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A Subspace Decomposition Approach toward Recognizing Valid Pulsatile Signals

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Abstract

Following recent studies, the automatic analysis of intracranial pressure (ICP) pulses appears to be a promising tool for the prediction of critical intracranial and cerebrovascular pathophysiological variations during the management of many neurological disorders. A pulse analysis framework has been recently developed to automatically extract morphological features of ICP pulses. The algorithm is capable of enhancing the quality of ICP signals, recognizing valid (not contaminated with noise or artifacts) ICP pulses, and designating the locations of the three ICP sub-peaks in a pulse. This paper extends the algorithm by proposing a singular value decomposition (SVD) technique to replace the correlation based approach originally utilized in recognizing valid ICP pulses. The validation of the proposed method is conducted on a large database of ICP signals built from 700 hours of recordings from 67 neurosurgical patients. A comparative analysis of the valid ICP recognition using the proposed SVD technique and the correlation based method demonstrates a significant improvement in terms of 1- Accuracy (61.96% reduction in false positive rate while keeping true positive rate as high as 99.08%); 2- Computational time (91.14% less time consumption); all in favour of the proposed method. Finally, this SVD based valid pulse recognition can be potentially applied to process pulsatile signals other than ICP because no proprietary ICP features are incorporated in the algorithm.

Keywords

Intracranial pressure; haemodynamic signal; Pulsatile signal; singular value decomposition; noise and artifacts; intracranial pressure pulse reference library

1. Introduction

In many neurological disorders such as traumatic brain injuries or brain tumours, the continuous measurement of different physiological signals like Electrocardiogram (ECG), Intracranial Pressure (ICP), Saturation of Peripheral Oxygen (Spo₂), and Arterial Blood Pressure (ABP) are an important part of the patient diagnosis or treatment procedure. For example, studies show that the dynamic of the ICP signal is related to intracranial compartment compliance and

vascular physiology and that variations of the ICP signal are linked to the development of intracranial hypertension (Contant *et al.*, 1995; Takizawa *et al.*, 1987; Hornero *et al.*, 2005; Fan *et al.*, 2008; Czosnyka *et al.*, 1999) and cerebral vasospasm (Cardoso *et al.*, 1988), acute changes in the cerebral blood carbon dioxide levels (Cardoso *et al.*, 1983; Portnoy and Chopp, 1981) and changes in the craniospinal compliance (Chopp and Portnoy, 1980). Therefore, the automatic extraction of the morphological properties of these physiological signals is an essential step towards a better monitoring, understanding and forecasting of intracranial and cerebrovascular pathophysiological changes.

The reliable processing of these continuous signals is a challenging task since they can be contaminated by several types of noises and artifacts. Given its significance, noise and artifacts handling has been approached by using algorithms based on diverse paradigms. One paradigm is to create filtering algorithms that separate noise from signal. Some examples of filtering Electromyogram (EMG) noise from ECG can be found in (Hu and Nenov, 2006; Iravanian and Tung, 2002; Kotas, 2004; Paul *et al.*, 2000; Thakor and Zhu, 1991). Many other algorithms are built on a different paradigm that does not attempt to recover or enhance the signal but rather to recognize valid portions of the signals for information extraction. For example, Sun *et al.* (2006) have defined a signal abnormality index (SAI) to distinguish valid ABP pulses from the noisy ones. The algorithm flags ABP beats by intelligently setting constraints on physiological, noise/artifact and beat to beat variation values. More recently, this ABP SAI algorithm has been utilized to provide better heart rate extraction (Li *et al.*, 2008) and to reduce false alarms for critical arrhythmias (Aboukhalil *et al.*, 2008).

In our previous work (Hu *et al.*, 2009), we have developed an algorithm for Morphological Clustering and Analysis of ICP Pulse (MOCAIP). This algorithm performs an automated analysis of continuous ICP pulse waveform by enhancing ICP signal quality, recognizing valid ICP pulses, and optimally designating the three well established sub-components in an ICP pulse.

For the recognition of valid ICP pulses, MOCAIP depends heavily on the matching of the morphology between a test pulse and a reference library of already validated ICP pulses. Despite its potential to be generalized to other pulsatile signals usually seen in clinical environments, the algorithm needs further improvement in several aspects. One concern is the computational time required for performing a large number of correlation analyses to determine the validity of a pulse. The second concern is related to the management of the reference pulse library of valid ICP pulses, which would include questions on the cardinality of the pulse library (number of pulse members in the library) and how to maintain the diversity of the library while controlling the redundancy. Further improvement of the accuracy of valid ICP recognition is also preferred.

