ANNALS of Faculty Engineering Hunedoara – International Journal of Engineering
Tome XIII [2015] – Fascicule 3 [August]
ISSN: 1584-2673 [CD-Rom; online]
a free-access multidisciplinary publication of the Faculty of Engineering Hunedoara

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THE USE OF INFORMATION ENTROPY IN EXTRACTING THE IRREGULARITIES OF AUTONOMOUS SYSTEMS

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Abstract: Information system is of considerable importance in preserving the predicted functioning of diverse systems, such as autonomous robotic systems. Its dynamics is in many cases highly nontrivial with a finite probability of errors caused by nontrivially interfering causes. It is, therefore, of importance to predict possible errors, configure the system so that it can function, at least partially, with these errors and altogether validate it.Among the variety of types of errors, in this article we concentrate on errors of gradual and distributed rise. We utilise the information entropy approach to extract the errors during the phase of their gradual rise. Algorithm is given for attributing the information entropy to the part of information system and for using it to extract irregularities in predicted dynamics of information system and overall of the autonomous robotic system.
Keywords: automatic robotic system, error development, information entropy

1. INTRODUCTION

With a finite percentage, errors accompany regular dynamics of diverse systems, including autonomous robotic systems. It is a fact that many types of errors develop rather fast, usually unobserved until they reach rather high intensity. However, many types of errors develop gradually, starting from a minute, even infinitesimally small deviation that build-up in time.

Extracting these errors, and moreover finding their cause or causes, is by no means trivial. Error development and propagation is usually masked with regular dynamics and its accompanied fluctuations in the initial development interval. Furthermore, since autonomous systems operate in a usually rather uncharacterised environment, the limits of fluctuations occurring in regular dynamics are even more broadened. Illustrative cases of functioning autonomous robotic systems in a broad class of environments are well covered in the existing literature, see e.g. [1-6].

In this paper we concentrate on the class of errors that develop gradually within autonomous robotic systems. Gradual development means that characteristic time between the initial, infinitesimally small influence of error and the error in its fully-developed form, is rather large compared to characteristic time of regular dynamics. As an illustration, let us consider that central computer of a distributed information system, a part of an autonomous robotic system, samples several sensors periodically, with time interval between successive samples equal to 20 ms. Then, every error, which develops in time intervals that are at least one order of magnitude larger than stated 20 ms, falls into category of gradually developing error. That is because one can trace its development during several time intervals. In this example we considered that collected data contains information about developing error. While that is definitely not the only case, in this paper we concentrate on projections of developing error in the corresponding data collected dynamically within information system, a part of the complete autonomous system, which itself is otherwise unspecified. Approaches to more general cases are given elsewhere [7-11].

Along with stated assumptions, that formulate the context, a non-trivial question is posed that we have tried to answer: is there a reliable method that can extract the developing error in real-time conditions? We have tried to answer such a question by finding the very method. Corresponding method for developing error extraction is sought in form of information entropy-based algorithm for finding the statistically significantly improbable deviations between the observed and predicted dynamics of the autonomous robotic system, i.e. of data about it as collected within the informatic system. In section two we present the corresponding model, in section three simulate the occurrence and development of a particular type of error, and conclude the paper in section four.

2. MODEL

The model consists of the following elements: two, mutually independent sensors, one processing unit and accompanied algorithms for data analysis. It is based on the model described with additional details elsewhere [4, 5].

Sensors provide the central unit with regularly sampled data. Sensors operate independently one of another in regular mode. Central unit analyses data and, among the quantities which are determined on the basis of sensors' outputs, calculates appropriately averaged information entropy. Using moderate assumptions, we prescribe range of information entropy values which belong to the interval of regular conditions. In that sense, value of information entropy which exits the interval of regular conditions, marks occurrence of the failure. Since entropy changes are of gradual character, one can follow augmentation of the failure and relatively slow degradation of the regular state.

Many sensors used in realistic systems can be analysed in the stated way. If autonomous robotic system represents unmanned aerial vehicles, or aircrafts which is in autopilot mode or which utilises fly-by-wire system, then diverse sensors for sampling air-data are examples of two aforementioned sensors[4, 5].

In regular conditions, constant flow of data from sensors to processing unit is assumed to occur through ideal communication channel, thus without additional error in data transfer. Set of data from two sensors in regular conditions is assumed uncorrelated.

