

ADVANCED PHYSIOLOGICAL MONITORING OF FCS SOLDIERS

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Problem – The Future Combat Systems (FCS) requirement 3.2.1.8.6.7 (page 68 of S786-52000, System of Systems Objective Capabilities Specification for FCS) calls for an accurate and timely “physiological monitoring system to report Soldier medical status, when mounted or dismounted, to unit leaders and medical personnel.” Such monitoring requires continuous real-time assessment of each soldier’s observable physiological status. Typical battlefield events include (but certainly are not limited to) drowsiness, excessive fatigue, dehydration, overwhelming stress, shock from various battlefield traumas (e.g., blood loss from wound(s), broken bone(s), heat or cold exposure), and response to chemical/biological/radiological agents. Medical personnel cannot monitor the huge volume of continuous, real-time, physiological data from two thousand soldiers in the Unit of Action, so the monitoring system must include a capability for (quasi)-autonomous real-time analysis and assessment of the data.

Solution – Prognostics Solution – The Oak Ridge National Laboratory (ORNL) has developed an advanced statistical methodology that forewarns of physiological events from process indicative data, x_i . The analysis steps follow. (1) Check the data for quality. (2) Remove confounding artifacts (e.g., eye blinks from scalp brain waves) by fitting a parabola in the least-squares sense over a moving window of length $2w+1$, with w data points on each side of the current central point, and taking the central point of the fit as the best estimate of the low-frequency artifact, f_i . The residue, $g_i = x_i - f_i$ is essentially artifact-free. (3) Discretize the artifact-free signal, g_i , into one of S integer symbols, $0 \leq s_i \leq S-1$. (4) Create a d -dimensional vector, $y(i) = [s_i, s_{i+\lambda}, \dots, s_{i+(d-1)\lambda}]$, using an appropriate time lag, λ . (5) Tabulate the occurrences of this vector in the discretized (binned) d -dimensional phase space to obtain an approximate distribution function (DF). The location and visitation frequency of the phase-space bins capture the essence of the physiologic dynamics. In particular, (un)altered parameters/dynamics result in an (un)changed DF. (6) Repeat (5) for each contiguous, non-overlapping data segment to form DFs for the nominal (baseline) and sequel unknown (test) states, in which the bin populations are denoted by Q_i and R_i , respectively. (7) Compare the baseline and test DFs via phase-space dissimilarity measures (PSDM) defined as:

$$\chi^2 = \sum_i (Q_i - R_i)^2 / (Q_i + R_i), \text{ and } L = \sum_i |Q_i - R_i|,$$

where the sums run over the populated cells of the phase space. (8) Define a set of renormalized dissimilarity measures (RDMs), as the number of standard deviations from the baseline average. This approach allows assessment of the power of the PSDM as detectors of condition change, in comparison with traditional nonlinear measures (TNM), such as correlation dimension, Lyapunov exponents, Kolmogorov entropy, or mutual information. This method allows a meaningful comparison of the TNM and PSDM in the face of the disparities in range and variability. Distant (nearby) states have large (small) RDM, which we interpret as forewarning of departure from (closeness to) nominal state. (9) Indicate condition change (event forewarning) after a specific number of sequential RDM occurrences above a certain threshold.

Results – For all the applications to date, PSDM provide consistently better discrimination of condition change than TNM. Indeed, while TNM distinguish fairly well between regular and

chaotic dynamics, they cannot discriminate between *slightly different* chaotic regimes, especially for limited, noisy data. The reason for this enhanced performance is clear from the definitions: the PSDM compare the two quantities by first subtracting them locally and then summing these differences over the whole phase space; in TNM, the quantities are first averaged over the whole phase space and the averages are then compared. Medical applications to date (all successful) include: (a) forewarning of human epileptic seizures from scalp brain waves; (b) forewarning of cardiac fibrillations and (c) fainting from human electrocardiogram (ECG) data; (d) detection of septic shock due to inhaled endotoxin from rat ECG data; (e) detection of breathing difficulty from pig chest sounds. Timely detection of physiological condition change for such diverse applications lends strong credibility to the robustness of this advanced methodology.

Status – The method involves high-fidelity laboratory integration of the basic technological elements into software that analyzes archival data on a desktop computer for forewarning of failure in a simulated environment. The methodology handles limited, noisy, time-serial data (e.g., scalp brain waves, chest heart waves, chest sounds) and provides robust indications of change in the physiological dynamics (e.g., up to five hours forewarning of an epileptic event). The analysis is much faster than real-time, and can handle multiple streams of biomedical data (e.g., brain waves and heart waves). No special hardware is required, and the software adds no additional weight or bulk. ORNL has been granted six U.S. patents on the approach (with two additional patents pending). Consequently, the technology readiness level is 5 (TRL5).

Prototype – On-going development of the methodology includes a graphical user interface for the operator, robust software for the condition-change analysis, and implementation on a hand-held device (e.g., personal digital assistant) for on-line analysis of real-time data. We expect to complete these improvements in 2004, which would allow qualification for TRL6. Developments needed for TRL7 (suitable for clinical or field testing) involve primarily: (i) extensive statistical validation for specific physiological event(s) in an appropriate operational environment (measures of success include true-positive and true-negative rates, and the forewarning time distribution); and (ii) quasi-automatic determination of robust sets of parameters for analyst-independence.

Conclusion – Our innovative method combines several original advances to achieve sensitivity that is at least one order of magnitude higher than that of competing methods. The presence of a new, robust artifact filter allows for using physiological data that is contaminated by large amounts of noise/artifacts, as is typically the case in non-clinical environments, especially in the battlefield. This paper will provide methodology details, analysis results, status of the technology development, a roadmap for technology deployment, and specific suggestions for near-term FCS soldier applications.

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