The present work addresses these problems in the original MOCAIP algorithm by utilizing singular value decomposition (SVD) to define a signal and a noise subspace. Then an acceptance criterion based on the ratio of the energies of the projected signal in both subspaces has been applied for validating new pulses. The bases of the signal subspace would be treated as a new equivalent reference library of valid ICP pulses. This new reference library is a parsimonious representation of the original one but with efficient extensibility because it can be diversified with new pulses without adding any redundancy. In this paper, we first present an overview of the MOCAIP framework and its constituents with an emphasis on the correlation based approach for the valid ICP recognition. Then the proposed SVD technique is explained and its efficacy is evaluated on a set of clinical data and compared to the correlation based method. Finally, the clinical relevance, advantages, and limitations of the proposed method are discussed.

2. Materials and Methods

2.1. An Overview of the MOCAIP algorithm

Signal processing capabilities in existing commercial ICP monitoring devices remain poor providing clinicians with limited amount of information that is confined to the mean ICP, while ICP waveform contains much more useful information for forecasting intracranial and cerebrovascular pathophysiological changes (Wilkinson *et al.*, 1979; Chopp and Portnoy, 1980; Whitfield *et al.*, 2001). As a result, MOCAIP algorithm, a pulse analysis framework developed recently for automatic extraction of morphological features of ICP pulses in real time, is a promising tool for the future patient management. The MOCAIP algorithm is able to enhance ICP signal quality, to recognize valid ICP pulses and to detect the three sub-peaks in an ICP pulse. In the following subsections, we will review the constituents of this algorithm.

2.1.1. Pulse Detection—MOCAIP starts by segmenting the continuous ICP into a sequence of individual ICP pulses. To this end, MOCAIP combines an ICP pulse extraction technique (Hu *et al.*, 2008a) with the ECG QRS detection (Afonso *et al.*, 1999) that first finds each ECG beat. The pulse detection algorithm additionally incorporates interval constraints to make it robust to spurious QRS beat detection.

2.1.2. Pulse Clustering—ICP recordings collected from the bedside monitors can be contaminated by several types of noise and artifacts, e.g., high frequency noise that originated from measurement or amplifier devices, transient artifacts from patient movement, noise from measuring sensor detachment or noise due to low quantization level. Examples of a valid ICP pulse and several other pulses contaminated with noise have been represented in Figure 1. Instead of applying ICP morphology analysis using individual pulses, a representative cleaner pulse is extracted from a sequence of consecutive ICP pulses. A hierarchical clustering approach (Kaufman and Rousseeuw, 2005) is used to find the main ICP pulse cluster in the sequence, the centroid of which is referred as the dominant pulse.

2.1.3. Pulse Validation—Pulse clustering provides a robust solution to eliminate transient perturbations in the ICP signal. However, a dominant pulse extracted from a signal sequence might not correspond to a valid pulse. This is the case when the whole signal segment is heavily contaminated by artifacts. To identify valid ICP pulses automatically, MOCAIP proposes to use a reference library of validated ICP pulses. The construction of this library was treated as a training process that involved data sets from multiple patients. A pulse is judged to be valid if it belongs to a cluster whose average pulse correlates with any of the reference ICP pulses with a correlation coefficient greater than r_1 . To avoid false rejection of a valid cluster, due to the incompleteness of the reference library or inappropriate r_1 , the rejected pulses by the first step will be further assessed by characterizing the coherence of the pulse cluster to which it belongs, against r_2 (self identification test). If a pulse fails both tests, it would be declared as a non-valid pulse.

2.1.4. Detection and designation of three subcomponent peaks—Once a valid ICP pulse has been extracted from the previous step, MOCAIP detects a set of peak candidates (or curve inflections). Each of them is potentially one of the three peaks. The extraction of these candidates relies on the segmentation of the ICP pulse into concave and convex regions which produces a pool of multiple peak candidates. To identify the three peaks from the set of candidates, MOCAIP relies on a Gaussian model to represent the prior knowledge about the position of each peak in the pulse. The assignment is chosen such that it maximizes the probability to observe the peaks given the prior distributions. These priors have been previously learned from the library of valid ICP pulses.

