict, the periods where ambient noise is likely to increase significantly above average values. This in turn would help preventing, or at least reducing, noise during the identified critical periods.

2. DATA BASE

The study has been done using a database provided by EcuDap, a company based in Burgos, Spain. EcuDap has developed a system (SAS 2000) to monitor, record and visualise level of noise in different living environments and has installed the system at a number of ICUs in different Spanish hospitals. The developed “Sound Ambience Supervisor” system, SAS 2000, performs a continuous recording and logging of sound pressure levels and other relevant parameters in the ICU (temperature, humidity, luminosity, movement detection). Measurements are logged once every minute and the recorded data, communicated to the network in order to be accessed and displayed via dedicated web page. The access to data is provided by assigning permissions that divides users into different roles to enable them to access data and at various levels of priority in terms of quantity of data and forms of visualization.

The data analysed with the SSA in this paper have been registered in Vigo Hospital ICU over the period 01/02/2019 – 07/03/2019 (35 days). As an example, a snapshot of the graphical display of measured SPL provided by the SAS 2000, showing the levels of noise measured over a period of 11 days in one of the monitored ICUs is provided in Figure 1.

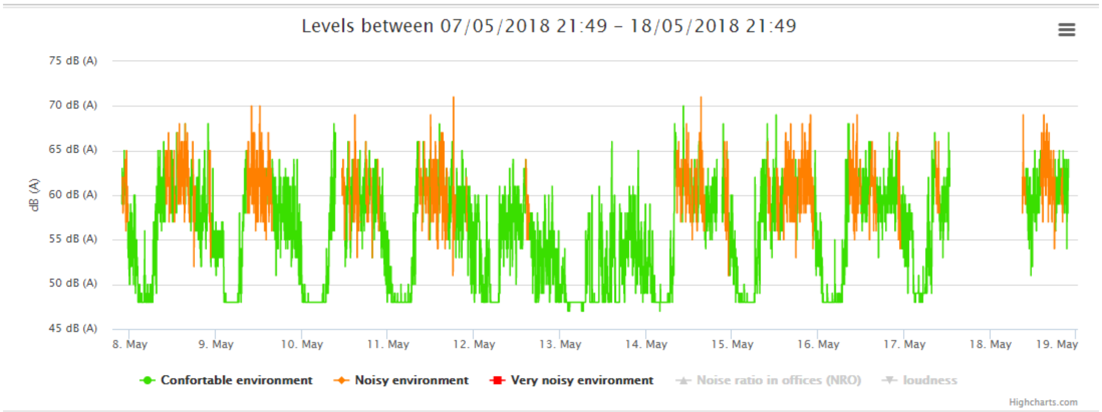


Figure 1. SPLs measured in ICU over a 11-day period

The raw time-series of measured SPLs in this figure shows the significant SPL variations both during the day as well as through the 11 days period captured by this measurement. Noticeable, some data is missing, towards the end of the measurement period, indicating the possible malfunction of the data-logging system. An approach to estimate the missing data in the recorded time-series, relying on estimating the individual components extracted via SSA is proposed and demonstrated in this work. Achieved interpolation accuracy is high and can be controlled by considering lower or higher number of SSA components in the estimation process.

The rest of the paper is organised in the following way. Basic theory of SSA algorithm is discussed in the next section. Following this, results of the SSA applied to time-series of measured SPLs are given in section 4 of the paper. Some conclusions are drawn and presented in the last section of the paper.

3. SINGULAR SPECTRUM ANALYSIS (SSA) OVERVIEW

The Singular Spectrum Analysis (SSA) [9], [10], [11] is a model-free, data-driven technique for data decomposition and analysis closely related to principal component analysis (PCA) [12], [13], [14] and similar data analysis methods. In the recent years, SSA has been successfully applied for feature extraction and perhaps more relevant to this work for time-series analysis in different areas of science, engineering and economy. The name of this method implies the use of singular value decomposition algorithm, where a set of obtained eigenvalues and corresponding eigenvectors gets added together to either obtain suitable decomposition of a time series or to extract components with particular oscillatory behaviour from time series. Some of the tasks SSA is especially well suited in solving include finding trends of different resolution, smoothing, extraction of seasonality components, simultaneous extraction of cycles with small and large periods, extraction of periodicities with varying amplitudes, finding structure in short time series and change-point detection.

