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DETECTION OF HUMAN FALL EPISODES BASED ON COORDINATES OF BODY TAGS AND NUMERICAL DIFFERENTIATION

This paper presents a new method for detection of changes in alignment of the human body, particularly the fall, on the basis of signals acquired from the position sensors placed on the body of the monitored person. The sensors are located on the cuffs, waist and chest. Transformation of data sequence collected from sensors is proposed in order to best distinguish between the collapse from the normal movement. It is based on nonlinear combination of the first two derivatives of the signals being read. Because data from the sensors is sent asynchronously, a numerical algorithm for unevenly sampled data differentiation is proposed. Derivative values are calculated in equidistant nodes through differentiation of a polynomial, which is adjusted by minimizing the mean square error. The developed method can be used in home care telemedicine systems, where it is necessary to long term monitor of multiple vital parameters of people under care.

1. INTRODUCTION

Telemedicine is medicine at a distance, which combines in a harmonious manner the elements of telecommunication, computing and medicine. It involves the exchange of information and data (pictures ultrasound, MRI, ECG) between different "objects" - patient, physician, clinic, hospital, etc.. High-resolution images, as well as highly accurate interactive audio-visual transmission in real time are sent through modern technology, using fast processors and algorithms for digital signal processing and compression. Video systems work on the public ISDN digital transmission lines, the global network Internet, and satellite lines.

Home care telemedicine systems are the fastest growing way to supervise or monitor the patient's health status, and progress in rehabilitation. The system often results in data exchange (transfer of examination results) "from the patient to the doctor" to make the diagnosis, which also comes from a distance. Telemedicine is very important for both doctor and patient. The doctor is able to provide various information about the patient's treatment at very large distances. On the other hand, the patient can perform all testing alone in the house and immediately send it by special medical devices to the doctor. The application of this system is also pleased to patients who are unable to frequent visits to the doctor. Home care telemedicine systems introduce more new technologies, which are used to improve the treatment.

Examples of application areas of telemedicine techniques include monitoring of pregnant women [3], as well as home care of the elderly [1]. The latter issue is part of the area known as assisted living. It incorporates, among other things, supervision of daily living activities, alarming in case of deterioration of health of supervised person and coordination of health care services. Among the factors to be monitored there is information about a person's movement activities, in particular the detection of situations that raise suspicion of a fall or injury. However, the amount of information from data acquisition activities of supervised persons is significant, which creates a need to develop methods to automatically detect such situations [5, 6]. Typical methods of acquisition of such data are: video monitoring or reading the information on the location of human from sensors located on his or her body [8]. The latter approach, together with the use of wireless transmission, ensures obtaining precise information about the location and positioning of the person’s body.

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This article presents a proposal for the transformation of the signals read from the position sensors in order to best extract the information about the possible fall of the human body. The method is based on an analysis of the acceleration, which is obtained as a second derivative of position coordinates. Emphasis was laid on the difficulties associated with uneven spacing between the times of the readings from individual sensors. In order to reduce the negative effects of this phenomenon a method of numerical differentiation has been proposed, which is based on polynomial approximation.

2. METHODOLOGY

2.1. MONITORING SYSTEM

A typical movement monitoring system using signals from wireless sensors placed on human body is presented in Figure 1. Sensors can be placed in different areas of the body, especially on the torso, limbs, or even on the head. However, it is recommended to select their position, limiting as little as possible a daily life activity. The article [4] presents traffic monitoring system consisting of four sensors on the wrists, chest and waist. This article also describes the effect of the experiment involving the monitoring of movements of selected five people in an artificial environment that provides the conditions similar to those an elderly person lives every day. The total surface area of the experiment was about 25 square meters. The signals from the sensors were transmitted wirelessly to a receiving station located on the walls of the rooms. Average sampling rate was 10 Hz, but readings were unevenly spaced. Moreover, the interference and obstacles that occured between the sensors and the receiving station caused that part of the data from some sensors was lost.