Let us concentrate now on the case of failure and model it appropriately. It is assumed that the effect of failure will be traceable in modified outputs of both sensors. That is not the only case, as one can have modification of sampled data in only one sensor, or in more than two sensors. On the on hand, the case of failure in which output of only one sensor is modified was analysed previously. On the other hand, we expect that the case of failure which modifies outputs of many sensors within the same time interval is not substantially different from previously stated case of two modified sensor outputs.

Information entropy is considered a robust enough measure to reveal possible regularities among variations in statistical properties of different sensor outputs, even if they are of different order of magnitudes, or with different characteristic delay.

For numerical simulations the transferred types of data are denoted as x_1 and x_2. The amount of the realistic quantity that they represent is an analogous quantity. Yet, in accordance with the modern, prevalent case, we assume that x_1 and x_2 are digitalised, thus discrete variables. Their resolution is considerably larger than resolution by which we will differentiate different states of the system later in the formalism. Overall, we denote time series of these variables as $\{x_{i,k}\}$ with $i = 1$, or 2 and k being the (discrete-)time interval. Averages and accompanied standard deviations of measured data are $\overline{x}_i$ and σ_{xi}, respectively, and we further consider that these quantities do not differ significantly from the expected values $E(x_i)$ and square rotes of variances $\sigma(x_i)$, respectively, of normal distributions which we use as underlying distributions of measured data. In other words, all time series are sufficiently representative to be considered as statistically equivalent data series.

For random variabley and z having joint probability distribution p(y, z) the information entropy is determined as follows [5]

$$H_{yz} = -\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(y,z)\mathrm{ld}p(y,z)\mathrm{d}y\mathrm{d}z\,, \tag{1}$$

with $\mathrm{ld}(\cdot)$ denoting $\log_2(\cdot)$. For mutually independent variables that entropy transforms into sum of entropies of individual variables, $H_{yz} = H_y + H_z$. Following previous assumptions all written entropies can be determined without significant differences from the corresponding, finite time series

$$H = -\sum_{\mathrm{n}} f_{\mathrm{n}}\mathrm{ld}f_{\mathrm{n}}\,, \tag{2}$$

with f_n being the relative frequency of occurrence of the state n of a random variable. Summation in (2) is performed by all achievable states of the underlying random variable, or variables. For discrete variables x_1 and x_2 states are self-defined while for originally analogous variable, prior to summation its domain needs to be made discrete. Since in implementation usually an analogue-digital converter is implemented it is often the case that we calculate the entropy directly using summation for digital variable. If data are regularly updated, in such a way that newly received data enter the a time series and the oldest data in that time series are removed from it, one can determine a new value of information entropy for each change of time series. If there is a relatively large number of data in a series then changes between successively determined information entropies will also be relatively small, yet in time there can be a trend in changing their values. For a set of information entropies determined for a time series in N consecutive time units, the accompanied average values and standard deviation of these information entropies are, respectively, as follows:

$$\overline{H} = \frac{1}{N}\sum_{\mathrm{i}=1}^{N} H_{\mathrm{i}}, \tag{3}$$

$$\sigma_H = \sqrt{\frac{1}{N}\sum_{\mathrm{i}=1}^{N}(H_{\mathrm{i}} - \overline{H})^2}\,. \tag{4}$$

Time window N for averaging the information entropy is somewhat arbitrary. It needs to be sufficiently larger than 1 time unit yet sufficiently smaller than original time series.

After determining (3) and (4) one can represent the original random variable with its statistical measures, which are also time dependent. Any trend, i.e. systematic deviation of underlying random variable from original distribution will be revealed in occurrence of systematic change in (3). It is then opportune to constantly determine (3) for one, two or more variables and check whether there is non-regular trend observable in it.

For any change observable in time dependence of (3), or possibly in (4) the application of definite statistical procedures is needed in order to state, with a given reliability level, whether it is statistically improbable that the change is random, or not.

3. RESULTS

We list representative results in a special case of one variable. Furthermore, let us consider the case of air-speed indicator measuring speed of an unmanned aerial vehicle [5]. We characterize the regular state with average speed of 370,4 km/h = 200 kt, and standard deviation of 5,56 km/h = 3 kt which implements several diverse influences. In regular state the average information entropy is 5,18 bit, and its standard deviation 0,06 bit. We use time series of 1000 data and combine them in 60 different categories.