SSA algorithm consists of two complementary stages – decomposition and reconstruction of the given data set with each of those two stages again performed through two separate steps. Decomposition is implemented via data embedding stage followed by the singular value decomposition of the embedded data. Reconstruction comprises grouping and diagonal averaging stages. Details of those sub-stages are described below.

3.1 Embedding

Basic SSA algorithm treats the univariate, i.e. one-dimensional time series of length L, $Y_L = (y_1, y_2, ..., y_L)$. Embedding stage transforms this series into multi-dimensional series, matrix of the form $\mathbf{X} = [X_1, X_2, ..., X_K]$ where columns of this matrix, i.e. vectors $X_i,\ i = 1, ..., K$ are so called lagged vectors, $X_i = (y_i, y_{i+1}, ..., y_{i+M-1})^T$. The length of the lagged vectors is determined by the choice of embedding parameter M, which is usually called window length, since the process of embedding can be viewed as sliding the window of length M along the time series, extracting lagged vectors and arranging them into matrix X. The matrix X obtained through this process is a Henkel type matrix and in the context of SSA is usually referred to as trajectory matrix. Using an embedding window of size M, will therefore produce an $M \times K$ size trajectory matrix, where $K = L - M + 1$ is a parameter determined by the choice of the window length M.

3.2 Singular Value Decompositions (SVD)

The second step of decomposition part of SSA algorithm performs an SVD on the generated trajectory matrix $\mathbf{X}$ to obtain three new matrices $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{\Sigma}$:

$$\mathbf{X} = \mathbf{U\Sigma V}^T \tag{1}$$

Alternatively, matrices $\mathbf{U}$, $\mathbf{V}$ and $\mathbf{\Lambda}$ can be obtained via eigendecomposition of matrix products $\mathbf{XX}^T$ and $\mathbf{X}^T\mathbf{X}$ since :

$$\mathbf{XX}^T = \mathbf{U\Sigma V}^T \left(\mathbf{U\Sigma V}^T\right)^T = \mathbf{U\Sigma V}^T\mathbf{V\Sigma U}^T = \mathbf{U\Sigma}^2\mathbf{U}^T \tag{2}$$

and

$$\mathbf{X}^T\mathbf{X} = \left(\mathbf{U\Sigma V}^T\right)^T \mathbf{U\Sigma V}^T = \mathbf{V\Sigma U}^T\mathbf{U\Sigma V}^T = \mathbf{V\Sigma}^2\mathbf{V}^T \tag{3}$$

Elements of matrix $\mathbf{\Sigma}$ are non-negative values, known as the singular values of **X**, while the columns of matrices **U** and rows of matrix **V** represent the eigenvectors of matrices $\mathbf{XX}^T$ and $\mathbf{X}^T\mathbf{X}$ respectively. The diagonal matrix $\mathbf{\Sigma}^2$, usually denoted as $\mathbf{\Lambda}$ now contains the corresponding eigenvalues λ_i for the eigenvectors in **U** and **V**, i.e.

$$\mathbf{\Sigma}^2 = \operatorname{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_n\} = \operatorname{diag}\{\sigma_1^2, \sigma_2^2, \ldots, \sigma_n^2\} \tag{4}$$

Individual matrices $\mathbf{E}_i$, corresponding to each $\mathbf{u}_i, \mathbf{v}_i$ set of eigenvectors from **U** and **V** can be obtained using:

$$\mathbf{E}_i = \mathbf{u}_i \mathbf{v}_i^T \tag{5}$$

and the SVD of trajectory matrix $\mathbf{X}$ represented as the summation of those matrices:

$$\mathbf{X} = \sum_{i=1}^{M} \sigma_i \mathbf{E}_i \tag{6}$$

3.3 Grouping

Grouping stage is the first stage of the reconstruction part of SSA and involves grouping of the elementary matrices $\mathbf{E}_i$ defined with (5). into *P* groups and summing of the matrices from each group. This stage basically starts by splitting the set of indices $i = 1, 2, ..., M$ into a number of disjointed sets. Selection and number of those is usually done manually, by the user but can be difficult and cumbersome for the large data sets. Elementary matrices corresponding to indices from each set are then added together to form a new group of matrices $\mathbf{D}_j,\ j = 1, 2, ...P$.

