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ORIGINAL ARTICLE

Sequentiality of Daily Life Physiology: An Automatized Segmentation Approach

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Abstract Based on the hypotheses that (1) a physiological organization exists inside each activity of daily life and (2) the pattern of evolution of physiological variables is characteristic of each activity, pattern changes should be detected on daily life physiological recordings. The present study aims at investigating whether a simple segmentation method can be set up to detect pattern changes on physiological recordings carried out during daily life. Heart and breathing rates and skin temperature have been non-invasively recorded in volunteers following scenarios made of "daily life" steps (13 records). An observer, undergoing the scenario, wrote down annotations during the recording time. Two segmentation procedures have been compared to the annotations, a visual inspection of the signals and an automatic program based on a trends detection algorithm applied to one physiological signal (skin temperature). The annotations resulted in a total number of 213 segments defined on the 13 records, the best visual inspection detected less segments (120) than the automatic program (194). If evaluated in terms of the number of correspondences between the times marks given by annotations and those resulting from both physiologically based segmentations, the automatic program was better than the visual inspection. The mean time lags between annotation and program time marks remain <60 s (the precision of annotation times marks). We conclude that physiological variables time series recorded in common life conditions exhibit different successive patterns that can be detected by a simple trends detection algorithm. Theses sequences are coherent with the corresponding annotated activity.

Keywords Physiology · Daily life · Sequentiality · Segmentation

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1 Intro/Rationale

The life of an individual can be described as a series of activities considered as elements of behaviours that are sequentially linked together. The transitions between successive behaviours are attributed, in animals, to survival and contextual constraints (Thayera and Laneb 2000; Sih 2011). However, the physiological organization (coherent activation of concerned physiological functions) inside a given activity duration, or even inside each series of activities of a given behaviour, remains unclear. For example, final respiratory output involves a complex interaction between the brainstem and higher centres, including the limbic system and cortical structures. Thus, respiration, which is important in maintaining physiological homeostasis, and emotions coexist (Homma and Masaoka 2008). In addition, the processes of prioritization between interacting homeostatic systems are commonly unknown (Goldstein and Pinshow 2002). Indeed, the physiology of an individual revealed under laboratory conditions is unlikely to reflect realized responses to the complex variable stressors to which it is exposed in the wild (Metcalfe et al. 2012). Moreover, Atallah and Yang (2009) reported that the relationship between physiological parameters and activity could be variable between subjects.

If one assumes that a physiological organization exists inside each activity of daily life (Amigoni et al. 2003), physiological variables characteristic of an individual state should evidence a stable configuration of the physiological organization corresponding to each activity, or at least corresponding to each behaviour of a sequence. Moreover, one can expect that the pattern of evolution of physiological variables observed during each activity differs from those observed during the previous and the next activities. Following these hypotheses, such pattern changes should be evidenced on non-invasive physiological recordings of daily life.

The problem of pattern segmentation (and, subsequently, recognition) of physiological variables time series has been already addressed in details (Coiera 1993; Haimowitz et al. 1995; Charbonnier et al. 2004) in the context of critically ill patients monitoring. These time series are often non-stationary and they usually exhibit patterns such as trends, level changes, spikes and periods of stability. Sophisticated methods have been proposed for filtering these signals (Chieu et al. 2006), usually in order to eliminate false alarms (Lanius and Gather 2010) or to localize singularities (Guméry et al. 2008). The segmentations carried out on filtered signals are then interpreted in terms of clinical state.

In our context the segmentation and recognition of patterns in physiological variables time series will be used to test the hypothesis that different physiological organizations are successively invoked in common life. In order to obtain initial arguments in favour of this hypothesis, the aim of the present study was to investigate whether a simple segmentation method can be set up to detect pattern changes on non-invasive physiological recordings in healthy volunteers carrying out daily life behaviour sequences. Two procedures have been tested, a visual ordered inspection of physiological signals and an automatic program based on a trends detection algorithm applied to one physiological signal.