2.2. Proposed SVD Based Method for Valid ICP Pulse Recognition—The MOCAIP algorithm performs a correlation analysis to recognize valid ICP pulses employing a reference library of expert-validated ICP pulses. Correlation analysis is itself a time consuming process, especially in the MOCAIP when one needs to repeat this analysis for multiple times until a threshold on the value of correlation coefficient, r_1 , is achieved. This poses a potential challenge for implementing the MOCAIP algorithm in real-time applications. Another challenge for the current correlation based method was related to the improvement of the accuracy of valid ICP validation. In order to decrease the probability of rejecting a truly valid pulse, one needs to have a highly diverse collection of ICP pulses. This can be accomplished by a trivial extension of the library, adding more pulses to the existing library regardless of how much the newly added pulses contribute to the diversity of the library rather than its redundancy. Although this extension can improve the accuracy of valid ICP recognition, it also deteriorates the computational time, an outcome of the increase in the number of correlation analysis performed between a test pulse and pulse members of the extended library. In the following subsection, we propose a SVD based method which addresses all the above issues and can replace the correlation based method for valid ICP recognition.

2.2.1. Singular Value Decomposition for the pulse validation—Suppose that a reference library consists of N valid physiological pulses (e.g., ICP pulses) and each pulse is represented by m_n samples in time domain ($n = 1, \dots, N$). By applying a stretching/shrinking technique in the time scale, e.g. Spline interpolation, we can make all the pulses in the library have the same length M .

Now let us define a matrix $A_{M \times N}$ as $[P_1, \dots, P_N]$, where P_n is n^{th} normalized pulse in the library (normalization can be done by subtracting the mean of the pulse and dividing the results by the pulse standard deviation). Note that $r = \text{rank}(A) \leq \min(M, N)$. If we do a SVD decomposition (Konstantinides and Yao, 1988; Laub, 2005) on matrix A , then we get

$$A = U \sum V^T, \text{ where } \sum_{M \times N} = \begin{bmatrix} S_{r \times r} & 0_{r \times (N-r)} \\ 0_{(M-r) \times r} & 0_{(M-r) \times (N-r)} \end{bmatrix}, \quad (1)$$

U and V are the left and right singular vectors, respectively and superscript T means transpose of the matrix. Now we can decompose the orthogonal matrix U to $U_{M \times M} = [U_1 \ U_2]$ where U_1 is an $M \times r$ matrix. It can be shown that the columns of U_1 and U_2 are the orthonormal basis vectors for range of A , $R(A)$, and the orthogonal complement of range of A , $R(A)^\perp$, respectively. $S_{r \times r}$ is a diagonal matrix whose diagonal elements are the nonzero singular values σ_i , $i = 1, \dots, r$. Each σ_i represents the amount of energy along the corresponding singular vector in U_1 . The smaller the singular values are, the less energy along the corresponding singular vector is, so the small singular values are usually considered to be noise. A truncated SVD where we just keep singular vectors corresponding to the first I significant singular values is representative of a noise-reduced signal subspace, and then the complement of this space can be considered as the noise subspace. In practice, choosing the value of I is dependent on the nature of data.

Now we define the new effective reference library as the set of bases for the defined signal subspace, $\mathbf{U} = [u_1 \ u_2 \ \dots \ u_I]$. In other words, the effective reference library only consists of I pulses where each pulse is a singular vector corresponding to one of the I significant singular values (usually $I \ll N$). The effective reference library of valid pulses can be employed to assess the validity of a new test pulse as follows. First the test pulse is resized in the time

domain (using spline interpolation to make its length equal to M) and normalized. Then the resized and normalized pulse b will be projected on the signal subspace ($\mathbf{b}_1 = \mathbf{U}\mathbf{U}^T b$) and noise subspace ($\mathbf{b}_2 = b - \mathbf{b}_1$) and the ratio of the energy of the projected signal in both subspaces will be calculated. If this ratio is greater than a threshold ϖ , then the enquired signal is considered as a valid physiological signal, otherwise the signal would be assessed as a non-valid one. The above procedure can be written in the mathematical form as

$$\begin{cases} \text{Ratio}_{Energy} = \frac{\text{Energy of the projected signal in the signal subspace}}{\text{Energy of the projected signal in the noise subspace}} = \frac{\|\mathbf{b}_1\|^2}{\|\mathbf{b}_2\|^2} \\ \left\{ \begin{array}{ll} \text{If } \text{Ratio}_{Energy} \geq \varpi \Rightarrow & \text{Enquired signal is valid.} \\ \text{otherwise} & \Rightarrow \text{Enquired signal is not valid.} \end{array} \right. \end{cases} \quad (2)$$