3.4 Diagonal Averaging

Diagonal averaging is the process of turning each grouped matrix $\mathbf{D}_j$ obtained in the previous, grouping stage back into time series. Obtained time series are the additive components of the initial time series Y_L. The *k*-th element of the time series corresponding to matrix $\mathbf{D}$ can be obtained by averaging elements $d_{i,j}$ of this matrix over all indices i and j such that $i + j = k + 2$. This procedure is known as diagonal averaging or Hankelisation of a matrix $\mathbf{D}$. Once each $\mathbf{D}_j$ matrix is turned into time series, those can be added back to recover the original time series Y_L.

More formally, process of diagonal averaging can be described using equation:

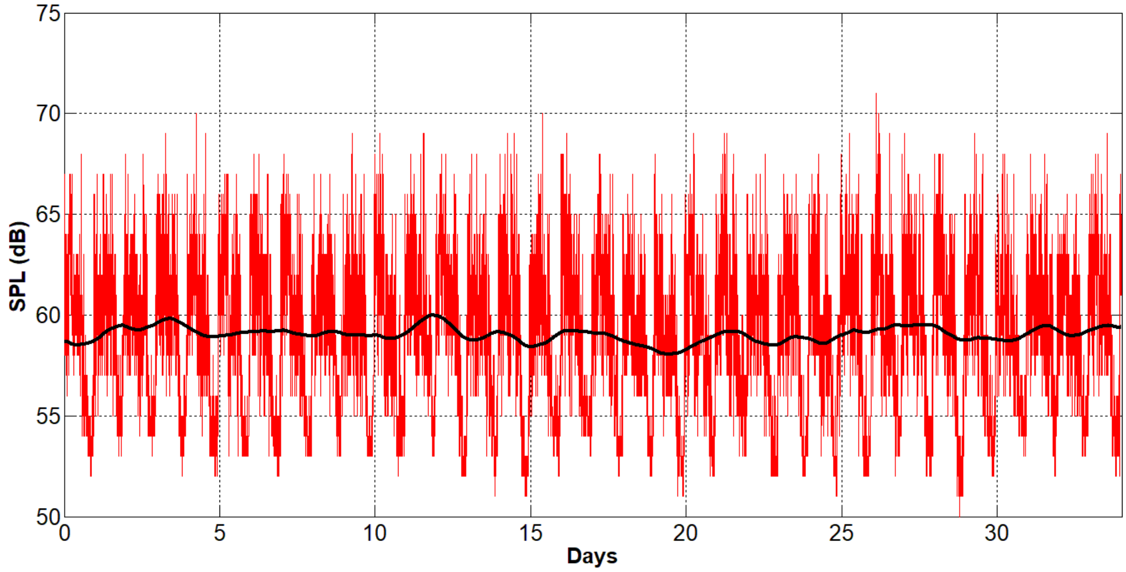
$$y_k = \begin{cases} \dfrac{1}{k}\displaystyle\sum_{m=1}^{k} d^*_{m,k-m+1} & \text{for } 1 \le k < L^* \\ \dfrac{1}{L^*}\displaystyle\sum_{m=1}^{L^*} d^*_{m,k-m+1} & \text{for } L^* \le k \le K^* \\ \dfrac{1}{N-k+1}\displaystyle\sum_{m=k-K^*+1}^{N-K^*+1} d^*_{m,k-m+1} & \text{for } K^* < k \le N \end{cases} \tag{7}$$

where $K = N - L + 1$, $L^* = \min(L, K)$ and $K^* = \max(L, K)$.