Figure 1 shows a simplified image of the human with sensors that transmit data to receivers placed near them. These data are expressed in the form of Cartesian coordinates relative to a fixed reference point. This figure also shows an example of one of the trajectories of motion sensors for the selected time period. These trajectories are illustrated by the projections on the planes formed by pairs of coordinate axes.

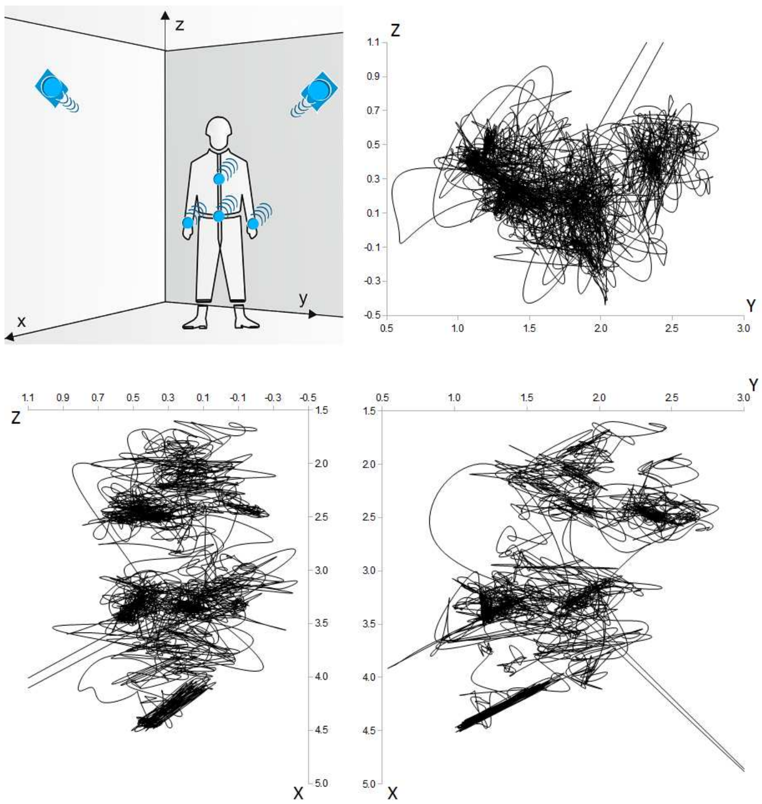

Fig. 1. Scheme of movement monitoring system (upper left) and projections of exemplary signal from single sensor on planes formed by pairs of axes

Methods for detecting the abrupt changes in body position, in particular the fall, are often based not only on the values of the positions from sensors, but also on the speed of change of these values. It has a natural interpretation as a derivative of the received signal. Moreover, it is possible to search for decision rules based on second order derivative, which is here interpreted as the acceleration, i.e. a measure of dynamics of changes in the location. For this reason, the method described here for solving the problem of unevenly spaced sampling is focused on the numerical calculation of the derivatives of this signal. Postulated properties of this method are the most accurate representation of the unknown signal derivative value in the selected moments of time, as well as robustness to the occurrence of samples with values significantly different from the actual location coordinates.

2.2. TIME ALIGNMENT OF SAMPLES

Each sensor sends, at the specified time, information on its location in the form of three Cartesian coordinates. However, the signals from various sensors come in different times. They are usually transmitted in certain time sequences, although at uneven intervals. Moreover, it is possible that information from some sensor is lost or ignored for another reason. This creates the need for a transformation of the original set of samples into the data sequence of uniform intervals on the timeline. There are different approaches to the problem of unevenly sampled data, among which can be found, for example, the use of computational intelligence methods [2]. These methods include, among others, grouping data as well as nonlinear and adaptive filtering [7].