Table 1 Population data and number of records

Subjet #	Sex	Age	Height (cm)	Weight (kg)	Nb records
1	H	27	178	74	3
2	F	25	169	59	2
3	F	25	165	63	1
4	F	30	172	80	2
5	H	28	183	67	1
6	H	24	177	57	1
7	H	26	186	75	2
8	H	63	189	90	1
		Mean (SD)	Mean (SD)	Mean (SD)	Total
		31 (11)	177 (8)	71 (11)	13

2 Materials and Methods

2.1 Population, Protocol and Measurements

8 healthy volunteers (3 females, 5 males) participated in the study, providing informed consent. The local and national ethics committees have previously approved the study (no. Afssaps: 2008-A00273-52). Subject data are gathered in Table 1. The protocol consisted in the simultaneous recording of data from ambulatory sensors for 2 subjects at each time. This protocol is needed to obtain realistic scenarios. Subjects # 1, 2, 4 and 7 are permanent members of the research team and were asked to participate more than once in order to provide a “companion” to other subjects when needed.

The system used was the EQ-01 sensor unit (monitoring belt; Equivital, Hidalgo). Heart and breathing rates (HR and BR, respectively), skin temperature (ST), position (P) and motion (M) data were recorded with a 5 s sampling period (HR, P and M) or 15 s sampling period (BR and ST). Data were saved as text files. Subjects were asked to come in the lab with work material and lunch at 11 a.m. and were given a scenario made of “daily life” steps: computer work and/or paper document reading, meal, stairs climbing or descending, nap, walking between rooms. The order of the steps and their durations were changed from 1 day to the other in order to avoid subjects investigated twice or more to undergo the same scenario.

An observer, undergoing the scenario, wrote down annotations during the recording time. The same observer annotated all recordings. Annotations are simply the date (in minute, relative to the recording start) and type of each change of activity including unscheduled event (phone call, caught,…). Annotations served as reference for evaluating the different segmentation procedures tested. Activity data (P and M) were used only for visual confirmation of annotations. As an example, physiological signals evolution during the second recording on subject #2 is presented in Fig. 1.

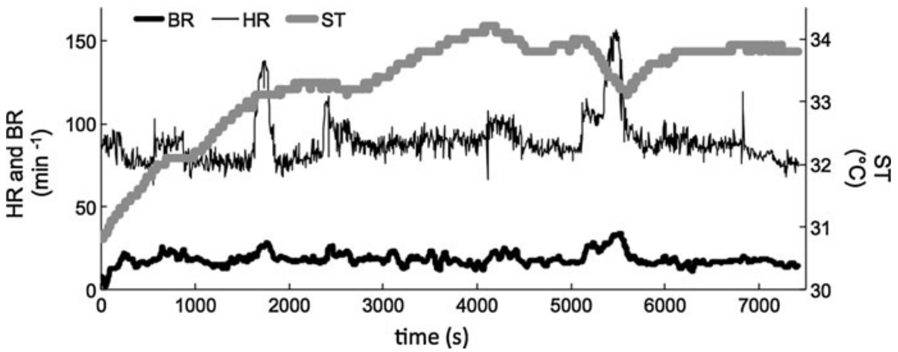

Fig. 1 Physiological signals recorded on subject # 2 (record #7). *HR* heart rate, *BR* breathing rate and *ST* skin temperature

2.2 Segmentation

The segmentation of the recordings has been carried out on physiological variables (HR, BR and ST) by two concurrent methods: a visual inspection by two experts and an automatic segmentation program.

The visual segmentation procedure consisted in visual inspection of one physiological signal and determination of segments of simple trends (monotonic increase, monotonic decrease, stability) on it. The first signal examined gave a first segmentation, which was refined by considering the possible variations of the second and the third signals inside each initially detected segment. Figure 1 illustrates the fact that ST and HR exhibit more distinguishable phases of increase, decrease or stability than BR. Then, based on preliminary study (data not shown), the visual segmentation procedure applied to all recordings, consists in a first segmentation based on the examination of ST, followed by a second segmentation based on HR recordings.

