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Data Fusion of Electrophysiological and Haemodynamic Signals for Ventricular Rhythm Tracking

Preliminary Results Based on the IMPROVE Data Library

One of the functions of patient monitoring systems used in critical-care units (CCUs) is to detect, characterize, and automatically generate alarms for each potential life-threatening event. One important physiological signal to track is the ventricular rhythm (VR) [1, 2]. VR is presently tracked either by observation of the electrocardiogram (ECG) or by following the haemodynamic response, typically by observing a pressure channel [3]. This is especially true of the monitoring of VR in the large number of patients admitted to CCUs after proven or suspected myocardial infarction (MI) or with severe myocardial ischemia.

Disturbances of VR in this setting may relate to rate, rhythm, or the morphology of the ventricular complexes within the electrocardiograph (ECG) trace. These events are common in this setting and may be associated with life-threatening complications or sudden cardiac death. Early detection and prompt treatment of these potentially lethal events along the lines agreed upon by the European Resuscitation Council is the very essence of "coronary care." There is no reason to doubt that this discipline can be extrapolated to other clinical situations where a patient may be at risk of myocardial ischemia or MI.

Although VR tracking seems a relatively simple monitoring task, the signal lacks robustness and its efficiency remains limited despite great research efforts during the last two decades [4-6]. Several reasons can explain this limitation; among these are:

- the composite nature of the noise (stationary and transient) superimposed within the signal(s) that the VR is derived from,

- the low level of signal-to-noise ratio in a high "noise" environment of the CCU, and
- sensor failures, which lead to false alarms and missed detections.

This article aims at demonstrating how the cause of the ventricular contraction (VC), reflected by its electrophysiological precursors (ECG), and its related effect on the haemodynamic system (here characterized by the systemic arterial pressure (SAP), sometimes called the mean systolic arterial pressure, (MSAP)) can be fused together for a VR tracking purpose. Data fusion of heterogeneous signals, such as ECG and SAP, appears to be an interesting alternative to overcome the relative drawbacks of signal processing on univariate channels. Behind the clinical aim of providing a more robust VR signal, this article exemplifies how to manage such heterogeneous data when asynchronous events represent the same VC.

From an engineering perspective, the main objectives of this article are first to present a formal representation of the problem of VR tracking and, secondly, to introduce a novel signal-processing architecture that is able to manage and fuse cardiovascular data that are both asynchronous and heterogeneous. The evaluation of the performance of this signal-processing system uses a very noisy data set extracted from the IMPROVE data library (DL) [7].

Problem Statement

Let us suppose we observe the two-dimensional random process, $X(k)=[X_1(k) X_2(k)]^T$, where k denotes the discrete time index, while subscripts 1 and 2 refer, respectively, to the ECG and SAP channels:

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$$X_1(k) = \sum_{i=1}^{NV} E_i(k - t_i) + B_1(k)$$

$$X_2(k) = \sum_{j=1}^{NV} S_j(k - t'_j) + B_2(k)$$

$E_i(k)$ and $S_j(k)$ are assumed to be realizations of the E and S stochastic processes, respectively, with expectations $E(k)$ and $S(k)$ such that:

$$Pr(E(k) \neq 0 | k < 0, k > K_E - 1) = 0$$

$$Pr(S(k) \neq 0 | k < 0, k > K_S - 1) = 0$$

Hence,

$$E_i = \{E_i(t_i), \dots, E_i(t_i + K_E - 1)\}$$

and

$$S_j = \{S_j(t'_j), \dots, S_j(t'_j + K_S - 1)\}$$

can be both considered as short-term signals, occurring, respectively, at times t_i and t'_j . E_i and S_{j-i} correspond, respectively, to the ECG and SAP components of the same i th VC. For the other terms, E_i represents the i th QRS complex while S_i represents the i th SAP systolic pressure wave. Although the time series, $TS_1 = \{t_i\}$ and $TS_2 = \{t'_j\}$, that describe the true time occurrences of $\{E_i\}_{1 \leq i \leq NV}$ and $\{S_j\}_{1 \leq j \leq NV}$ are asynchro-

nous, they are strongly correlated, since the time series $\Delta = \{\Delta_i = t_i - t'_i\}$ here is related to a physiological representation of the electromechanical delay.