This section presents a simple method for solving the above problem, which enables to find a transformation of the original data set to obtain a result as a value of the derivative of unevenly sampled signal in the selected nodes. Assume that the vector consisting of all three coordinates of the position is described by the following symbol.

$$\mathbf{v}(t) = [x(t), y(t), z(t)] \tag{1}$$

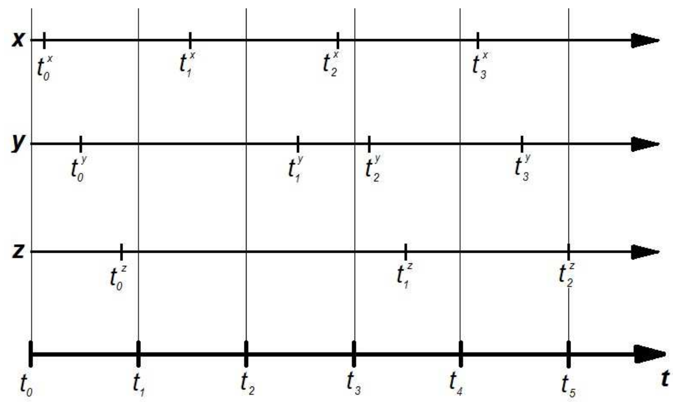

Fig. 2. Schematic construction of a set of time-aligned samples

General idea of a set of time-aligned samples is shown in figure 2. Detailed construction of this procedure is described below for the first Cartesian coordinate, namely *x*. For the remaining coordinates the method is identical. Time-aligned samples should be placed in the moments t_n. Since these samples are used for the numerical determination of derivatives positions of the sensors, it is necessary to define the distance vector of measurement times of the individual samples from time t_n:

$$\mathbf{s}^{x,n} = \left[s_{-N}^{x,n}, \ldots, s_{-1}^{x,n}, s_0^{x,n}, s_1^{x,n}, \ldots, s_{N-1}^{x,n}\right] \tag{2}$$

The number *N* determines the radius of neighborhood of time t_n measured in samples. It is assumed that the vector contains an even number of elements and the element at index 0 is located in a non-negative distance from time t_n:

$$s_{-N}^{x,n} < \ldots < s_{-1}^{x,n} < 0 \le s_{0}^{x,n} < s_{1}^{x,n} < \ldots < s_{N-1}^{x,n} \tag{3}$$

It is possible to express this through an index defined by the earliest sample of the time not exceeding t_n

$$I^{x}(t) = \min\{i : t_i^x \ge t\} \tag{4}$$

$$s_k^{x,n} = t^{x}_{I^x(t_n)+k} - t_n \tag{5}$$

The interpretation of these numeric quantities is illustrated in figure 3.

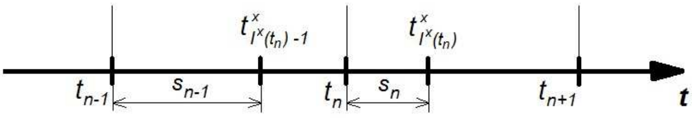

Fig. 3. Interpretation of index *I* and distance *s*

The last element of the input data for the process of differentiation is the vector of coordinate values read from the sensor

$$\mathbf{x}^n = \left[\tilde{x}_{-N}^n, \ldots, \tilde{x}_{-1}^n, \tilde{x}_0^n, \tilde{x}_1^n, \ldots, \tilde{x}_{N-1}^n\right] \tag{6}$$

and the components of such vector are expressed by index *I*:

$$\tilde{x}_k^n = x_{I^x(t_n)+k} \tag{7}$$

2.3. NUMERICAL DIFFERENTIATION

The basic idea of the numerical differentiation of the data set presented in the previous section consists in finding a polynomial of fixed order *D* that approximates the coordinate values in equidistant nodes t_n. Of course, the nodes corresponding to the input values are located in arbitrary distances, represented by vector $\mathbf{s}^{x,n}$. The resulting polynomial can be differentiated in a symbolic manner, which leads to estimating the value of the derivative at the point node.

