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APPLYING KALMAN FILTER FOR THE TASK OF THE BIOMETRIC DATA TIME SERIES UNIFICATION

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The use of the recursive Kalman filter for restoring missed values and time series frequency unification is discussed for the use case of biometric data collected from the user-grade devices to monitor the mental and physical load on the user while working with some software or hardware product. Specifics of applying filter to the biometric data is considered, as well as simplifying the implementation with the high-level pykalman software library.

Working with a computer, whether it is interacting with a specific application or simply with a graphical shell, involves cognitive, visual and motor processes. Categories of the same name can be distinguished for the loads experienced by the operator in the course of work.

A promising approach to determining the effectiveness of the user's work is to measure the user's body parameters associated with physical and cognitive load (for example, heart rate, blood pressure, skin electrical conductivity, β-rhythms of the brain, etc.) during work. Until recently, the use of this approach was limited by the low prevalence and high cost of the required equipment, but recently a significant number of devices with biometric sensors have appeared in the area of fitness and entertainment (photoplethysmographic heart rate sensors in fitness trackers and smart watches, consumer devices that register gaze direction or brain electric activity, etc.).

All these devices have the following advantages from the researcher's point of view [1, 2]:

- they are capable of continuous monitoring,
- they allow transmitting data to a personal computer,
- they widely available on the market due to mass production.

However, given that biometric measurements are indirect and are affected by extraneous external and internal factors [2], at least paired measurements are appropriate (for example, galvanic skin response measured in pair with heart rate). Therefore, the use of a heterogeneous set of biometric data obtained from several unrelated sources, aimed at building a model from the most complete set, creates additional problems, since it usually turns out that some time series have a higher sampling rate than others do.

Different-frequency time series of data require preliminary transformation. In this case, either the data of lower frequencies are interpolated to the upper frequency [3], or the data of higher frequencies are aggregated to the lower one. Depending on the parameter type, a higher frequency is aggregated into a lower frequency by either averaging, summing, or taking a representative value.

Time aggregation leads to the loss of information originally present in the sample, and the loss of information, in turn, reduces the accuracy and efficiency of the forecast [4]. In addition, frequently used interpolation methods do not fully utilize all available information about the sample. Interpolation requires reducing a low frequency variable to a higher frequency by recovering some missing measurements. The formation of missing data can be performed either immediately in the process of comparing and analyzing the measurement results (using a model that reflects the behavior of the corresponding biometric parameter), or in two stages, when the missing data are first interpolated (based on the existing model or statistically), and then the comparison and analysis of the results use the resulting time series [4]. Obviously, no method can be called universal.

To unify the time series of biometric data, we tested the use of the recursive Kalman filter (KF). This recursive filter calculates an estimate of the state of the indicator for the current cycle of work, using the estimate of the state (in the form of an estimate of the state of the indicator and an estimate of the error in determining this state) on the previous cycle of work, as well as measurements on the current cycle.

Each iteration of KF includes two phases: extrapolation and correction. During extrapolation, the filter obtains a preliminary estimate of the state of the system $\hat{x}_{k|k-1}$ for the current step according to the final assessment of the state from the previous step (or a preliminary assessment for the next step according to the final assessment of the current step, depending on the interpretation). This preliminary estimate is also referred to as the prior state estimate, since observations of the corresponding step are not used to obtain it. In the correction phase, the a priori extrapolation is supplemented with relevant current measurements to correct the estimate. The corrected estimate is also called the posterior state estimate, or simply the estimate of the state vector $\hat{x}_k$. Usually, these two phases alternate: extrapolation is performed based on the results of the correction until the next observation, and the correction is performed together with the observations available at the next step, etc. However, if for some reason the observation turned out to be unavailable, then the correction stage can be skipped and extrapolation uses the unadjusted estimate, (a priori extrapolation). Similarly, if independent measurements are available only in separate cycles of work, corrections are still possible (usually using a different observation matrix H_k).

To test the effectiveness of unification of biometric data time series using the Kalman filter, the Python library *pykalman* was used, which contains the implementation of KF as a smoothing filter.