Similar to I , the best value choice for ϖ is dependent on the nature of data. One reasonable option would be to set it equal to ξ , where ξ is the minimum of the computed Ratio_{Energy} between all resized and normalized pulses in the original library; the columns of matrix A . In other words,

$$\xi = \min_{i=1, \dots, N} (\text{Ratio}_{Energy}^{(i)}) \quad (3)$$

This value selection guarantees that the proposed valid ICP recognition method will correctly assess the validity of a test pulse which is very similar to any of the pulses in the original validated pulse library.

Although the shrinking/stretching/normalizing of a pulse in the time domain preserves the shape of the signal on which the proposed SVD based method evaluates the validity of the pulse, it changes certain information in the pulse. To solve this problem, the resized and normalized signal would be solely utilized for the purpose of valid ICP recognition. This means that if the proposed method assesses a pulse as a valid one, then the original pulse (non-interpolated and not normalized) will be used for further processing, e.g. peak detection and designation.

2.2.2. An efficient procedure for extending an existing reference library—Suppose that we have already made an effective reference library of a specific physiological signal with the described SVD method. Then, further expansion of this reference library can be done in an efficient fashion by following a procedure which calculates the amount of the contribution of a valid pulse candidate to the diversity of the existing library. First we resize, normalize and project the pulse candidate to the signal subspace and noise subspace defined by the existing reference library. Then if the ratio of the energy of the projected signal in both subspaces (Ratio_{Energy}) is smaller than ξ defined in equation (3), we will add a unit vector in the direction of the pulse candidate to the library. This selective extension of the library will diversify the existing library, avoid any redundancy and guarantee the future correct assessment of any pulse candidate which is similar to the newly added pulses.

2.3. Patient Data

The dataset used in our experiments originates from the UCLA ADULT HYDROCEPHALUS CENTER and has been previously used to evaluate MOCAIP (Hu *et al.*, 2009). The usage of this archived data set was approved by the UCLA Internal Review Board. The protocol used during its acquisition is presented below and some properties are discussed. The ICP and ECG data were collected from 67 inpatients including 33 females and 34 males whom were treated

for various intracranial pressure related conditions; hydrocephalus (48 patients), idiopathic headache (8 patients), shunt malfunction (4 patients), Chiari malformation (2 patients), head injury (1 patient), depression (1 patient), craniotomy wound infection (1 patient), Tumour (1 patient), syringomyelia (1 patient). Patients' ages ranged from 14 to 94 years with the mean and standard deviation of 60 and 21, respectively. No explicit criteria were used to select the aforementioned patients other than the availability of both ICP and ECG signals. ICP was monitored continuously using Codman intraparenchymal microsensors (Codman and Schurtleff, Raynaud, MA) placed in the right frontal lobe. Simultaneous cardiovascular monitoring was performed using the bedside GE monitors. ICP and lead II of ECG signals were archived using either a mobile cart at the bedside that was equipped with the PowerLab SP-16 data acquisition system (ADInstruments, Colorado Springs, CO) with sampling frequency of 400Hz or the BedMaster system that collects data (sampling frequency of 240 Hz) from the GE Unity network which the bedside monitors were connected to. Signal files in this archive were transformed into the Chart Binary file format for further processing. Signal segments, each approximately five-hour long, were extracted for every 12 hours of available data (total of 158 signal segments). The extracted ICP and ECG signal segments were subsequently processed by MOCAIP and a dominant ICP pulse was generated for every 3 minutes of recording resulting in 14903 raw dominant pulses. All these 14903 dominant pulses were assessed by visual inspection and manually annotated as a valid ICP pulse (a typical triphasic ICP pulse (Cardoso *et al.*, 1983) or a non-valid ICP pulse (caused by noise or artifacts or wrong QRS detection). As a result of this assessment, 13611 were annotated as valid pulses accounting for 91.33% of total dominant pulses.