$B_1(k)$ and $B_2(k)$ represent noisy activities observed on the ECG and SAP channels, respectively. They do not correspond to any ventricular activity of interest, namely the QRS complexes and the systolic pressure waves to be detected, but they can corrupt them and even completely mask their observation. Throughout this article, no further hypothesis is assumed about the properties of $B_1(k)$ and $B_2(k)$. (To illustrate the difficulties in managing noisy situations, examples of representative situations to be processed are depicted in Fig. 3.)

The problem addressed in this article comprises the correct labeling of all NV-successive VC. By formulating the problem statement in this way, we propose to track the VR from data that are not only multichannel but also multimodal. We are aware of approaches that use multichannel/monomodal data, e.g., multilead surface ECGs or vectorcardiograms (VCGs), in the case of work by Gritzali [5].

Although VR tracking seems a relatively simple monitoring task, the signal lacks robustness and its efficiency remains limited.

Proposed Detection Structure

The previous problem statement is generally examined from a distributed detection perspective and different methods have been proposed to characterize the problem. The first method comprises the optimization of certain criteria (e.g., Bayes or Neyman-Pearson) on each channel and then uses classical logical operations for decision making [8]. Some refinements to this last approach have been proposed [9]. Another solution consists in optimizing the fusion rule [10, 11], while a third strategy aims to optimize certain criteria for the whole decision structure [12], including each elementary detector and the fusion node [13]. But all these approaches remain inadequate when dealing with asynchronous decisions.

Nevertheless, fusion rules, which consider the number of decisions that each detector takes over a fixed observation interval $[0, \tau]$ to be Poisson-distributed, have been proposed by Chang, et al. [14], to deal with such cases. But, again, this is inappropriate for our problem due to the transient and repetitive character of the events to be detected. These last considerations have led us to propose a novel processing architecture, depicted in Fig. 1. In this three-level architecture, two detectors, namely, D_1 and D_2 , working independently on each channel, track, respectively, the short-term signals $\{E_i\}_{1 \leq i \leq NV}$ and $\{S_j\}_{1 \leq j \leq NV}$. Then, the outgoing sequences of time-stamped labels, denoted DS_1 and DS_2 , are combined by the matching procedures, M_1 and M_2 , yielding to two redundant and complementary sequences of matched events,

1. Synoptic diagram of the proposed VC detection structure based on ECG and SAP data fusion.

2. Pictorial description of the matching procedures: a) M_1 , and b) M_2 (see text).

MS_1 and MS_2 . These latter events are finally merged into two output sequences of time-stamped labels, FS_1 and FS_2 , by a data-fusion node, F . This fusion center does not fuse only symbolic information, that is, the presence or absence of a ventricular event, but also numeric information related to the time occurrences of the ECG and SAP components of each estimated VC.

Level 1: Detection

Level 1 aims to estimate the true time series, TS_1 and TS_2 , from the noisy activities, $B_1(k)$ and $B_2(k)$. Estimating TS_1 or TS_2 is usually solved by constructing a decision statistic that enhances the waves, $\{E_i\}_{i \in \mathcal{I}_{ENV}}$ or $\{S_j\}_{j \in \mathcal{I}_{ENV}}$, of interest, while minimising the influence of the corresponding noisy activities, $B_1(k)$ or $B_2(k)$. The statistic is then thresholded to derive the detected time sequence, either

$DS_1 = \{(E, \hat{t}_i)\}$ or $DS_2 = \{(S, \hat{t}'_j)\}$, wherein the labels E and S are added to fulfill the requirements of the subsequent levels L1 and L2.