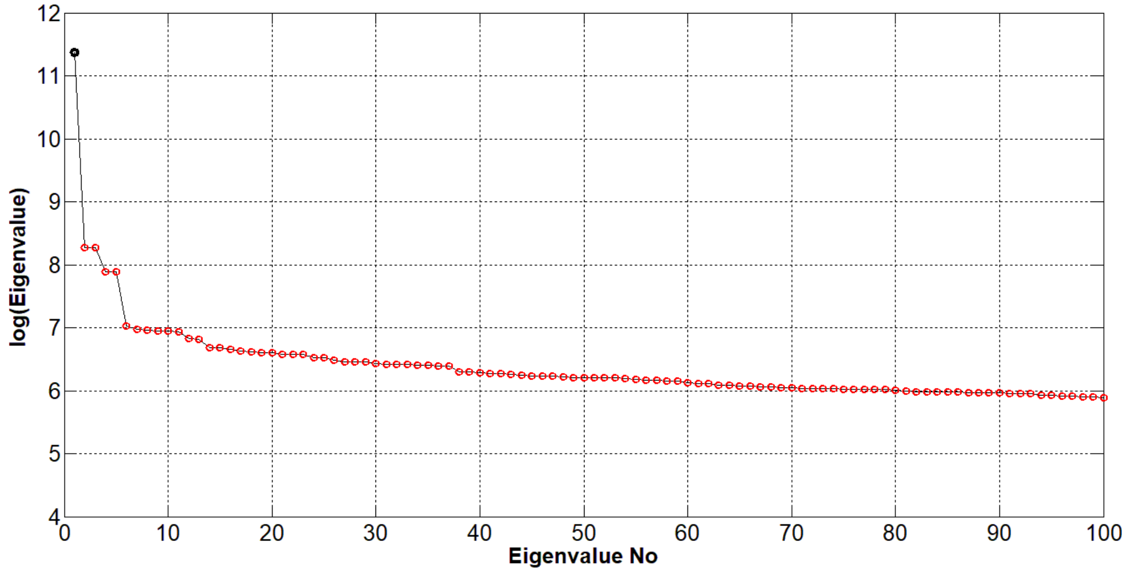
4. RESULTS

4.1 SPL Time-Series Analysis

The use of SSA based method has been illustrated on the SPL time-series recorded in the hospital in Vigo over the period over 35 days, from 01/02/2019 – 07/03/2019. Raw recorded SPL and its eigenvalue spectrum are shown in Figure 2. To “compress” the eigenvalue plot, the log of the originally obtained eigenvalues have been calculated and shown. In addition to that, only the first 100 values are shown. First and strongest component extracted via SSA, usually denotes DC or a very low frequency trend present in the time series. This component is also plotted Figure 2 a).



a)

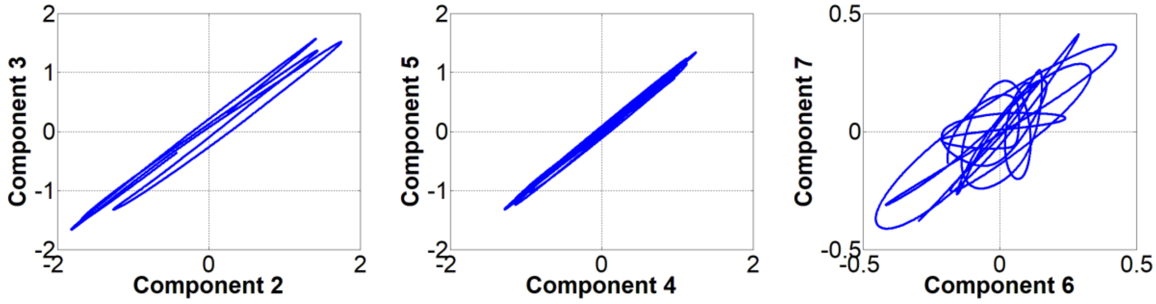


b)

Figure 2. a) Raw SPL Time-Series with Extracted Trend and b) First 100 Eigenvalues

SSA components, apart from the first component, come in pairs. This is indicated with very similar magnitudes of successive eigenvalue pairs (e.g. 2 and 3, 4 and 5, 6 and 7) in the eigenvalue plot from Figure 2b). This property is also illustrated by plotting two successive SSA components against each other. This is done for components 2-7 and shown in Figure 3. Those plots also reveal the phase shift between two components from the pair. From Figure 3 a) and b) it is clear that the phase shift between the components 2 and 3 as well as 4 and 5 is close to zero while there exists a small phase shift between components 6 and 7, Figure 3 c).

Figure 4 illustrates the process of reconstructing the SPL timeseries by adding the extracted components together. The middle column in this figure shows the frequency content of added components while the right column illustrates the result of adding indicated components together compared to original time-series. It is worth pointing out that the negative values on y-axis, do not really indicate “negative dBs”, but rather, a deviation from the extracted DC or trend component, shown in Figure 2 a).



a) b) c)

Figure 3. Pairing of Two Successive Extracted Components Against Each Other

The analysis of the frequency content of the extracted components, plotted in the middle column of Figure 4 reveals the periodicity hidden in the time series. The events that happen once per day are explained by the components 2 and 3 from the extracted set. Events happening twice per day are significantly weaker and present in components 4 and 5 of the extracted set. Frequency and period of each pair of first 12 extracted components is indicated in Table 1.