The construction of the original reference library of valid ICP pulses used in the MOCAIP was done as follows. Up to 10 validated dominant ICP pulses were selected from each of the 158 signal segments in a completely random fashion. This resulted in 1440 valid ICP pulses with the mean ICP of 3.1 ± 7.2 mmHg. The mean amplitude of these ICP pulse was 6.6 ± 3.3 mmHg. A histogram of the mean ICP for the 1440 pulses in the reference library has been shown in Figure 2. The high percentage of patients with negative mean ICP can be related to the sitting position of the patients at the time of monitoring.

2.4. Data analysis and validation protocol

To perform SVD on the original ICP reference library, we chose M as the 90th percentile of the lengths of pulses in the library. After resizing and normalizing all the pulses, we performed singular value decomposition on the matrix $A_{428 \times 1440}$. As we mentioned before, in practice, choosing the best value of $\hat{I}$ is dependent on the nature of data. For this study, we define

$$E_K = \frac{\sum_{i=1}^K \sigma_i}{\sum_{i=1}^r \sigma_i}, K=1, \dots, r. \quad (4)$$

Note that E_K represents the percentages of the total energy that exists in the signal subspace (the space whose bases are the singular vectors corresponding to the K largest singular values of the matrix A). We hypothesize that the knee point of the plot of E_K curve for different values of K is a good candidate for the value of $\hat{I}$ (a knee point (ψ) is defined as the point with the maximum perpendicular distance from the straight-line which connects the beginning and end point of the concave region of the curve).

We test this hypothesis by taking different values of I and then evaluating the performance of the proposed valid ICP recognition by implementing a two-fold cross validation as follows.

We randomly split the original library of 1440 pulses into two independent subsets (subsets do not include data from the same patient) where each includes 720 pulses. Let us name these two sets as train-set1 and train-set2. For each of the training sets, the corresponding independent testing set was constructed by removing all the file segments in original dataset (14903 pulses) from the patients in that training set. Then for each value of I , the following procedure was implemented for each fold. First the singular value decomposition was performed on the corresponding training set and an effective reference library was constructed by taking the singular vectors corresponding to the I most significant singular values. The validity of all dominant ICP pulses in the corresponding independent testing set was assessed using the proposed energy ratio test and the true positive rate (TPR) and false positive rate (FPR) were calculated by systematically changing the threshold ϖ for energy ratio comparison as $\log_{10} \varpi = C \times \log_{10} \zeta$, where ζ is defined in equation (3) and $C = [10 \ 5 \ 4 \ 3 \ 2 \ 1 \ 0 \ -5 \ -10]$ in Decibel (dB). Please note that since ϖ is a measure of signal-to-noise-ratio (SNR), it can be expressed in dB. Following the calculation of TPR and FPR for each fold, the results are averaged to produce a single Receiver-Operating-Characteristics (ROC) curve for the corresponding value of I . Then the whole area under the ROC curve (AUC) has been calculated. Note that the final goal of this study is to demonstrate that the proposed SVD based method can achieve (at least) the same level of TPR as that of the correlation based method by introducing a lower FPR. Based on our previous study (Hu *et al.*, 2009), the lowest level of FPR that correlation based method could achieve is associated with a TPR of 97%. As a result, throughout this paper, the TPR of 97% has been chosen as the criterion of the comparison and for any ROC curve, the partial area under the curve for TPR greater than 97% ($AUC_{97\%}$) and the value of FPR when $TPR=0.97$ (Π_{FPR}) have been also calculated.

The comparison of the performance of ICP pulse validation using the proposed method and the correlation based method has been done using the whole dataset of 14903 pulses. In applying both methods to each of the 158 segments, the reference library has been modified accordingly by removing entries from the same patient. This can be seen as a 67-fold cross-validation (one fold for each of the 67 patients) such that the training set of each fold consists of 1440 randomly selected pulses from all the patients excluding one. So each test set is made of ICP pulses of the patient data that were excluded from the training set. For the proposed SVD method, I was set equal to knee point (ψ) and C was systematically changing as $[10 \ 5 \ 4 \ 3 \ 2 \ 1 \ 0 \ -5 \ -10]$ in dB to produce the points along the ROC curve. For the correlation based method, $r_2 = 0.9$ and r_1 was systematically changing as $[1 \ 0.99 \ 0.97 \ 0.95 \ 0.92 \ 0.9 \ 0.85 \ 0.8 \ 0.5]$.