Among QRS complex detectors proposed during the last two decades, two have been retained to be tested and compared in estimating the TS_1 and TS_2 series. The first, denoted D_1^{GR} , has been proposed recently by Gritzali [5] as a generalization of several other QRS complex detectors. The second, denoted D_1^{PT} , is derived from the QRS complex detector of Pan and Tompkins [15], which is usually considered as one of the most efficient QRS complex detectors for noisy situations. Its input band-pass filter has been redesigned to take into account the 100 Hz sampling frequency of the ECG signal as well as 50 Hz power-line interference.

SAP, as other blood-pressure signals, can be roughly considered as a serrate-like signal, wherein discontinuities coincide with systolic ejection time points, so that a simple derivative filter should be well suited to detect these arrival times. As a consequence, the length transformation proposed by Gritzali was retained.

Level 2: Matching

Matching aims to enhance the likelihood of each outcoming time-stamped label from the previous level by searching for a suitable match on the opposite channel with a time-stamped label that may correspond to the same VC. This match is performed starting from either channel by testing for the electromechanical delay between match candidates. As described in Fig. 2(a), the matching procedure, M_1 , proceeds from channel 1 according to the following steps:

3. Examples of noisy situations managed from the subset of the IMPROVE data library.

Table 1. Definition of the fusion rules used for a fusion node F acting as a logical operator AND.

F ≡ AND		
Input	Output	
MS_1 / MS_2	FS_1	FS_2
$(E, \hat{t}_i, S, \hat{t}_j)$	$(E, \hat{t}_i)$	$(S, \hat{t}_j)$
$(E, \hat{t}_i, \emptyset, 0)$	—	—
$(\emptyset, 0, S, \hat{t}_j)$	—	—

From each time-stamped label $(E, \hat{t}_i) \in DS_1$:

1) open, on channel 2, a 2σ wide search window $W_{1 \rightarrow 2} = [\hat{t}_i + \hat{\Delta} - \sigma, \hat{t}_i + \hat{\Delta} + \sigma]$,

2) within $W_{1 \rightarrow 2}$, search for a match with $(S, \hat{t}'_j) \in DS_2$ such that $k = \text{ArgMin}_j |\hat{t}_i - \hat{t}'_j + \hat{\Delta}|$

3) If k does not exist, append the 4-tuple $(E, \hat{t}_i, \emptyset, 0)$ in MS_1 and go to step 7

4) otherwise, search for a better match, $(E, \hat{t}_i, S, \hat{t}'_k)$, such that $\hat{t}_i < \hat{t}'_k \leq \hat{t}_i + 2\sigma$

5) if j does not exist, append the 4-tuple $(E, \hat{t}_i, S, \hat{t}'_k)$ in MS_1 and go to step 7

6) otherwise, append the 4-tuple $(E, \hat{t}_i, \emptyset, 0)$ in MS_1

7) $i=i+1$, return to step 1

The search-window parameter, σ , and the estimated mean electro-mechanical delay, $\hat{\Delta}$, are considered fixed parameters. Their magnitudes will be defined later. At step 3a, $\emptyset$ and $\hat{t}'_k = 0$ will indicate to the subsequent fusion node, F , that the time-stamped label $(E, \hat{t}_i)$ remains unmatched. Besides, it must be pointed out that each time-stamped label, $(S, \hat{t}'_j) \in DS_2$, once matched, cannot be reassigned by M_1 .