The algorithm of the automatic segmentation program is restrained to the analysis of skin temperature signal trends. Indeed, this signal presents, on all recordings, a series of simple trend parts and does not exhibit a rapid dynamic, except isolated single values different from identical preceding and following ones. Accordingly, the first step of the algorithm consists in replacing theses isolated values by the value of their neighbours. The algorithm then carries out a filter on the slope of the signal, calculating at each time step its mean value on an adjustable number (n_p) of points. The sign of this "filtered slope" at each time step constitutes a new signal made of 1, -1 and 0 values for positive, negative and null mean slopes, respectively. A segment of constant mean slope is then detected if an adjustable number (n_s) of successive mean slope signs are equal. When a segment is detected, if the next slope sign is the same, the segment is widened with one more point, and so on. If the next slope sign is different, the algorithm looks for detecting a new segment. The optimal set of parameters ($n_p = 4$, $n_s = 6$) was the one that led to the best concordance of the number of detected segments to the number of segments given by annotations on the same two recordings (#8 and #2). This set of parameters proved also to be optimal on the other recordings and was thus retained for the whole analysis. The algorithm has been implemented as macros Excel.

2.3 Physiological Segmentations Evaluation

The first evaluation of segmentations based on physiological signal has been carried out on the total number of segments detected on all recordings by these two approaches as referred to the total number of segments defined by annotations. A paired *t* test was subsequently used to compare the number of segments detected on each recording by the program ($n_{S,P}$) to the number of segments detected on each recording by visual inspection ($n_{S,V}$).

The final quantitative evaluation of the two segmentations based on physiological signal (visual inspection and automatic program) relies on the definition of a correspondence between the time marks given by annotations and those resulting from both physiologically based segmentations. We have first stated that a correspondence between an annotation time mark and a physiological time mark can be considered only if the absolute time lag between these marks is less than 240 s (4 min). Indeed, the shortest activity included in the scenarios was 3 min long and the precision of annotation time mark was ±1 min. If a time mark of one series could correspond to two time marks of the other, the best correspondence (smaller absolute time lag) only was kept. We have subsequently compared the number of correspondences between physiologically based segmentations and annotation time marks ($n_{C,A/P}$: number of correspondences between annotation time marks and program time marks; $n_{C,A/V}$: number of correspondences between annotation time marks and visual time marks) by a paired t-test. We finally evaluated the mean time lags between corresponding time marks ($\Delta t_{A/P}$: time lag between annotation and program time marks; $\Delta t_{A/V}$: time lag between annotation and visual inspection time marks).

3 Results

3.1 Visual Inspection Performance

Intra- and inter-expert concordance was satisfying: we obtained a difference of 1 at much between experts or repeated inspections $n_{S,V}$ on each recording, and <1 min between corresponding (experts or repeated) visual inspection time marks.

3.2 Number of Segments Detected

The annotations resulted in a total number of 213 segments defined on the 13 records, the best visual inspection detected less segments (120) than the program using the optimised algorithm (194, for detailed results on each recording, see Table 2). The paired t-test shows that $n_{S,P}$ is significantly higher than $n_{S,V}$ ($p < 0.001$).

Table 2 results for each record of the evaluation of the two approaches for segmentation of physiological recordings

Record #	Subject #	$n_{S,A}$	$n_{S,P}$	$n_{S,V}$	$n_{C,A/P}$	$n_{C,A/V}$	$\Delta t_{A/P}$ (s)	$\Delta t_{A/V}$ (s)
1	1	16	13	7	8	5	−5	4
2	2	16	4	5	3	4	−6	0
3	3	13	3	4	2	3	2	28
4	4	16	17	7	8	6	−34	−48
5	1	19	13	9	9	8	−23	30
6	5	18	22	16	13	10	−58	−11
7	2	16	14	12	11	8	−20	−24
8	6	17	18	12	13	10	−50	−14
9	7	16	22	13	12	10	−11	4
10	8	17	21	7	10	5	−35	−34
11	1	17	17	7	9	4	3	14
12	7	15	14	10	8	7	−14	−40
13	4	17	16	11	10	9	−26	−32

