Expert Systems with Applications 41 (2014) 295–305

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Classification of physiological signals for wheel loader operators using Multi-scale Entropy analysis and case-based reasoning

Shahina Begum [a,*], Shaibal Barua [a], Reno Filla [b], Mobyen Uddin Ahmed [a,c]

[a] School of Innovation, Design and Engineering, Mälardalen University, Sweden
[b] Emerging Technologies, Advanced Engineering, Volvo Construction Equipment, Sweden
[c] Center for Applied Autonomous Sensor Systems, Örebro University, Sweden

ARTICLE INFO

Keywords:
Sensor fusion
Case-based reasoning
Multi-scale entropy analysis
Physiological signals
Classification

ABSTRACT

Sensor signal fusion is becoming increasingly important in many areas including medical diagnosis and classification. Today, clinicians/experts often do the diagnosis of stress, sleepiness and tiredness on the basis of information collected from several physiological sensor signals. Since there are large individual variations when analyzing the sensor measurements and systems with single sensor, they could easily be vulnerable to uncertain noises/interferences in such domain; multiple sensors could provide more robust and reliable decision. Therefore, this paper presents a classification approach i.e. Multivariate Multiscale Entropy Analysis–Case-Based Reasoning (MMSE–CBR) that classifies physiological parameters of wheel loader operators by combining CBR approach with a data level fusion method named Multivariate Multiscale Entropy (MMSE). The MMSE algorithm supports complexity analysis of multivariate biological recordings by aggregating several sensor measurements e.g., Inter-beat-Interval (IBI) and Heart Rate (HR) from Electrocardiogram (ECG), Finger Temperature (FT), Skin Conductance (SC) and Respiration Rate (RR). Here, MMSE has been applied to extract features to formulate a case by fusing a number of physiological signals and the CBR approach is applied to classify the cases by retrieving most similar cases from the case library. Finally, the proposed approach i.e. MMSE–CBR has been evaluated with the data from professional drivers at Volvo Construction Equipment, Sweden. The results demonstrate that the proposed system that fuses information at data level could classify 'stressed' and 'healthy' subjects 83.33% correctly compare to an expert's classification. Furthermore, with another data set the achieved accuracy (83.3%) indicates that it could also classify two different conditions 'adapt' (training) and 'sharp' (real-life driving) for the wheel loader operators. Thus, the new approach of MMSE–CBR could support in classification of operators and may be of interest to researchers developing systems based on information collected from different sensor sources.

1. Introduction

Operating working machines in construction, mining, agriculture and forestry requires much mental and physical effort. The efficiency of these machines depends on the performance of the human operators/drivers. Monitoring and diagnosing the operators when they are exhausted with mental/physical workload is important feedback for an operator, especially a professional operator where an accident could have large consequences both on lives and economical costs. However, identification of mental/physical state and generating alarm due to stress, sleepiness, fatigue etc. is difficult while driving and still a scientific challenge. Today, different sensors enable clinician to determine psychological status with high accuracy. However, since there are large individual variations, analyzing data from a single sensor source could deteriorate the classification result. Data that are collected from multiple sensor sources could provide us more reliable and robust information of these psychophysiological parameters. For instance, if one sensor measurement is influenced by a certain noise or interference other sensor measurements could still support the system. As human beings, we have the natural ability to fuse signals that are coming from different sources and supports in reliable and feature-rich judgment. Using multiple sensor signals to achieve more reliable assessment of diagnosis this is what (i.e., naturally performed multisensory data fusion) experts' are doing in real life while diagnosing these psychophysiological parameters.

This paper investigates sensor signal fusion in a case-based classification scheme by means of MMSE algorithm (Ahmed & Mandic, 2011, 2012). Here, five sensor measurements i.e., Inter-beat-Interval

* Corresponding author.
E-mail addresses: Shahina.Begum@mdh.se (S. Begum), Shaibal.Barua@mdh.se (S. Barua), Reno.Filla@volvo.com (R. Filla), Mobyen.UddinAhmed@mdh.se, Mobyen.UddinAhmed@oru.se (M.U. Ahmed).

0957-4174/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.eswa.2013.05.068

(IBI) and Heart Rate (HR) from Electrocardiogram (ECG), Finger Temperature (FT), Skin Conductance (SC) and Respiration Rate (RR) are combined at low-level fusion applying MMSE algorithm to classify physiological parameters i.e., stressed or healthy of wheel loader operators. The proposed system has been evaluated with the data collected from 18 wheel loader operators. The main goal is to investigate whether the proposed system MMSE–CBR is able to classify the operators despite large individual variations and noises/interferences of the environment.

The rest of the paper is organized as follows: Section 2 presents the background of physiological sensor signals fusion. It also discusses about CBR and entropy analysis. Section 3, describes related work. Section 4, illustrates the study design for the data collection. In Section 5, the methods are described in detail. The experimental work is presented in Section 6. Section 7 discusses the evaluation results. Finally, Section 8 ends with concluding remarks.

