Abstract

Bio-potentials and Electrodermal Activity (EDA) are useful in the field of psycho physiology since they both provide valuable information about physiological responses to various stimuli and situations, including emotional and psychological states. The differential dermal potentials (DDP) considered in this study are a special type of EDA signals that are acquired in differential mode from the limbs of a subject. These signals have been introduced very recently and quite a few successful applications using these signals have also been demonstrated. Hence it is useful to model these signals and study their characteristics in detail for a deeper understanding of human physiology and behavior.

The aim of this work is to develop various models of the differential dermal potentials and to determine the use and efficacy of the parameters derived from these models in studying and/or classifying human conditions.

One of the first steps for developing a model is to determine the signal order. This aspect has been addressed in this work from a new perspective based on the derivation of the sample autocorrelation function (ACF) of three types of signals. The signal order is determined in terms of its zero crossing lag (ZCL), which is the lag value at which the 1^{st} zero crossing of the sample ACF of the signal occurs. Closed form solutions for the ZCL are determined for these 3 types of signals: a) the deterministic i^{th} order power law series, denoted as y_{dk}; b) the stochastic i^{th} order power law series, denoted as y_{sk}; c) the deterministic polynomial series y_{pk}; and these are used to determine the ZCL of the acquired signal, denoted as y_k, which is modelled as a n^{th} order stochastic polynomial.

There exists a one-to-one map between the ZCL and its order i for the y_{dk} signal. This in conjunction with the shift in the ZCL within limits due to noise or polynomial coefficient interactions forms the basis for determining the order n of the time-series signal y_k for all the models proposed in this work.

Three different models have been proposed in this work which are denoted as i) the stochastic ACF-ZCL model, or simply ACF model; ii) the KF_{LPC} model; and iii) the KF_{TS} model.

In the proposed stochastic ACF-ZCL model, the deterministic trend or tonic component of these signals is the polynomial regression time series with the order n as determined using the ZCL while the resultant error time series represents the stochastic phasic component.

The Kalman filter (KF) is a popular technique used to clean these noises and obtain dynamic system models that respond to internal and external valid inputs. The popular autoregressive (AR) modelling approach provides the required linear prediction coefficients (LPC) of the state space model. The KF model developed in this work using this standard approach is termed the KF_{LPC} model. The proposed ACF model is used to derive ab-initio another KF model. y_{pk}, which is the polynomial time-series (TS) developed in the ACF model, is used to obtain the description of its state space model and so it is termed the KF_{TS} model. The KF_{LPC} and KF_{TS} models differ in their underlying state space model descriptions.

These three models have been determined for a total of 5706 DDP signals in order to compare them in terms of their parameters and statistical characteristics. The ACF model is also compared with corresponding models whose orders are determined using the standard partial ACF (PACF) method. The various parameters of the robustness and sensitivity metrics of the two KF models are also compared.

The results show that the deterministic tonic component of the ACF model typically has a lower order polyfit component than the corresponding PACF model and the ACF model residuals follow the beta distribution more consistently. The ACF model as well as both KF models provide consistent tonic and phasic components. Several system characteristics are quite similar for both KF models. However, the KF_{LPC} model estimates show a distinct bias and the nature of the metrics in the two KF models are distinctly separate.

The parameters obtained from each of the three models have been used individually to study the effect of long duration of rest on a subject. A total of 272 sets of independent signals obtained from subjects in restful supine condition for 10 minutes have been used for the study. For this, each of these signals have been segmented into 5 non-overlapping sets, or states, of 2-minutes signals.

The changes in the maximal entropy of the tonic component of the ACF model of the acquired signals with increasing rest support an existing research finding that the subject achieves a fully rested condition typically within 4-6 minutes of no-nap supine rest. Furthermore, the variations of the ZCL, system order, mean of the tonic component, SD as well as the spectral entropy of the residuals of this model support the emerging determinism of the system with rest.

The spectral entropy (SE) of the KF_{TS} model is an useful identifier of the tonic components, the phasic components and the noise residuals. The medians and ranges of the SE in these 3 cases indicate a sequential departure from regularity to irregularity as expected. No such distinguishing features are observed for the KF_{LPC} models.

Two other human conditions have been classified in this study using the random forest (RF) classifier in WEKA, version 3.9.4 classification software on these models. These are:
(i) hypertensive and normotensive classification or detecting the presence or absence of hypertension in subjects
and (ii) sitting and supine posture classification or detecting the change in posture of human subjects.

In case of the hypertensive classification, only 3, 3 and 1 parameters of the ACF, KF_{LPC} and KF_{TS} models respectively are identified to be most significant. In the posture change study, 5 parameters are selected for the ACF model while only 1 parameter is selected in case of both the KF models.

The ACF parameters for classifying hypertension are all normalized variances of the phasic components, while for the posture change the chosen parameters are 2 each from the phasic and the tonic components and 1 model coefficient. In case of both the KF models for both classifications, the chosen parameters are all related to the process noise covariance q_{com} for the compromise metric.

Three standard cross-validation (CV) methods have been applied on the selected model parameters of the 3 models in both the classification studies. These are 10 fold CV (10FCV), leave one out CV (LOOCV) and leave one subject out CV (LOSOCV). In all cases, it is observed that the results of 10FCV and LOOCV are either identical or very close. However, since the subject bias effect is expectedly removed in LOSOCV, the results for the method differ significantly from those of the other two methods.

The features selected for the ACF model provide the most reliable and best F1-score result in case of the hypertensive classification. The balanced and highest specificity establishes the utility of the KF_{TS} model also in this classification despite the overall drop in F1-scores.

In case of the sitting and supine posture classification, the KF_{LPC} and ACF models show high 10FCV accuracies and relatively low or medium effects of subjective bias for the classification of posture change. The KF_{TS} model with its single selected feature is not suitable for this differentiation.

These studies validate all three proposed models. Their utility in studying and/or classifying 3 different human conditions have also been ascertained in terms of the effect of these conditions on the individual model parameters and metrics.