$$x = \sum_{i=0}^{D} a_i t^i \,, \quad \frac{dx}{dt} = \sum_{i=1}^{D} i a_i t^{i-1} \tag{8}$$

The criterion for selection of the polynomial coefficients is to minimize the distance defined as follows

$$G_N = \sum_{j=-N}^{N-1} \left(\tilde{x}_j - \sum_{i=0}^{D} a_i \left(s_j\right)^i \right)^2 \tag{9}$$

The minimum should be found with respect to polynomial coefficients. This is a convex function, therefore in order to find the minimum it is sufficient to determine the stationary points. This leads to the following equations:

$$\frac{\partial G_N}{\partial a_m} = -2 \sum_{j=-N}^{N-1} \left(s_j\right)^m \left(\tilde{x}_j - \sum_{i=0}^{D} a_i \left(s_j\right)^i \right) = 0 \tag{10}$$

$$\sum_{i=0}^{D} a_i \left(\sum_{j=-N}^{N-1} \left(s_j\right)^{m+i} \right) = \sum_{j=-N}^{N-1} \left(s_j\right)^{m} \tilde{x}_j \tag{11}$$

which, after simple transformations may be written in matrix form:

$$\mathbf{Ja} = \mathbf{Hx} \tag{12}$$

The corresponding matrices are defined as follows

$$\mathbf{J} = \begin{array}{cc} \begin{array}{c} k \\ \downarrow \end{array} & \\ \begin{bmatrix} \ddots & & \\ & \sum_{j=-N}^{N-1} \left(s_j\right)^{m+k} & \\ & & \ddots \end{bmatrix} & \leftarrow m \end{array}, \tag{13}$$

$$\mathbf{a} = \left[a_0, a_1, \ldots, a_D\right]^T, \ \tilde{\mathbf{x}} = \left[\tilde{x}_{-N}, \ldots, \tilde{x}_0, \ldots, \tilde{x}_{N-1}\right]^T \tag{14}$$

$$\mathbf{H} = \begin{bmatrix} 1 & \ldots & 1 & \ldots & 1 \\ s_{-N} & \ldots & s_0 & \ldots & s_{N-1} \\ \vdots & & \vdots & & \vdots \\ \left(s_{-N}\right)^D & \ldots & \left(s_0\right)^D & \ldots & \left(s_{N-1}\right)^D \end{bmatrix} \tag{15}$$

It is worth emphasizing that obtaining the estimator of the derivative at a specified node does not require explicit calculation of all the polynomial coefficients. Thus, introducing an auxiliary vector **d**, and solving the above equations (12), the result can be written in the following concise form

$$\left.\frac{dx}{dt}\right|_{x=0} = a_1 = \mathbf{d}^T \mathbf{J}^{-1} \mathbf{Hx} \tag{16}$$

$$\mathbf{d} = \left[0,1,0,\ldots,1\right]^T \tag{17}$$

If it is necessary to numerically determine the higher order derivatives, the above described method can be used repeatedly. Obviously after the first use of this method a sequence of values with equal distances is created. However, this does not prevent from the application of the method because it is general in nature.

3. PRELIMINARY RESULTS

This article presents only preliminary results for the problem of preparing unevenly sampled signals from position sensors, focusing on determining the derivatives of first and higher order. In order to illustrate the nature of the waveforms generated by processing the input data figure 4 shows the values of the Euclidean norms for acceleration vector for the selected portion of signals from the database described in the article [4]. These values were calculated using the following formula:

$$S(n) = \left(\sum_{i=0}^{M} \left(x''(t_n)\right)^2 + \left(y''(t_n)\right)^2 + \left(z''(t_n)\right)^2 \right)^{\frac{1}{2}} \tag{18}$$

The value M=4 determines the number of sensors. In this example, the following values of parameters in the procedure of numerical differentiation were taken: N=3, D=3. The Figure 4 shows also the graph of this waveform smoothed using arithmetic moving average denoted by $\bar{S}(n)$. The radius of this moving average was 5 samples. The smoothed version highlights the local maxima, which can be regarded as a criterion for initial selection of time intervals suspected to be a fall or other threat. Taking into account changes in the amplitude of the norms of this vector is the basis for the development of methods for detection of movement events. However, since the amplitude changes also occur in intervals covering normal activities, it will be necessary to include additional criteria based on the individual components of the signals derived from sensors.