2. Background

2.1. Sensor signal fusion

Sensor signal fusion is a method that gives us the resulting information while using multiple sensors. According to Wilfried (2001), "*Sensor fusion is the combining of sensory data or data derived from sensory data such that the resulting information is in some sense better than would be possible when these sources were used individually*". Commonly, sensor signal fusion can be achieved either by combining multiple sensor data sources or data from a single source over a period of time could also take part in the fusion process. Signals can be fused or combined in three-level models (Cremer, Schutte, Schavemaker, & Breejen, 2001):

(1) *Low-level or Data level fusion* combines raw (unprocessed) sensor data,
(2) *Intermediate-level or Feature level fusion* combines the representative features extracted from sensor signals
(3) *High-level or Decision level fusion* fuses findings (or detection probabilities) of multiple sensors.

Multi-sensor information fusion is the process of integrating data or information from multiple sensors to improve quality and accuracy of the information that cannot be obtained using the sources individually. The main advantage of using data/information from all available sources is that it helps to enhance the diagnostic visibility, increases diagnostic reliability and consequently reduces the number of diagnostic false alarms. Some of the traditional methods for sensor fusion are: Kalman filter (Rodger, 2012), Weighted decision methods (voting techniques), Neural networks (Ataei, Aghakouchak, Marefat, & Mohammadzadeh, 2005), Clustering algorithms (Wang, Wang, & Jiang, 2006), Bayesian inference (Cou, Fraichard, Bessiere, & Mazer, 2002) methods. Information fusion is available in the vehicle research in many cases for automatic vehicle control systems to increase reliability, efficiency and security (Lee & Chung, 2012; Mirabadi, Mort, & Schmid, 1996; Rodger, 2012; Smith, Brandt, & Papanikolopoulos, 1994). However, to our knowledge, research on multi-sensor data fusion for monitoring or classifying drivers' status is limited in the literature. Yet, the greater the necessity of monitoring drivers using multiple physiological sensors in a reliable and autonomous fashion the more valuable the area of research would be.

2.2. Case-based reasoning

CBR is a methodology for problem solving and learning. According to Kolodner (Kolodner, 1983) "In case-based reasoning, a reasoner remembers previous situations similar to the current one and uses them to help solve the new problem". So, learning from the past and solving new problems based on previously solved cases is the main approach of CBR. The first step in developing a CBR system is to formulate a case. These cases can be instances of things or a part of a situation that we have experienced. The case comprises unique features to describe a problem. In CBR, past cases are stored in a case library or case base. A reasoning cycle of CBR with 4 Re-s: Retrieve, Reuse, Revise and Retain is commonly used to implement such a cognitive model (Aamodt & Plaza, 1994).

(1) *Retrieval* it searches the case-library for cases similar to the problem description and retrieves the most similar cases.
(2) *Reuse* it uses the solution of a previous case. However, usually the best matching case does not always provide a complete solution for a new problem case and therefore adaptation of the solution is often required to use it for a new case. This adaptation or change of the best matching cases is usually complex and requires domain knowledge.
(3) *Revise* the proposed solution from the reuse step is evaluated and if necessary repaired in the revise step.
(4) *Retain* the confirmed solution is saved into the case library as learned case.

In reality, experts in diagnosing human state i.e., stress, tiredness, drowsiness etc. rely heavily on their past memory to solve a new case. Knowledge elicitation is another problem in such a domain, as human behavior or our responses to these psychological parameters is not always predictable. Even an experienced clinician in this domain might have difficulty to articulate his knowledge explicitly. Sometimes experts make assumptions and predictions based on experiences or old cases. In CBR, this elicitation can be performed with the previous cases in the case base. Thus, CBR is especially suitable for instance for psychophysiological stress diagnosis when the domain is difficult to formalize and is empirical.

2.3. Entropy

Entropy and complexity measures have widely been applied for the analysis of time series signals. Entropy is introduced by Shannon (Shannon & Weaver, 1975) for information theory. It is considered as a generic measure of system disorganization and the basis of the concept connected to thermodynamics "*Any macroscopic system which is in time t0 in given time-invariant outer conditions will reach after a relaxation time the so-called thermodynamic equilibrium. It is a state in which no macroscopic processes proceed and the state variables of the system gains constant time-invariant values*". While the system reaches at thermodynamic equilibrium the entropy of the system reaches its maximum. Later, in 1984 it has been applied to a power spectrum of a signal (Johnson & Shore, 1984). In signal processing, entropy shows the irregularity, complexity or unpredictability characteristics of a signal. The expected value of information contained in a message can be quantified by entropy. If X is a single discrete random variable than the entropy $H(X)$ is measure of its average uncertainty. Entropy can be calculated using Eq. (1)

$$H(X) = -\sum_{i=1}^{n} p(x_i) \log p(x_i) \tag{1}$$

where, X is the random variable with n outcomes that is $X = \{x_i := 1, 2, \ldots, n\}$ and $p(x_i)$ is the probability mass function of x_i. Eq. (1) refers to Shannon Entropy.

Entropy has received much attention to quantify complexity of physiological signals in healthy and diseased systems. Healthy sys-