To explore the sensitivity of the performance of the proposed method to the selection and number of ICP signals used for the initial SVD, we decrease the number of ICP pulses in the original reference library of $N = 1440$ valid ICP pulses to $\left[\frac{N}{2} \ \frac{N}{4} \ \frac{N}{8} \ \frac{N}{16} \ \frac{N}{32} \ \frac{N}{36} \right]$ by randomly excluding ICP pulses in the original reference library. Then the performance of the proposed method has been evaluated by calculating the three aforementioned parameters related to the ROC curve of valid ICP recognition (AUC , $AUC_{97\%}$ and Π_{FPR}) using a 67-fold cross validation.

3. Results

Figure 3-(a) shows the singular spectrum of the matrix A constructed from the original ICP reference library used in the MOCAIP (The plot of singular values versus their index number), while figure 3-(b) is the plot of the defined E_K . Please note that the knee point of this curve is at $\psi = 18$. This shows that the effective reference library only consists of 18 pulses.

The ROC curves of recognizing valid ICP pulses for different values of $I = [6 \ 18 \ 54 \ 162]$ using a two-fold cross validation are shown in figure 4. For this purpose, our randomly constructed

train-set1 has a mean ICP of 2.65 ± 6.53 (mmHg) and includes data from hydrocephalus patients (24 patients), shunt malfunction (2 patients), chiari malfunction (2 patients), idiopathic headache (3 patients), depression (1 patient), craniotomy wound infection (1 patient), tumour (1 patient). The data from the remaining 35 patients in the study formed train-set2 with the mean ICP of 3.61 ± 7.75 (mmHg). As this plot shows, the performance of ICP validation for $I = 18$ which is equal to the knee point of E_K curve, is considerably better than those for the other values of I .

Table 1 summarizes the computed values of the three parameters related to the ROC curve (AUC , $AUC_{97\%}$ and Π_{FPR}) of valid ICP recognition for 12 different values of I as [6 14 15 16 17 18 19 20 21 22 54 162]. The numbers show that as I starts to increase; both AUC and $AUC_{97\%}$ increases as well until $I = 18$. Then any further increase in I would cause a decrease in the value of both AUC and $AUC_{97\%}$. Since the maximums of both areas are achieved at $I = 18$, we can conclude that the knee point of E_K is really the optimal number of bases for the signal subspace. Now if we define the sensitivity of the ICP pulse validation to the number of

pulses in the reference library as $Sen = \frac{\Delta AUC_{97\%}}{\Delta I} \Big|_{I=\hat{I}}$, then we observe that the proposed SVD method has sensitivity of at most 2.28 % when I changes in the neighborhood of $\hat{I}$ as $[\hat{I} - 4 \hat{I} + 4]$.

The comparison of the performances of the valid ICP recognition on the dataset of 14903 pulses with a 67-fold cross validation using the proposed SVD based method and the correlation based method has been demonstrated in figure 5. We observe that the lowest FPR by the correlation based method is achieved by setting $r_1 = 1$ which results in (FPR=28.92%, TPR=97.00%) with the total computational time of 16370 seconds. By setting $C=3$ dB, the proposed SVD method can achieve approximately the same TPR (TPR=96.61%) with much lower FPR (FPR=6.61%) at an expense of 170 seconds of computational time. If we set r_1 to its default value of 0.97 based on the original version of the MOCAIP (Hu *et al.*, 2009), then the computation time of correlation based method decreases to 1927.2 seconds and the TPR exceeds 99%. But at the same time the FPR increases to 47.48% which is fairly high. SVD based method can again achieve the same level of TPR (above 99%) with much lower FPR (FPR=18.06%) and the computational time (170 seconds). Please note that the computational times were obtained using an Intel® Xenon® CPU, E 3110 @ 3.00 GHz and 4.00 GB RAM.