$n_{S,A}$ number of segments given by the annotations, $n_{S,P}$ number of segments detected by the program, $n_{S,V}$ number of segments detected by visual inspection, $n_{C,A/P}$ number of correspondences between annotation time marks and program time marks, $n_{C,A/V}$ number of correspondences between annotation time marks and visual inspection time marks, $\Delta t_{A/P}$ mean time lag between annotation and program time marks for the record, $\Delta t_{A/V}$ mean time lag between annotation and visual inspection time marks for the record

3.3 Number of Correspondences

The total number of correspondences was greater for program (116) than for visual inspection (89). A paired t-test applied on individual values of $n_{C,A/P}$ and $n_{C,A/V}$ shows that $n_{C,A/P}$ is significantly higher than $n_{C,A/V}$ ($p < 0.005$). This result indicates that program segmentation is closer to annotation segmentation than visual inspection segmentation.

3.4 Time Lags Between Annotation Marks and Physiological Marks

The mean time lags between annotation and program time marks ($\Delta t_{A/P}$) are negative in 10/13 cases. Whatever the sign, they remain <60 s (the precision of annotation dates). This result indicates that the program segmentation provides relatively late segment detections as compared to annotation but within the annotation precision range. Similarly, the mean time lags between annotation and visual inspection time marks ($\Delta t_{A/V}$) are always <60 s.

Figure 2 illustrates the correspondences between annotations and program segmentation on the same recording as in Fig. 1 (incidentally, it also provides an example of scenario). The 13 correspondences between segmentations from annotations and program exhibit a similar behaviour: vertical lines denoting a segment change detected by the program are late relative to changes of activity marked by annotations. As indicated by arrows, it happens that program

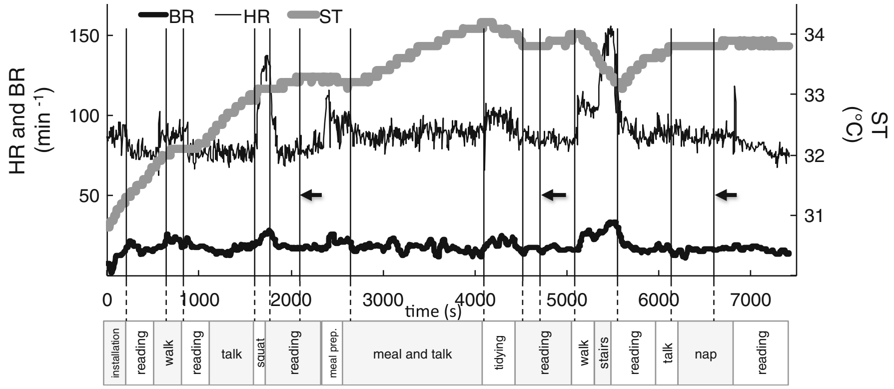

Fig. 2 Physiological signals of Fig. 1 (record #7) superimposed with annotation segments (at the *bottom*) and program segmentation (*vertical lines*). *HR* heart rate, *BR* breathing rate and *ST* skin temperature. The *vertical lines* indicated by *black thick arrows* do not correspond to any annotated change in activity

segmentation detects phases that do not correspond to any activity change during reading (twice) and nap (once). On the other hand, the program does not detect the difference between walk and stairs while heart frequency signal exhibits a clearly distinct pattern for each activity.

4 Discussion

The present study was carried out to see if a simple segmentation method could detect pattern changes on non-invasive physiological recordings obtained in daily life conditions.

4.1 Discussion on Methods

The protocol used was based on a scenario made of “daily life” steps, the order and durations of which were changed from 1 day to the other. Moreover, volunteers could influence the scenario: they were allowed to finish reading a page or ending a meal at will. In these conditions, a perfectly reproducible protocol was not possible. As the physiological behaviour related to a given activity is influenced by the preceding activity, which, in our protocol, is not always the same, our protocol is clearly not fitted to a deepened physiological analysis.

Two rather simplistic segmentation methods have been tested in this study. The visual inspection method is obviously submitted to subjectivity but the results given in terms of inter and intra-observer reproducibility are convincing.