Table 1. Periodicity of the SSA components

COMPONENT(S)	FREQUENCY (*DAYS*$^{-1}$)	PERIOD (*HOURS*)
1	0	-
2+3	1	24
4+5	2	12
6+7	3	8
8+9	4	6
10+11	5	4.8
11+12	6	4

The periodicity of the captured time series indicates that the significant levels of noise generated in the ICU can be attributed to daily operation schedule in the ICU. Visits and regularly scheduled activities of staff in the unit are therefore main causes of those components. However, a significant portion of the noise is of random nature.

A possible way to discriminate periodic noise from random or background noise is to split the components in groups and then form subgroups of the recorded time-series as indicated in Figure 5. This strategy can be useful in showing more clearly the periodic patterns in measured SPLs and separating it from the random fluctuations, i.e. noise. Figure 5 shows three components of the recorded SPL obtained by grouping a number of extracted SSA components together. The first plot is obtained by adding components 2 to 10 and contains almost all of the periodicity of the recorded SPL. Midday points for each day are indicated in this plot, as well as on the other two plots from this figure.

The second plot contains components 11 to 100 and mostly contains the random part of the recorded time-series. Components above the component number 100 are shown in the third plot and indicate that significant levels of noise are contained even in the high order components. It is interesting to note the position of midday, i.e. 12.00 am points indicated in Figure 5. Almost all of the indicated midday points closely correspond to peaks in the periodic component of the signal, which can be attributed to increased levels of activity in the monitored ICUs around this period of the day. Midday points for Sundays are also indicated in each plot.

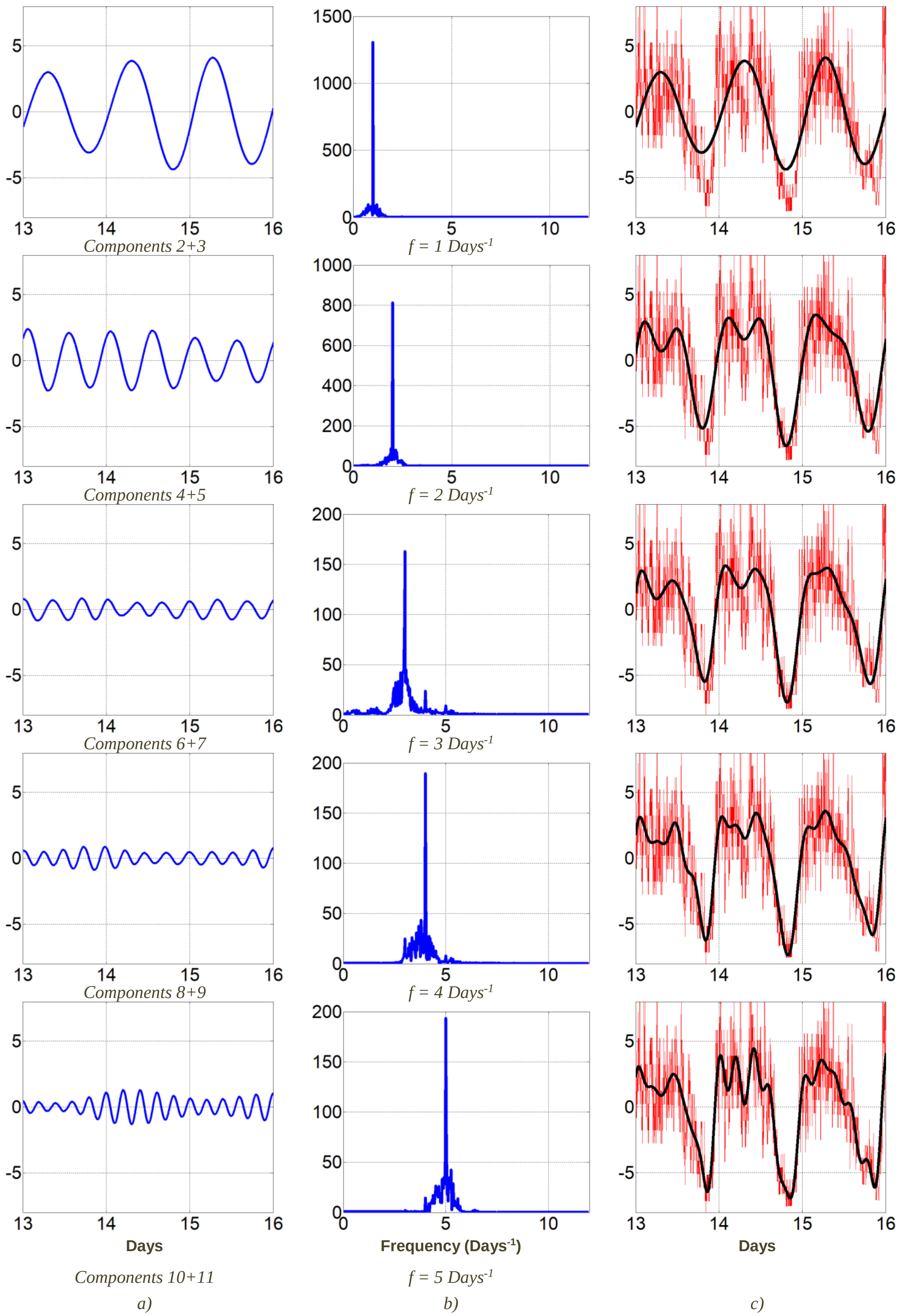
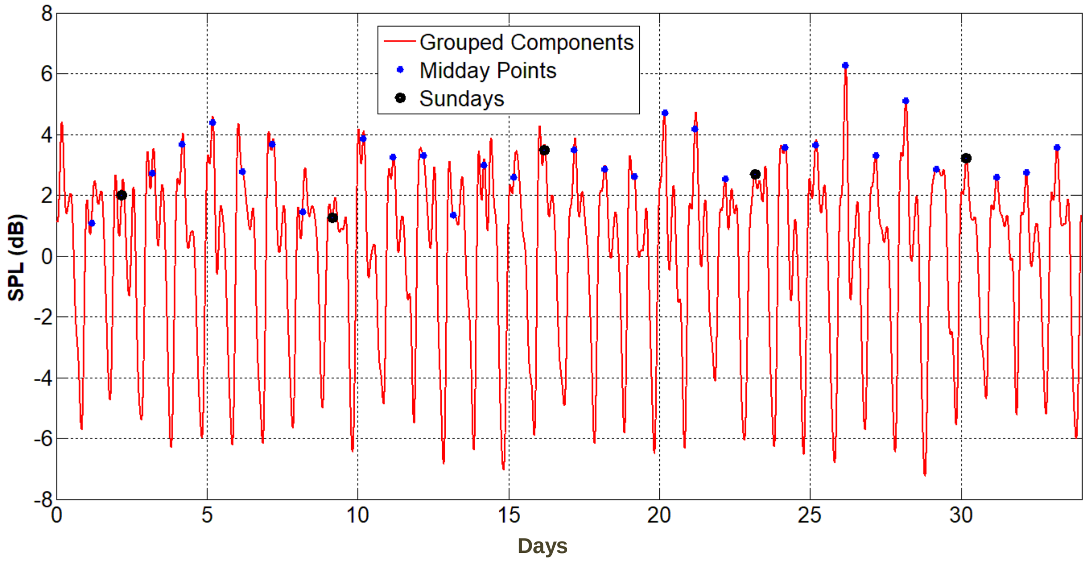