The matching M_2 procedure proceeds similarly on channel 2, as depicted in Fig. 2(b). From $(S, \hat{t}'_j) \in DS_2$, the 2σ wide search window

$$W_{2 \rightarrow 1} = [\hat{t}'_j - \hat{\Delta} - \sigma, \hat{t}'_j - \hat{\Delta} + \sigma]$$

is opened on channel 1, within which the best time-stamped label, $(E, \hat{t}_l) \in DS_1$, is searched so that:

$$l = \text{ArgMin}_i |\hat{t}'_j - \hat{t}_l - \hat{\Delta}|$$

In case of no match candidate in $W_{2 \rightarrow 1}$, the 4-tuple $(\emptyset, 0, S, \hat{t}'_j)$ is arbitrarily pro-

The proposed approach can easily be extended to the processing of an N -dimensional input signal.

duced in MS_2 . Otherwise, the 4-tuple $(E, \hat{t}_l, S, \hat{t}'_j)$ is temporarily created in MS_2 , and then validated, unless a better match candidate, $(E, \hat{t}_l, S, \hat{t}'_m)$, is detected such that $\hat{t}'_j < \hat{t}'_m \leq \hat{t}'_j + 2\sigma$. Here again, any time-stamped label $(E, \hat{t}_l) \in DS_1$ cannot be assigned twice. Finally, it can be stressed that the output sequences of the 4-tuples of MS_1 and MS_2 will not be exactly the same as the incoming time-stamped label sequences and will also include their own missed detections and false alarms.

Level 3: Fusion

At this level, the sequences MS_1 and MS_2 are fused together to give two output sequences of time-stamped labels, FS_1 and FS_2 , with the former related to the ECG channel and the latter to the SAP channel. First, redundancy in information that may exist between MS_1 and MS_2 is filtered to avoid twice processing 4-tuples present in both sequences. Then, the remaining 4-tuples, $(X, \hat{t}_i, Y, \hat{t}'_j)$, where $(X, Y) \in \{(E, S), (E, \emptyset), (\emptyset, S)\}$, are fused sequentially and separately. Due to the Boolean character of labels X and Y , two logical fusion operators have been alternately used for this purpose, namely, the AND and OR logic operators. For both, matches $(X, \hat{t}_i, Y, \hat{t}'_j)$ such that $(X, Y) \equiv (E, S)$ are considered as nonconflicting and are, as a matter of fact, equally processed. Each match, $(E, \hat{t}_i, S, \hat{t}'_j)$, is split by the fusion node, F , into a pair of time-stamped labels, $(E, \hat{t}_i)$ and $(S, \hat{t}'_j)$, that are added, respectively, in the output sequences FS_1 and FS_2 . But

4. VC detection ROC curves obtained at the output of Level 1 (detection), for the three detectors used, namely, D_1^{GR} , D_1^{PT} , and D_2^{GR} .

when dealing with conflicting matches, $(X, \hat{t}_i, Y, \hat{t}_j)$, for which $(X, Y) \equiv (E, \emptyset)$ or $(X, Y) \equiv (\emptyset, S)$, the AND and OR fusion operators act differently, as depicted in Tables 1 and 2. When acting as an AND, conflicting matches are simply disregarded by the fusion node, F , which means that all decisions, $(E, \hat{t}_i)$ and $(S, \hat{t}_j)$, taken at the first level that remain unmatched at the output of the second level, are *a posteriori* invalidated by F , which rather concludes the presence of artifacts at these times. But when acting as the logical operator OR, such decisions are not only validated by F , but true ventricular events are also inferred in FS_1 and FS_2 at times $\hat{t}_j - \hat{\Delta}$ and $\hat{t}_i + \hat{\Delta}$, respectively.

Results

Data Selection and Labeling

The proposed architecture has been tested on a noisy substract of the IMPROVE DL. We have chosen patient 2 as an example of someone who presented periods of unrest and variations of VR. As depicted Fig. 3, the noisy period includes parts of the ECG and SAP records in which there are, among others, a) total sensor failure in ECG as well as in SAP, and as a consequence, complete loss of signal; b) motion artifacts; and c) slow and abrupt baseline drifts. Other causes of noise in the data emanate from clinical interventions from nurse observations and care processes. For the creation of our noisy database, we have reassembled ECG and SAP signals that represent three hours of patient recordings, which correspond also to NV = 16650 successive VCs to be detected.