The detection algorithm is rather simple; accordingly, the optimisation process was simplified as much as possible. The resulting optimal parameter set proved to be similarly efficient on all records and was not further questioned.

The method used to evaluate the results given by each tested segmentation method relies on the hypothesis that the physiological organization should change approximately as frequently as the behaviour changes, so that the number of physiological segments should be of the same order of the number of activities. This raises the question of a phenomenological coincidence between theses two types of sequences. For example, Hautala et al. (2010) state "the role of physical activity as a determinant of heart rate variability is not well established." Indeed, reading and talking activities may be physiologically undistinguishable from a metabolic point of view (skin temperature being an indirect index of metabolic level), and this happened in our experiment as illustrated on Fig. 2.

Even if the time lag between the annotation events and the automatic segmentation is less than the precision of annotation time, the systematic difference may be discussed. The automatic segmentation imprecision (precision 1 min.) is of the same order as the annotation imprecision: the algorithm imprecision is linked to the filtering effect of the averaging included in it. The algorithm starts from data sampled every 15 s (in the case of skin temperature) and the filtering effect (averaging on 4 consecutive values) may induce an imprecision of about 1 min. The small time lag of automatic segmentation on annotations can then be attributed to the delay induced by filtering. On the other hand, time response of physiological control loops could be questioned. However, in the literature, time response of physiological control loops to activity changes are all within a fraction of a minute whatever the level at which the response is observed and the physiological function [see Henderson et al. (2002), Powell et al. (1998) and Westerhof et al. (2006) for example].

The large allowed matching range (maximum time lag between an annotation time mark and a physiological time mark) has been chosen in order to take into account the predictable delay between muscular activity change and the resulting effect, if any, of this metabolic level change in terms of thermoregulation. Other causes may induce changes in skin temperature trend: for example a change in the position of the sensor due to a change in the posture, and following a change in the thermal coupling of the sensor to the skin. In any case, the temperature sensor inertia can induce a delay between the cause and the measured temperature effect but the cause remains an event that can be interpreted in terms of physiology.

4.2 Discussion on Results

Our results clearly demonstrate that physiological variables time series recorded in common life conditions exhibit different successive patterns that can be detected by a simple trends detection algorithm. Theses sequences are coherent with the corresponding annotated activity sequence although some discrepancies exist between the numbers of detected segments. Indeed, usually $n_{S,A} > n_{S,P}$ and $n_{S,V}$ which indicates that the segmentation methods are not sensitive enough or that physiological organization does not differ between successive activities like reading and talk. However, in some cases (records # 4, 6, 8, 9 and 10) $n_{S,P} > n_{S,A}$ which remains to be interpreted in terms of a change in physiological organization during a given activity. Such changes did not manifest by an observable behaviour change.

We have first verified that the sequences given by a purely explorative visual method were realistic, which proved to be true as evidenced by encouraging results obtained on all records. The same holds for algorithm design: the results obtained with only one physiological signal (ST) were satisfying enough to analyse the algorithm performance without looking for more signals. However, in order to investigate and characterize physiological organisation, this algorithm needs to be improved. Two improvements are considered: (1) the qualitative trend analysis has to be changed to a quantitative one to detect important slope changes, and (2) other signals have to be taken into account, starting with heart rate.

Indeed, HR signal actually presents different characteristics, including an important noise and a very fast dynamic as evidenced by abrupt level changes, e.g. at time 600 ms in Fig. 1. Consequently, the algorithm built up for skin temperature is not suitable as such for an automatic segmentation of HR signal. In order to bring this signal into the framework of the presented segmentation algorithm, 2 steps were needed: (a) filter the signal in order to eliminate the noise, and particularly the outliers, and (b) re-sample the signal with a resolution similar to the one obtained on temperature (1/50 full scale) and a 15 s sampling period.

