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Machine Learning Approach to Microwave Sensing of Glucose Concentration: Method and Preliminary Results

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Abstract

In this work, a non-parametric regression approach is presented for potential applications in the framework of continuous and non-invasive monitoring of glucose concentration in blood. The full information content included in the frequency responseof microwave resonant sensors is taken into account. In particular, four parameters (*predictor variables*) of the aforementioned response are linked to the glucose concentration (*target variable*, namely: the maximum value, the resonance frequency, the -10 dB bandwidth, and the (signal) energy. Preliminary validations are discussed to show that, once known the values of the above predictor variables, an accurate estimation of the glucose concentration can be achieved.

1. Introduction

Diabetes is a pathological state arising when the body is no longer able to adequately regulate the values of theglucose concentration (GC) in the blood. It can very seriously affect the proper operation of heart, blood vessels, eyes, kidneys and nerves [1]. For this reason, it is important that blood glucose levels are adequately monitored, so to possibly prevent the above deleterious consequences.

The classic methodology for self-monitoring theblood glucose concentration is based on the analysis of a blood sample, usually taken from finger tips or from sub-cutaneous measurements, by means of suitable glucometers [2]. This methodology, however, has the crucial disadvantage to beinvasiveness, thus leading to negative outcomes, including the risk of infections and the increasing deformation risk of the site where the blood sample is taken. Furthermore, ambulatory monitoring devices are also plagued by relatively high error rates [2]. For this reason, non-invasive methodologies have been developed over time in order to make blood glucose monitoring less problematic[1]-[10].

Several techniques have been proposed in literature for the continuous and non-invasive monitoring of blood glucose concentration. Some of these are based on the analysis of saliva and/or tears, on Raman spectroscopy, on terahertz spectroscopy, on photoacoustic spectroscopy, on thermal measurements, on electrical impedance measurements [3]. Another methodology studied with keen interest is the dielectric spectroscopy based on microwave resonant sensors [2]. This relies on the fact that variations in blood glucose concentrationcan be linked to the variations in the (complex) dielectric permittivity of biological tissues, which, in turn, influences the frequency response of the microwave sensor [11]. In this regard, it is worth highlighting that an adequate design of the above sensors requires to preliminarily proceed with a suitable characterization of the dielectric permittivity of the involved biological tissues [11][12]. Even if carefully designed, resonant sensors usually deviate from the ideal characteristics, as, due to losses, they have a low quality factor (compared to the ideal one) and therefore a relatively wide frequency response. Furthermore, since the sensor responses are only acquired at a finite number of frequencies, it is possible that the actual resonant frequency is lost during the sampling process. For this reason, several signal processing algorithms have recently been proposed in order to sharp the frequency response of resonant sensors, thus obtaining more accurate and well-defined estimation of their resonance frequency [13]-[18].

Inspired by the results presented in [11], the advantage to consider additional characteristics of the frequency response of microwave sensors beyond the resonance frequency is exploited in this work. In particular, a regression approach is introducedin terms of four parameters pertinent to the frequency response (maximum value, resonance frequency, -10 dB bandwidth and energy), which areadopted as predictor variables, and the $GC$is assumed as the target variable to be estimated.

2. Method

For the purpose of the present work, microwave resonant sensors operating in reflection mode are considered, and the Return Loss ($RL(f)$) is assumed to be the frequency response, with $RL(f) = -20\,log10|\Gamma(f)|$ [19], f and $\Gamma(f)$ being the operating frequency and the reflection coefficient at the sensor input, respectively. For typical return loss trends of a microwave resonant sensor, the reader may refer to [13-18]. From a conceptual point of view, a regression model is assumed which is based on the following mathematical model:

$$GC = g(M, f_{ris}, B_{-10}, E; w) \qquad (1).$$

where M is the maximum value of $RL(f)$, f_{ris} is the resonance frequency, B_{-10} is the -10 dB bandwidth, E is the energy of $\Gamma(f)$, *i.e.* $E = \int_{f_{min}}^{f_{MAX}} |\Gamma(f)|^2 \, df$,with $[f_{min}, f_{MAX}]$ being the frequency observation interval. As regards the function $g(\cdot)$ and w (set of model parameters), they are determined by the available dataset, since a *non-parametric regression* approach is used [20]. In particular, two non-parametric regression methods are exploited, namely the Gaussian Process Regression [21] and the Regression Trees [20].

From an operational point of view, the first step is to obtain the dataset containing the values of M, f_{ris}, B_{-10} and E corresponding to the values of GC. Therefore, such values must be obtained experimentally or by simulations. From the above dataset, the non-parametric regression model is obtained which describes the link between the predictor variables and the GC. Once obtained the model, it is applied into the estimation system, exploiting the same sensor adopted to obtain the initial dataset, thus performing GC prediction. It is worth emphasizing that the approach proposed in the present work falls within the scope of machine learning [21]-[24], since the models relating the GC with the parameters of the sensor responses are just trained using the data contained in the dataset.

3. Results

For the implementation of the methodology introduced in the previous section, the sensor described in [11] is considered. To obtain the dataset, a simulation scenario is assumed with the above sensor immersed into water-glucose solution at different glucose concentrations in the range $[80{,}140]\ mg/dL$. The frequency observation intervalis set equal to $[2{,}2.7]\ GHz$. In particular, 110 values of GC are considered, thus leading to the generation of 110 return loss curves, from which the values of the predictor variables associated with the corresponding GC value are identified. Consequently, the dataset is represented by a matrix of 110 rows, with each row corresponding to a different return loss curve, and 5 columns, in which the first four columns correspond to the predictor variables, while the last one is inherent to GC. By means of the above dataset, the regression models discussed in the previous section are trained. Fig. 1 shows the GC estimations corresponding to 61 test curves (*i.e.* curves different from those adopted for training the regression models). As it can be seen, both theassumed regression models allow to obtain good estimations (predictions) for GC, with the regression trees methodology providing better results. Obviously, it is expected that, as the size of the dataset increases, *i.e.* considering a greater number of return loss curves corresponding to different values of GC, a smaller deviation of the estimated values from the expected ones should be achieved.

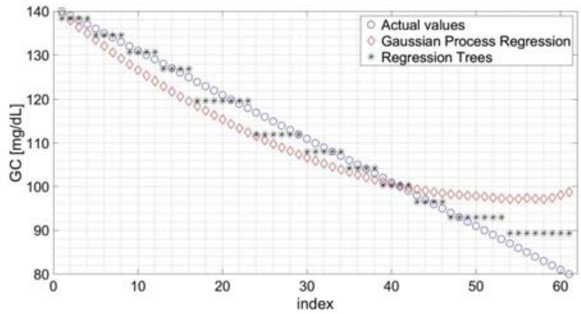

Figure 1. GC estimations from the adopted regression models.

4. Conclusion

In this paper, a machine learning-based approach for estimation of glucose concentration has been investigated, by exploiting the frequency response of microwave resonant sensors operating in reflection mode. This study actually fits into the important issue of continuous and non-invasive blood glucose monitoring. In particular, it has been shown that using appropriate non-parametric regression models, it is possible to obtain good estimations of the glucose concentration with a dataset of limited relative size. The concepts outlined in this preliminary study will be further developed and experimentally tested, focusing to the non-invasive monitoring of blood glucose concentration.

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