Table 2 summarizes the computed values of ψ , AUC , $AUC_{97\%}$ and Π_{FPR} when we use different number of pulses to perform the initial SVD. As this table shows, the knee point of (ψ) would be very close to 18 for different selection of the ICP pulses, unless this selection is prohibitively small (with fewer than 45 pulses). We also observe that although the performance of valid ICP pulse recognition declines with the decrease in the number of ICP pulses in the original reference library, this decline is not significant ($\Delta AUC_{97\%} \leq 5.82\%$) until the number of pulses in the library becomes fewer than 180. The set of randomly selected pulses with the cardinality of 180 ICP pulses which resulted in Π_{FPR} of 12.18% included data from 57 patients; hydrocephalus (41 patients), idiopathic headache (7 patients), shunt malfunction (3 patients), Chiari malformation (2 patients), head injury (1 patient), depression (1 patient), craniotomy wound infection (1 patient), Tumour (1 patient). This result demonstrates that the proposed SVD based method for the valid ICP pulse recognition has a low sensitivity to the selection and number of the ICP pulses as long as the collection of ICP pulses is diversified and has at least 180 ICP pulses.

4. Discussion

4.1. Advantages of the proposed SVD based method

For the purpose of the valid ICP recognition, the efficacy of the proposed SVD based approach, compared to the correlation based method in the original version of the MOCAIP, is demonstrated by its high accuracy, its low computational time, its capability to construct an effective reference library of valid ICP pulses with a low cardinality, and its extensibility. The proposed SVD based valid pulse recognition can be potentially applied to process pulsatile signals other than ICP because no proprietary ICP features are incorporated in the algorithm (Sapob *et al.*, 2009). In a recent study (Asgari *et al.*, 2009), we employed the proposed SVD based method to validate the ABP signals and compared the results with those of the ABP signal validation using SAI method (Sun *et al.*, 2006). The proposed SVD based algorithm development and evaluation were conducted using two completely different sets of data. The study showed that the proposed SVD based method compares favourably with (Sun *et al.*, 2006) and with the careful integration of the proposed SVD based method with some of the value-based abnormality conditions of the SAI method, the performance of ABP signal validation can be further improved.

4.2. Limitations of the proposed SVD based method

The proposed SVD based projection method starts by normalizing each pulse in amplitude scale so that all pulses are zero-mean and unit-variance. As a result, one limitation with the proposed method is that the validity of an ICP pulse is solely based on its shape and not on the absolute values of its features; e.g. mean value. It should be noted that although an ICP pulse is typically a tri-phasic signal, the exact morphology of the pulse is highly variable among different subjects and different pathophysiological states. Therefore, there is no guarantee that a global library will be always sufficient to cover all possible valid pulse morphologies. It may be necessary to always update the global pulse library for each individual using the algorithm described in Section 2.2.2. The cost of doing this is acceptable for processing long-term recordings of intracranial pressure signals.

4.3. Clinical relevance

The MOCAIP framework was initially developed to automatically analyse the continuous ICP waveform. This algorithm utilizes and integrates several biomedical signal processing and data analysis techniques including ECG QRS detection (Afonso *et al.*, 1999), hierarchical clustering, valid ICP recognition and an optimal peak designation algorithm. Since its initial development, the algorithm has been enhanced in terms of its accuracy for the ICP peak designation (Scalzo *et al.*, 2009). Another remaining concern with the MOCAIP algorithm was its computational cost, a prime issue for the online waveform analysis, and its accuracy for the valid ICP recognition. The proposed SVD based method addresses both of these concerns. This extension therefore would help future clinical investigations of the MOCAIP algorithm by processing continuous ICP to extract predictive information that may indicate dangerous acute brain structural and cerebral vascular changes including volumetric increase of the ventricles (Hu *et al.*, 2008b), the growth of intracranial lesions, and the development of cerebral vasospasm. This could help further elucidate whether the extended ICP monitoring using the MOCAIP could achieve a real-time recognition of the progression of various types of secondary insults to the brain after the initial stabilization of the primary injury, which is an ultimate goal of having a 24- hour monitoring of patients. In addition, some existing reports have shown that recognizing specific ICP patterns in overnight recordings, such as B-waves, may offer clues for differentiating shunt responders from non-responders when treating normal pressure hydrocephalus patients (Symon and Dorsch, 1975; Barcena *et al.*, 1997; Eide, 2006; Eide and Brean, 2006; Schuhmann *et al.*, 2008; Czosnyka *et al.*, 2007). Therefore, it can be

anticipated that the MOCAIP algorithm could be an enabling technique for automating analysis and recognition of overnight ICP patterns.