In order to denoise the HR signal, we performed a non-decimated wavelet decomposition (Nondecimated 1-D wavelet transform Matlab®) at level 30 using the Haar wavelet. The resulting signal that corresponds to the approximation of the decomposition is shown Fig. 3 as well as the automatic segmentation obtained after re-sampling at lower resolution and frequency. Globally, the automatic segmentation of the resulting HR signals gave results similar to those obtained on ST, even if somehow better, in terms of number of detected segments (95 %) as well as number of correspondences (75 %). A similar result was obtained on BR signals.

Once some segmentation is obtained, its interpretation in terms of physiology remains difficult as the physiological behaviour related to a given activity is influenced by the preceding activity, which, in our protocol, is not always the same. Moreover, the observed transients may be related to several causes including

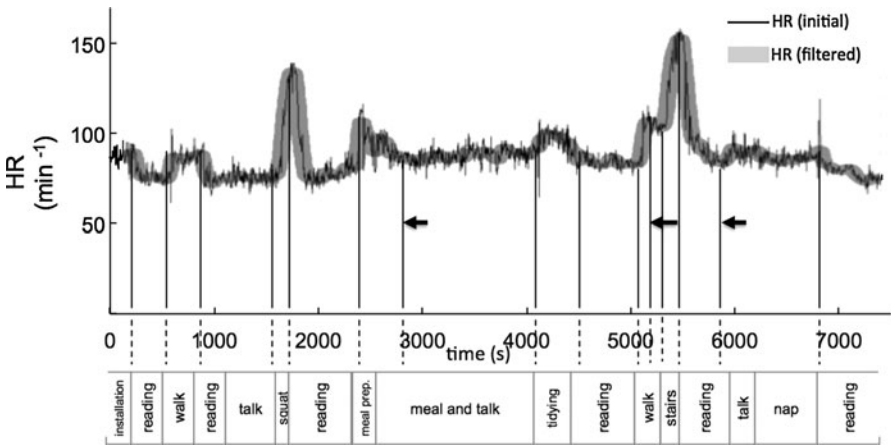

Fig. 3 Original HR signal, filtered HR signal and the result of the segmentation algorithm, presented on the same data as Fig. 1. The *vertical lines* indicated by *black thick arrows* do not correspond to any annotated change in activity

non-physiological ones. For example, ST changes (Fig. 1) can be attributed to a transient before thermal equilibrium (between $t = 0$ s and $t = 1{,}600$ s) or to a change in the heat flux between skin and sensor (between $t = 5{,}000$ s and $t = 5{,}500$ s). One can also argue about the transients detected by Skin Temperature and not annotated (thick arrows in Fig. 2): the first one (time about 2,000 s) is obviously an artificial separation of an exponential dynamic onto its initial rapid decrease and its final asymptotic behaviour; by the way, it is not accompanied by any noticeable change in HR and/or BR; the second one (time about 4,700 s) has no obvious interpretation as, during this reading phase, an "accident" is present at the same time on the BR signal (a similar phenomenon could exist on HR). One may suppose that this transition has been caused by an event that had not been annotated.

This study comes within the scope of an integrative physiological interpretation of the usually perfectly adapted responses to the complex variable stressors to which an individual is exposed in the daily life. The proposed approach starts from the hypothesis that the integrated physiologic responses to complex dynamical environment is a sequence, the organism being supposed to change its internal physiological organization scheme depending on the successive situations. Such a scheme should be constituted by a first-line mobilisation of dedicated resources associated with background maintenance of physiological regulations and controls, and scheme changes are supposed to result into changes in patterns of non-invasive physiological measurements. This approach could be complementary to the actual integrative approach based on dynamical systems where interactions between physiological functions are considered independent of time (Thomas et al. 2008; Fontecave-Jallon et al. 2009; Hernández et al. 2011) and then prioritization are not considered. These models may be submitted to changes in metabolism or environment constraints level but they are not able to decipher whether one function or another prevails.

Such a segmentation approach on physiological non-invasive measurements could be helpful in the applied fields of monitoring and support for ambulatory patients or physical exercise.