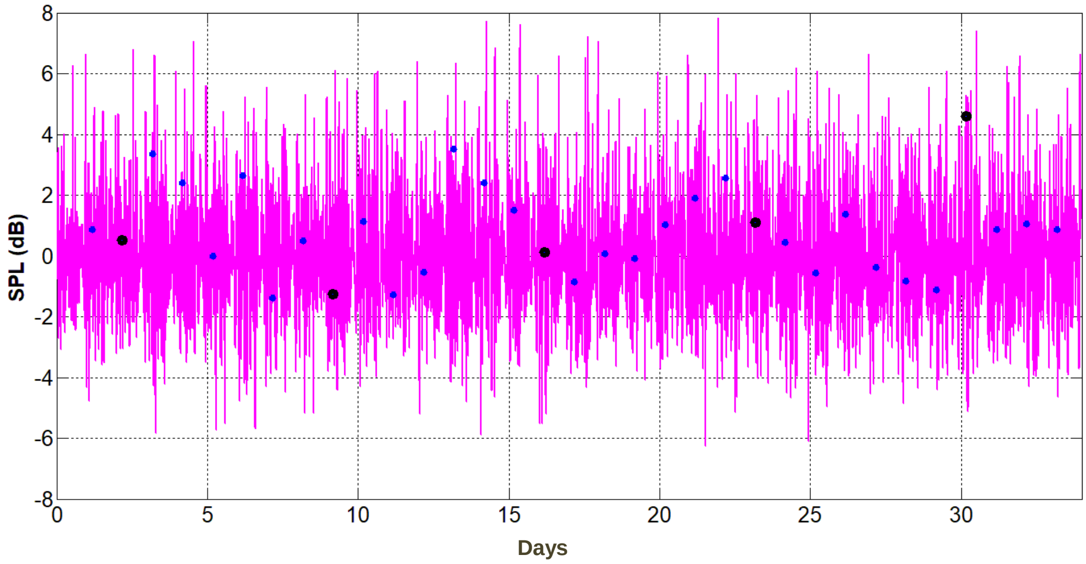
Figure 4. a) SSA Extracted Components (SPLs for days 13-16 shown), b) Spectrum, c) Aggregated v Raw SPL Time-Series (trend component not included in the aggregate)