5. Conclusion

The proposed technique for recognizing valid ICP pulses using the singular value decomposition technique significantly improves the correlation-based approach used in the recently proposed MOCAIP algorithm in terms of both accuracy and computational cost. In addition, this method has low sensitivity to the choice of number of bases in the reduced-noise signal space, the selection and number of ICP pulses to perform initial SVD. Finally, the proposed method may be potentially applicable to validate pulsatile physiological signal other than ICP pulses, e.g. ABP pulses and pulse Oximetry signals.

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Figure 1.

Representative examples of valid and non-valid (influenced by noise and artifacts) ICP pulse signals. Panel A displays an example of a valid ICP pulse with the three well established subcomponents. Panels B through F display non-valid ICP pulse signals resulted from wrong QRS detection, coughing, patient's movement, sensor detachment and contamination by high frequency noise, respectively.

Figure 2.

A histogram of the mean ICP values of the 1440 pulses in the original reference library used for the correlation based approach.

Figure 3.

(a) Singular value spectrum of the matrix A constructed from the original reference library 1440 ICP pulses. (b) Plot of E_K (percentage of the total energy in the space defined by the first K singular vectors of matrix A for the original ICP pulse reference library).

Figure 4.

Receiver operator characteristic (ROC) curves of recognizing valid ICP pulse for different values of $I = [6\ 18\ 54\ 162]$, each curve is generated by a two-fold cross validation and systematically changing the coefficient $C = [10\ 5\ 4\ 3\ 2\ 1\ 0\ -5\ -10]$ in dB.

Figure 5.

Receiver operator characteristic (ROC) curves of recognizing valid ICP pulse using 67-fold cross validation under the correlation based method in MOCAIP and the proposed SVD based method for $\hat{I} = 18$. For the correlation based method, $r_2 = 0.9$ and r_1 was systematically changing as $[1 \ 0.99 \ 0.97 \ 0.95 \ 0.92 \ 0.9 \ 0.85 \ 0.8 \ 0.5]$. For the proposed SVD based method, the coefficient values are the same as the one used in Figure 4.

Table 1

Three calculated parameters (AUC , $AUC_{97\%}$ and Π_{FPR}) related to the ROC curve of valid ICP recognition using the proposed SVD method and a two-fold cross validation when different numbers of bases (as [6 14 15 16 17 18 19 20 21 22 54 162]) have been taken to define the signal subspace. AUC is the area under the ROC curve for $0 \leq TPR \leq 1$. $AUC_{97\%}$ is the area under the ROC curve for $0.97 \leq TPR \leq 1$. Π_{FPR} is the FPR when $TPR=0.97$.

Number of bases	6	14	15	16	17	18	19	20	21	22	54	162
AUC	0.9326	0.9737	0.9704	0.9793	0.9769	0.9814	0.9806	0.9789	0.9764	0.9735	0.9509	0.9310
$AUC_{97\%}$	0.6614	0.8532	0.8334	0.8885	0.8988	0.9187	0.9076	0.8896	0.8779	0.8445	0.6990	0.6165
Π_{FPR}	0.3330	0.1387	0.1590	0.1043	0.938	0.0738	0.0852	0.1032	0.1152	0.1478	0.2994	0.3828

Table 2

The knee point and three calculated parameters (AUC , $AUC_{97\%}$ and Π_{FPR}) related to the ROC curve for valid ICP recognition using the proposed SVD method and the 67-fold cross validation on a set of randomly selected valid ICP pulses with different cardinalities [1440 720 360 180 90 45 20]. AUC is the area under the ROC curve for $0 \leq TPR \leq 1$. $AUC_{97\%}$ is the area under the ROC curve for $0.97 \leq TPR \leq 1$. Π_{FPR} is the FPR when $TPR=0.97$.

Number of randomly selected valid ICP pulses to perform SVD	1440	720	360	180	90	45	20
The knee point (ψ)	18	18	18	18	17	17	12
AUC	0.9803	0.9802	0.9791	0.9770	0.9677	0.9422	0.9105
$AUC_{97\%}$	0.9290	0.9289	0.9212	0.8708	0.7855	0.7558	0.4527
Π_{FPR}	0.0641	0.0644	0.0720	0.1218	0.2101	0.2399	0.5445