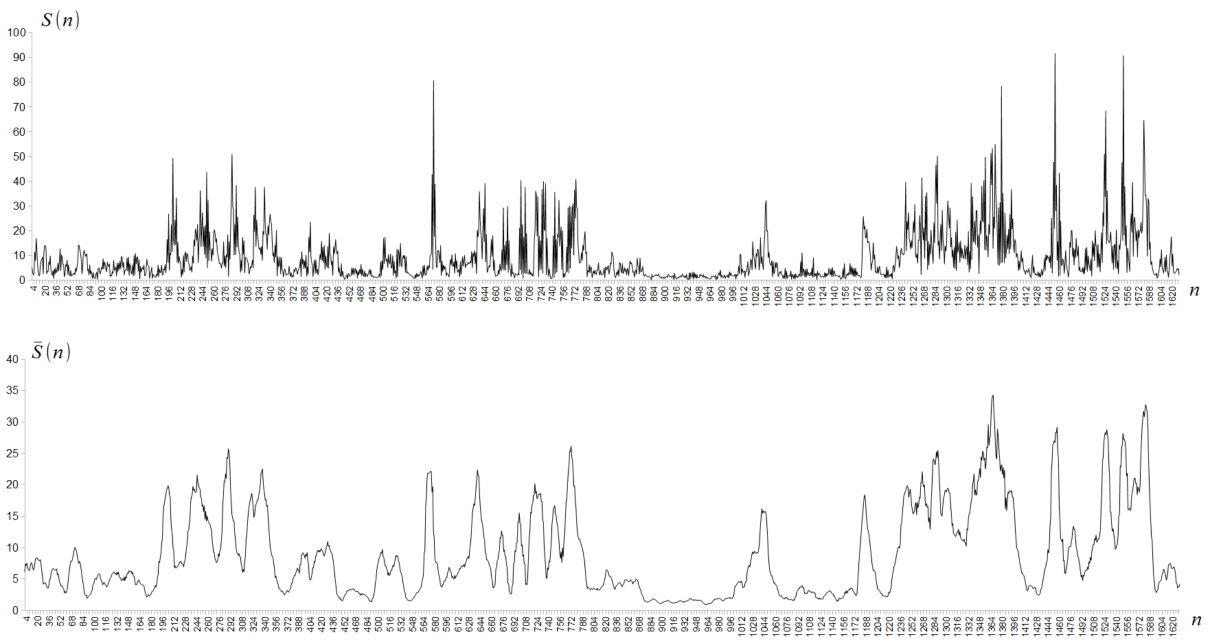

Fig. 4. Squared norm of second derivatives vector (above) and its smoothed version (below)

There are plans to further develop the methods of tracking and motion detection events, using the approach proposed here for preprocessing irregularly sampled data from the sensors. Time series representing the standard Euclidean vector derivatives does not contain complete information that allow to distinguish types of events, only their initial selection. Therefore, the development of a complete detection and classification module requires analysis of the movement of body tags relative to each other.

The sequences of the first and second derivatives, which are estimated based on the position signals form a multi-dimensional time series. Further steps of this method will include the analysis of the values in the surroundings of suspected incidents of falling or rising. Our investigation will be focused on development of the algorithms based on the classification, including the method of nearest neighbors, as well as Bayesian inference, including its extension in the form of fuzzy systems. Currently ongoing work includes fuzzy clustering of multidimensional signals derived from the sensors and learning fuzzy Takagi-Sugeno-Kang system. This system in combination with the Bayesian classifier is planned to detection of sudden changes in body position.

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