While the midday points closely correspond to peaks in the periodic subgroup of the signal shown in plot a) those points are mostly randomly distributed in both plots, b) and c) of Figure 5. It is also worth noting that the magnitude of the periodic component is not significantly higher compared to random part of the time-series shown in Figure 5 b) and c). Both, components shown in b) and c) are Gaussian in nature with variances of 2.662 and 1.79 respectively, leading to a conclusion that the contribution of components above the order of 100 for the measured time-series are still significant, which is slightly unusual when compared to some natural signals, where SSA components of such a high order can be omitted in the analyses and are usually treated as a "measurement noise".

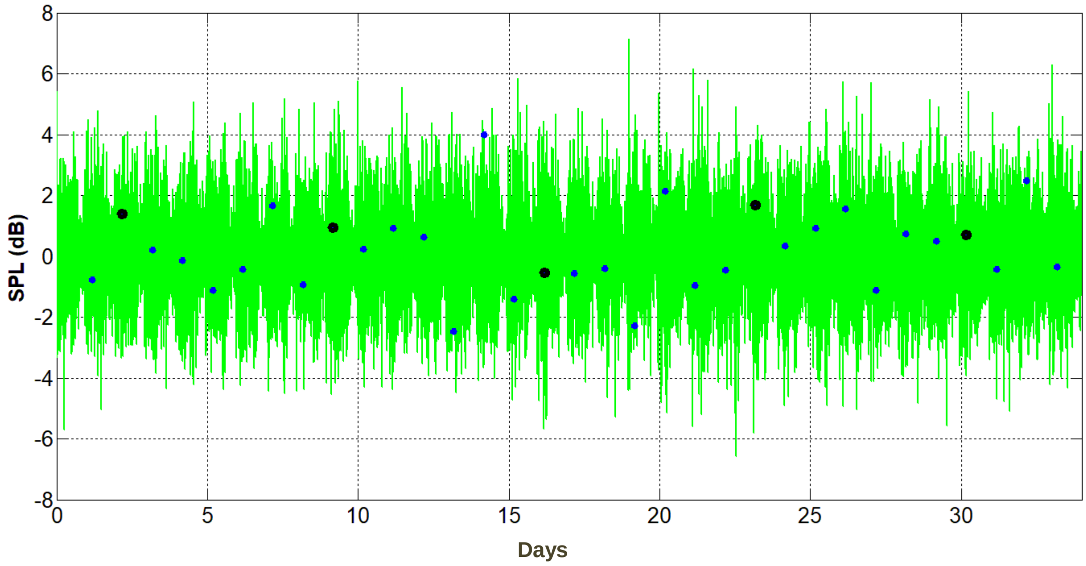
Interestingly, there is no discernible difference between Sundays and other days in the week, with midday points still corresponding to daily peak positions in the periodic subgroup and being randomly distributed in the other two "random" subgroups of the recorded time-series.



a) Components 2÷10



b) Components 11÷100



c) Residual

Figure 5. Grouping of extracted components (DC component omitted)