For irregular state we consider the hypothetical case in which measured speed erroneously measured in the limit of larger than average speeds, as follows:

$$x_{\mathrm{nonreg}} = \begin{cases} x_{\mathrm{reg}}, & x_{\mathrm{reg}} \le x_{\mathrm{G}}, \\ x_{\mathrm{G}}, & x_{\mathrm{reg}} > x_{\mathrm{G}}. \end{cases} \tag{5}$$

One illustration of such a modified distribution is shown in Figure 1.

In case of two variables, mutually independent, one starts similarly to case of one variable. Technical difference is that number of states is considerably larger than in case of one variable. Yet, there is a substantial difference in that an error which propagates in diverse measuring channels introduces a correlation to modifications of original distributions. We will consider representative cases in further publications.

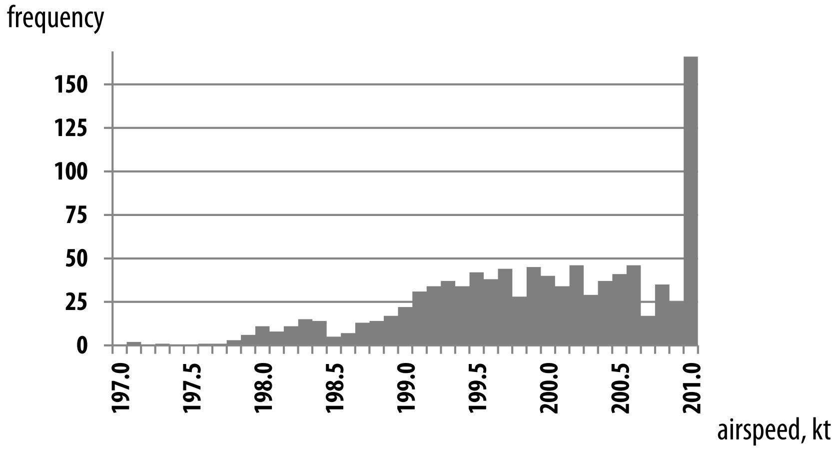

Figure1. Histogram showing frequency of a given measured airspeed in time series of measured speed with 1000 data in irregular state with $x_G = 201{,}0$ kt. Width of categories is 0,1 kt.

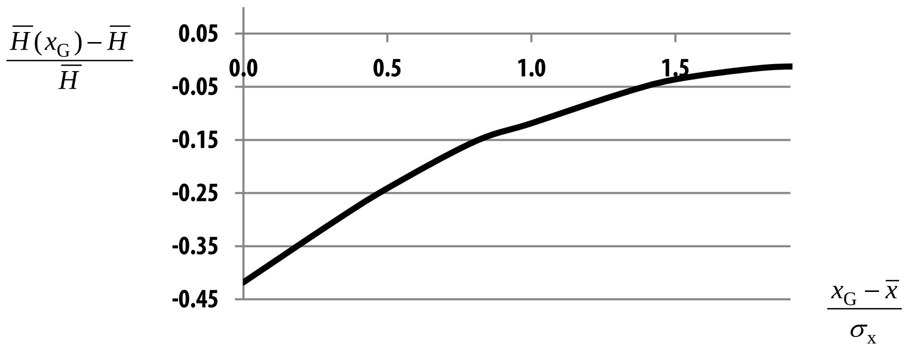

Figure 2. Relative change of entropy with scaled error level in case of one measured variable.

The cases considered are defined within a context of unmanned aerial vehicles, one representation of a large number of different types of the autonomous robotic systems. Specifically their speed of flight was considered as a representative variable which is, on the one hand important for regular functioning of a single unit or a group of units, and on the other hand subject to different external influences which possibly result in measurement errors. The formulated change in otherwise constantly measured data is by no means restrictive as it represents one of many possible changes in data, which can be straightforwardly implemented in the presented formalism. Information entropy was shown sensitive to relatively small changes in the measured variable.

If we simulate time series for different values of x_G one obtains relative change of average information entropy (3) as shown in Figure 2.

4. CONCLUSIONS

The approach to analysis of possible occurrence of errors, based on analysis of information entropy attributed to corresponding data series, has a potential in applications in autonomous robotic systems, as a software-implemented part of their processing unit.

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