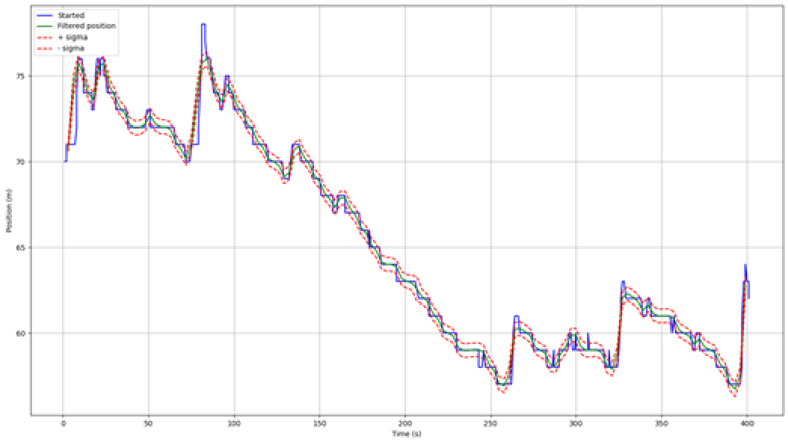

Figure 1 - The result of applying the filter

Both KF and its smoothing implementation are often used with parameters already set. In the case of the *pykalman* library, the KalmanFilter class can be initialized with any subset of the normal model parameters and used without fitting. All undefined parameters are set to their default values.

A smoothing implementation can include "future" measurements as well as past ones at the same computational cost $O(Td^3)$, where T is the number of time steps and d is the dimension of the state space.

In addition, the *KalmanFilter* class of the library implements the expectation maximization (EM) algorithm. This iterative algorithm is a way to maximize the probability of observed measurements.

In real biometric equipment, a temporary failure of one of the sensors occurs (for example, a short-term loss of contact), and the use of KF and EM allows you to handle this scenario.

An example of the application of KF on the time series of the galvanic skin response of the user [5] is available in fig. 1. Note that the use of KF is more effective for slowly changing biometric indicators, such as skin electrical conductivity and heart rate, and the least effective for such time series that are difficult to predict, such as electroencephalogram rhythms, which are the summed electrical noise of a subset of neurons in areas of the cerebral cortex.

Thus, it can be said that the use of frequency unification of the biometric data time series is appropriate when conducting complex biometric testing to assess the loads experienced by a human operator due to the heterogeneity of available biometric equipment and the need to use a set of available biometric indicators, and the Kalman filter is one of effective methods for solving this problem.

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ИССЛЕДОВАНИЕ ВОЗМОЖНОСТИ ПРИМЕНЕНИЯ НЕИНВАЗИВНОГО ОПТИЧЕСКОГО МЕТОДА ГЛЮКОМЕТРИИ

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The article highlights the problem of diabetes. Existing methods for determining the level of glucose in blood are considered. Much attention is paid to non-invasive methods for determining blood glucose. The method of near infrared spectroscopy was applied in practice. Based on the results obtained, this method has a place to exist, and it is also necessary to be improved to create a universal non-invasive glucometer.

В мире сохраняется тенденция роста числа людей, страдающих сахарным диабетом. В среднем этот показатель за год составляет 5 %. Официальная статистика показала, что за период с 1980 г. по 2014 г. число людей, болеющих сахарным диабетом, увеличилось до 422 миллионов. За 20 лет в Беларуси количество больных с сахарным диабетом выросло в 3 раза. По состоянию на 1 января 2019 г. на учёте находилось 336 тысяч человек. К 2030 году сахарный диабет станет 7-й причиной смерти во всём мире [1].

Уход за больными и лечение диабета (DCCT) показали, что более частый контроль глюкозы и инсулина в крови может предотвратить многие из долгосрочных осложнений сахарного диабета [2].

Как высокий, так и низкий уровень сахара в крови негативно воздействуют на организм человека. Недостаточный контроль гипергликемии (уровень глюкозы в крови слишком высок) приводит к множеству осложнений, связанных главным образом с поражением мелких и/или крупных сосудов (микро- и макроангиопатии). Долгое нахождение человека в состоянии гипогликемии (снижение уровня глюкозы ниже 3,3 ммоль/л) в конечном итоге может привести к гипогликемической коме. Длительная гипогликемия приводит к отеку вещества головного мозга, появлению мелкоточечных геморрагий в мозговые ткани, что в конечном итоге является причиной структурных нарушений в клетках коры мозга, их гибели [3].

Метод определения уровня глюкозы в органических жидкостях (кровь, ликвор и т.п.) называется глюкометрия, а устройство – глюкометр.

На сегодняшний день существуют такие типы глюкометров:

– фотометрические – уровень глюкозы в крови человека определяется в зависимости от окраски тест-зоны. Технология этих приборов, разработанных до-