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References

Amigoni F, Dini M, Gatti N, Somalvico M (2003) Anthropic agency: a multiagent system for physiological processes. Artif Intell Med 27:305–334

Atallah L, Yang GZ (2009) The use of pervasive sensing for behaviour profiling—a survey. Pervasive Mob Comput 5:447–464

Charbonnier S, Becq G, Biot L (2004) On-line segmentation algorithm for continuously monitored data in intensive care units. IEEE Trans Biomed Eng 51:484–492

Chieu HL, Lee W S, Kaelbling LP (2006) Activity recognition from physiological data using conditional random fields. Technical report, SMA Symposium

Coiera E (1993) Intelligent monitoring and control of dynamic physiological systems. Artif Intell Med 5:1–8

Fontecave-Jallon J, Abdulhay E, Calabrese P, Baconnier P, Guméry PY (2009) A model of mechanical interactions between heart and lungs. Philos Trans R Soc A 367:4741–4757

Goldstein DL, Pinshow B (2002) Taking Physiology to the Field: An Introduction to the Symposium. Integ Comp Biol 42:1–2. From the Symposium Taking Physiology to the Field: Advances in Investigating Physiological Function in Free-Living Vertebrates presented at the Annual Meeting of the Society for Integrative and Comparative Biology, 3–7 January 2001, at Chicago, Illinois

Guméry PY, Fontecave-Jallon J, Aïthocine E, Meignen S, Heyer L, Baconnier P (2008) Modified Structural Intensity for Singularity Localization in Noisy Signals: Application to Coherent Averaging for Event-Synchronous ECG Interference Cancellation in Diaphragmatic EMG Signals. Int J Adapt Control Signal Process 00:1-6

Haimowitz I, Phillip PL, Kohane I (1995) Clinical monitoring using regression-based trend templates. Artif Intell Med 7:473–496

Hautala AJ, Karjalainen J, Kiviniemi AM, Kinnunen H, Mäkikallio TH, Huikuri HV, Tulppo MP (2010) Physical activity and heart rate variability measured simultaneously during waking hours. Am J Physiol Heart Circ Physiol 298:H874–H880

Henderson LA, Macey PM, Macey KE, Frysinger RC, Woo MA, Harper RK, Alger JR, Yan-Go FL, Harper RM (2002) Brain responses associated with the Valsalva maneuver revealed by functional magnetic resonance imaging. J Neurophysiol 88:3477–3486

Hernández AI, Le Rolle V, Ojeda D, Baconnier P, Fontecave-Jallon J, Guillaud F, Grosse T, Moss RG, Hannaert P, Thomas SR (2011) Integration of detailed modules in a core model of body fluid homeostasis and blood pressure regulation. Prog Biophys Mol Biol 107:169–182

Homma I, Masaoka Y (2008) Breathing rhythms and emotions. Exp Physiol 93:1011–1021

Lanius V, Gather U (2010) Robust online signal extraction from multivariate time series. Comput Stat Data Anal 54:966–975

Metcalfe JD, Le Quesne WJF, Cheung WWL, Righton DA (2012) Conservation physiology for applied management of marine fish: an overview with perspectives on the role and value of telemetry. Philos Trans R Soc B 367:1746–1756

Powell FL, Milsom WK, Mitchell GS (1998) Frontiers review: time domains of the hypoxic ventilatory response. Respir Physiol 112:123–134

Sih A (2011) Effects of early stress on behavioral syndromes: an integrated adaptive perspective. Neurosci Biobehav Rev 35:1452–1465

Thayera JF, Laneb RD (2000) A model of neurovisceral integration in emotion regulation and dysregulation. J Affect Disord 61:201–216

Thomas SR, Baconnier P, Fontecave J, Françoise JP, Guillaud F, Hannaert P, Hernández A, Le Rolle V, Mazière P, Tahi F, White RJ (2008) SAPHIR: a physiome core model of body fluid homeostasis and blood pressure regulation. Philos Trans R Soc A 366:3175–3197

Westerhof BE, Gisolf J, Karemaker JM, Wesseling KH, Secher NH, van Lieshout JJ (2006) Time course analysis of baroreflex sensitivity during postural stress. Am J Physiol Heart Circ Physiol 291:H2864–H2874