Hand-annotation was performed by a clinician for both channels. The time series TS_1 and TS_2 were defined so that the time occurrences of the true events coincide, respectively, with the peaks of the QRS complexes and with the peaks of the systolic pressure waves for the SAP channel. Due to random sensor failure, or instrumentation saturation, about 1000 QRS ventricular complexes and 500 systolic pressure waves can be truly considered as undetectable events by any one-dimensional signal-processing method.

Level 1: Detection

Performances of the three VC detectors were compared with each other from the traditional receiving operating characteristic (ROC) curves. As recommended by the Association for the Advancement of Medical Instrumentation (AAMI) [16],

a beat-by-beat matching within 150 ms between beat labels from the annotated database used and those produced by the algorithm under test was required. Results are reported in Fig. 4. When focusing on the QRS-complex-detection ROC curves, no best QRS complex detector can be declared. Both provide: a) a very good detection probability (Pd close to 0.9) for a false-alarm rate greater than 10^{-2} , b) a significant loss of performance (Pd less than 0.1) for a false-alarm rate less than 10^{-3} . Between these two false-alarm rates, a rapid decrease in the detection probability can be observed for both detectors, which indicates a rather good bipolar behavior in the amplitude distribution of the corresponding decision statistics. Under these conditions, the QRS complex detector of Pan and Tompkins was retained.

A similar decrease is observed in the SAP detector ROC curve, but less abrupt, and for a false-alarm rate ranging from 10^{-2} to 10^{-4} . This better result does not imply a better ability for the length transformation of Gritzali to detect VC, but rather a more robust nature of the SAP compared with

the ECG for the particular case of our noisy database.

Level 2: Matching

The search window parameter, σ , and the mean electromechanical delay, $\hat{\Delta}$, were estimated in two steps. First, a very large search window was used to evaluate the spread in delay times, and second, both parameters were modified from the calculated distributions. As allowed by physiological representation of electromechanical delay values between ECG and SAP [17], $\hat{\Delta}$ was initially set to 120 ms, whereas a large value of 300 ms was given to σ , allowing the estimated mean electromechanical delay to be negative. Matching was then carried out first on the hand-

Table 2. Definition of the fusion rules used for a fusion node F acting as a logical operator OR.

F $\equiv$ OR		
Input	Output	
MS_1 / MS_2	FS_1	FS_2
$(E, \hat{t}_i, S, \hat{t}_j)$	$(E, \hat{t}_i)$	$(S, \hat{t}_j)$
$(E, \hat{t}_i, \emptyset, 0)$	$(E, \hat{t}_i)$	$(S, \hat{t}_i + \hat{\Delta})$
$(\emptyset, 0, S, \hat{t}_j)$	$(E, \hat{t}_j - \hat{\Delta})$	$(S, \hat{t}_j)$

5. Estimated mean electromechanical delay histogram: a) when estimated with the hand-annotated noisy database, b) when estimated at the output of the D_1^{PT} and D_2^{GR} detectors, both tuned with a 10^{-2} false-alarm rate.

6. VC detection ROC curves obtained at the output of Level 3 (fusion): a, b, c) when compared with the VC detection ROC curve of Level 1, channel 1, for three fixed amounts of SAP ventricular rhythm information fused with ECG; and d, e, f) when compared with the VC detection ROC curve of Level 1, channel 2, for three fixed amounts of ECG ventricular rhythm information fused with SAP. ROC curves obtained with the fusion node, F , acting as the AND operator, are depicted with symbol "X," while ROC curves depicted with the symbol "+" correspond to a fusion node, F , acting as the logic operator OR.

annotated noisy database, yielding the histogram depicted in Fig. 5(a), which confirms the initial value given to $\hat{\Delta}$. But, when matching was carried out at the output of the detectors, both tuned to a common 10^{-2} false-alarm rate, a novel value of 170 ms was achieved for $\hat{\Delta}$, as seen in Fig. 5(b). Moreover, an increase in the standard deviation can be observed, indicating the presence of a jitter phenomenon in the outcoming detection times from the first level. To compensate for this drawback, a large enough value of 100 ms was finally defined for σ , whereas a 145 ms value for $\hat{\Delta}$ was retained as a compromise between 120 ms and 170 ms. For the defined parameters σ and $\hat{\Delta}$, the MS_1 sequence resulted in 2.17% unmatched ECG detection points,

versus 8.45% unmatched SAP detection points in MS_2 .