4.2. Estimation of Missing Measurements

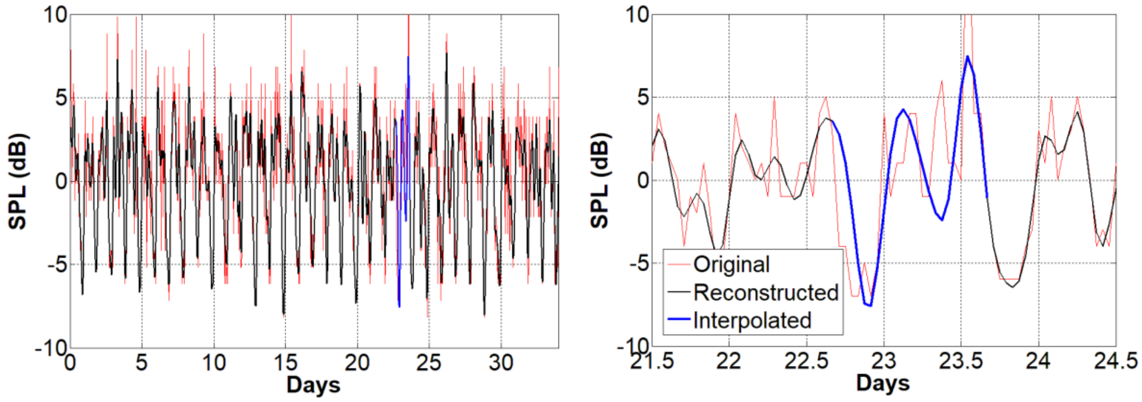
Measured SPLs can often suffer from gaps in recording, possibly due to malfunctioning of the measurement system, or more often due to problems in communication between the measurement point and server. This can be observed in Figure 1 where several readings are missing during the period around the 18/05/2018. Applied SSA technique can be used restore the missing measurements. One possible approach is outlined in Table 2.

Table 2. Interpolation of Missing Data using SSA Algorithm

1.	*Initialise the values of the missing samples in the SPL time series (setting all missing values to zero can be used)*
2.	*Perform the SSA on the complete set of data (including the section initialised in step 1) and replace the values in the initialised section with the new values*
3.	*Perform the SSA again on the new time series and replace the old values from the missing section with the ones from the newly reconstructed time series*
4.	*Keep repeating the step 3 as long as the newly estimated values differ significantly from the previous set of values (good measure of the difference between two sets is the mean square error between two estimated sets)*

The result of described data restoration approach for the SPL time-series analysed in section 4.1. is illustrated in Figure 6. Here, a one-day worth of SPL measurements has been removed from the original time-series starting on early afternoon on day 22 recorded in the time-series. To speed up the processing, data has been down-sampled by the factor of 60, so that the new data set contains one measurement per hour. In addition to that, it was decided to use only the first 5 SSA components in the interpolation process. Omitting the higher order components from the reconstructed time-series should provide a "denoised" reconstructed signal as illustrated in the first part of this section.

As it can be seen, the interpolated data correspond closely to original (i.e. "missing") data, with some of the random noise removed from the reconstructed time-series including the interpolated data.



a) b)

Figure 6. Restoring the Missing SPL Data using SSA Interpolation, a) SPL Time-Series with Restored Data, b) Detail of the Restored Region

4. CONCLUSIONS

Levels of noise in intensive care units (ICUs) in hospitals are generally too high, frequently reported to be many times above the levels prescribed by the World Health Organisation (WHO). To be able to devise and implement an effective strategy to reduce the levels of noise, it is important to analyse and understand the daily patterns and variations in SPLs in ICUs.

This paper describes one method based on SSA algorithm, that can be used for this purpose. SSA decomposes the measured SPL time-series into individual components whose significance and contribution to total time-series can be estimated via associated eigenvalues. The first extracted component can reveal the general, low-frequency trend in SPL variations and indicate seasonal variations in levels of noise or warn of longer-term increase in SPLs generated in ICUs. Grouping the other significant components together can reveal the periodic nature of the SPL variations while the residual or higher order components grouped together expose the contribution of the random fluctuations to total, measured SPL. For the ICU time series which has been analysed, it has been found that the contribution of the random variations in the measured SPL time-series is significant compared to the contribution of periodic signals, almost as significant as the contribution of the periodic activities and SPL component to total levels of noise in ICU. This leads to a conclusion that as well as looking at the periodic activities in the ICU, it is perhaps even more important to get a better insight into the nature and causes of random events contributing to excessively high levels of noise in hospitals and ICUs in particular. Subsequently, the measures for reducing those factors need to be well designed and implemented according to those findings.

It has also been shown that the SSA based time-series analysis can easily be extended to estimate the missing SPL measurements often encountered with many measurement systems. This paper proposes a simple method to accomplish this and shows some results to illustrate the effectiveness of the proposed approach. Further work in this area will focus on correlating the measured SPLs and in particular, influence and perception of each individual subgroup of measured SPL to patients' condition and wellbeing during their stay in hospital and ICU in particular.

5. ACKNOWLEDGEMENTS

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