Level 3: Fusion

Two kinds of experiments were conducted to evaluate the benefits of the proposed data-fusion approach in VR tracking, relative to the one-dimensional VC detectors used. First, VC detection performances were evaluated for each channel by means of ROC curves and for different amounts of VR information coming from the opposite channel. Figures 6(a-c) illustrate the QRS-complex-detection performances obtained for a decreasing amount of rhythm information coming from the SAP channel. Figures 6(d-f) correspond to the reverse case, where the ECG is considered this

time as extra information for SAP event detection in the data-fusion scheme. ECG and SAP detector ROC curves have been reported, respectively, in Fig. 6(a-c) and 6(d-f) for comparison purposes. Whichever case is considered, results obtained for the OR fusion rule show that the false-alarm rate remains, to a first approximation, lower bounded by the highest false-alarm rate present at the input of the fusion node. Conversely, for the AND logical fusion operator, the output false-alarm rate can be considered as upper bounded by the lowest input false-alarm rate. Compared with the ROC curves of both one-dimensional VC detectors used, data fusion yields to better results: a) for false-alarm rates less than $5 \cdot 10^{-3}$ —except for Fig. 6(f), where

7. VC detection ROC curves obtained at the output of Level 3 (fusion), for a fusion node, F , acting as an AND ("X"), or as an OR ("+"), logical operator, and for front-end detectors, D_1^{PT} and D_2^{GR} , both tuned with successive common false-alarm rates.

the ECG additional rhythm information remains inadequate, with a fusion node acting as an AND; and b) for the greatest false-alarm rates, but with a fusion node acting as an OR. In this experiment, best results were obtained for a 10^{-2} false-alarm rate, as reported Fig. 6(b) and 6(e), whether or not extra rhythm information comes from ECG or SAP.

A second experiment, classically used in distributed detection, consists in evaluating the data-fusion scheme when front-end detectors have been tuned with common false-alarm rates. Data-fusion results obtained in this configuration are shown Fig. 7 and compared with the ROC curves of each VC detector. An increase in the VC detection performance is always observed for the OR fusion rule, whereas the AND fusion operator makes the VC detector, based on data fusion, optimal for false-alarm rates less than $2 \cdot 10^{-2}$.

Conclusion

A novel approach for robust cardiac VR tracking, based on electrophysiologic and haemodynamic data fusion, has been described. Evaluation, performed on a short but noisy subset of the IMPROVE DL, shows better VC detection perform-

ances for the data-fusion approach than for the two other one-dimensional QRS detectors used, namely, the one proposed by Pan and Tompkins, and the length transformation of Gritzali. We are aware that the proposed data-fusion approach needs to be assessed on a larger database, such as the IMPROVE DL, as compared with a 2-D ECG detector, such as the one proposed by Gritzali [5]. But it must be emphasized that the proposed approach can easily be extended to the processing of an N -dimensional input signal, which can be either monomodal (N -lead ECG) or multimodal (ECG, invasive/noninvasive blood pressure signals, phonocardiogrammas, etc.), provided information related to the ventricular activity is available on each channel. Multichannel matching as well as fusion between ventricular events will be accordingly adapted, but the ability of this approach to deal with asynchronous detections remains unchanged. Other fusion operators such as the MAJORITY, or M among N, could be envisaged in this case. Finally, the proposed methodology remains valid for multichannel tracking of events other than the QRS complex, for example, the P wave, from a pair of surface and oesophageal ECG signals.

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