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Automatic Detection Method of Behavior Change in Dam Monitor Instruments Cause by Earthquakes

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ABSTRACT
A hydroelectric power plant consists of a project of great relevance for the social and economic development of a country. However, this kind of construction demands extensive attention because the occurrence of unusual behavior on its structure may result in undesirable consequences. Seismic waves are some of the phenomena which demand attention of one in charge of a dam safety because once it happens can directly affect the structure behavior. The target of this work is to present a methodology to automatically detect which monitoring instruments have gone under any change in pattern and their measurements after the seism. The detection method proposed is based on a neuro/fuzzy/bayesian formulation which is divided in three steps. Firstly, a clustering of points in a time series is developed from a self-organizing Kohonen map. Afterwards a fuzzy set is built to transform the initial time series, with arbitrary distribution, into a new series with beta distribution probability and thus enable the detection of changing points through a Monte Carlo simulation via Markov chains. In order to demonstrate the efficiency of the proposal the methodology has been applied in time series generated by Itaipu power plant building structures measurement instruments, which showed little behavior change after the earthquake in Chile in 2010.
Keywords - Dam Safety, Earthquakes, Artificial Neural Network, Sets Fuzzy, Monte Carlo Simulation.

I. Introduction

A hydroelectric power plant consists of a project of great relevance for the social and economic development of a country and its conservation demands engineering great capability which involves the commitment of high technic expertise personnel. Referring to dam structures the occurrence of unusual random behaviors may result in undesirable consequences both in economic and environmental levels as well as people safety [1]. Dam safety consists of a widely discussed issue worldwide.

Brazil has been worried with its dams health. On September 20 the law no.12.334 [2] came into effect, which establishes the National Policy of Safety of dams intended to be loaded with water for any use, temporary or permanent disposal of tailings and the accumulation of industry discards, in this context it was also created the National System of Dam Safety Information (NSDSI).

Afterwards, the resolution no.144 on July 2010 was created [3] which stablishes headings for the implementation of dam safety national policies, as well as its instruments application and action on the national information system on dam safety. Currently, companies in charge Brazilian dams adopt safety policies based on that law, so that to monitor safety through an instrument system installed in strategic positions along the dam, which allows large dam structure health monitoring, considering the occurrence of various random events such as water temperature, reservoir levels, and pluviometry variation.

One of the phenomena that calls the attention of ones in charge of a dam safety is the earthquakes both in little or large scales. The occurrence of an earthquake even if it happens far away from the dam, can bring structure behavior changes. Therefore, during the occurrence of an earthquake, it is necessary to analyze the measurement of a large number of instruments in order to identify possible behavior changes in the dam structures or basements. Thus, the identification of behavior change caused by an earthquake can be made manually through time series' graphics visual inspection of measurements generated by installed monitor instruments. Nevertheless, in case of a large number of instruments it is possible to considerably install the time for the conclusion all necessary analysis related to decision taking. Thus, a computing technology which is able to detect automatically behavior changes in a dam structure blocks, after an earthquake is of great interest for the personnel involved in dam safety management. However, generally, the existing techniques for such work are dependent on previous knowledge of the time series behavior coming from deterministic or statistic models.

In specialized literature there are some numeric methods for automatic detection change points in time series such as [4],[5]and [6]. In some time series it is not possible to obtain a previous knowledge applying the above techniques. A current study which seeks for the solution for this situation is presented in work[7], in which a neuro/fuzzy/Bayesian formulation is used in the detection of change points in time series without any previous knowledge of the data set. Besides having also the advantage of identifying incipient changes, or rather, changes which gradually affect the usual structure operation[8].

This piece of work presents an adaptation of the neuro/fuzzy/bayesian formulation for automatic detection of change points in time series applied to identifying behavior change in data generated by the dam safety monitor instruments. In order to evaluate it an application using time series from measure data of Itaipu dam's monitor instruments, which is located in Foz do Iguassu, Parana, Brazil. Such instruments registered little change in stochastic regime in its behavior (there was few changes and the measures returned to their historical regime), which happened after the earthquake in Chile on February 27th 2010.

II. Dam Safety

Dam safety can be defined as the providence of conditions which aim at maintaining he dam structure and operational integrity as well as preserving life, heath, prosperity and environment [2]. Concerning dam safety involved characteristics; they must be taken into consideration in the project and during all the dam operation. Hence, according to [9], a way to evaluate dam behavior and integrity is to adopt an instrument system which is able to monitor numerically, its geotechnical and structural state. An instrument plan aims mainly to ensure a proper safety level observing whether the premises set in the project are under control.

In general a monitor instruments system follows the norm NBR 8681 – Actions and safety of structures [10]sets out the necessary verification related to stability analysis of a dam made of concrete as to evaluate movement safety such as sliding, tumbling down, floating, pressure at the base of foundation and structure, deformation and vibrations [9].

Physically the movements mentioned to safety monitor are explained dueto the fact that the difference in water level creates a hydraulic gradient between upstream and downstream of a dam forcing the water from the reservoir go downstream so that the water level is balanced. For such, the water percolates mainly through the dam base solid. In the course of this process the water which penetrated the solid provoke upwards force under the dam; such force is called base suppression (as shown in $F_{Subpressure}$ in Figure 1). In the course of this process the water which penetrated the solid provoke upwards force under the dam; such force is called base suppression. In addition, the water of the reservoir also causes horizontal force which works from upstream to downstream over the dam, which is called hydrostatic pressure against the dam wall. (as shown in $F_{Reservoir}$ in Figure 1). These two main types of occurrence are considered destabilizing forces which combined may cause the tumbling or sliding of the dam wall both by directly efforts and by the relief of structure weight (as shown in P on Figure 1)[9].

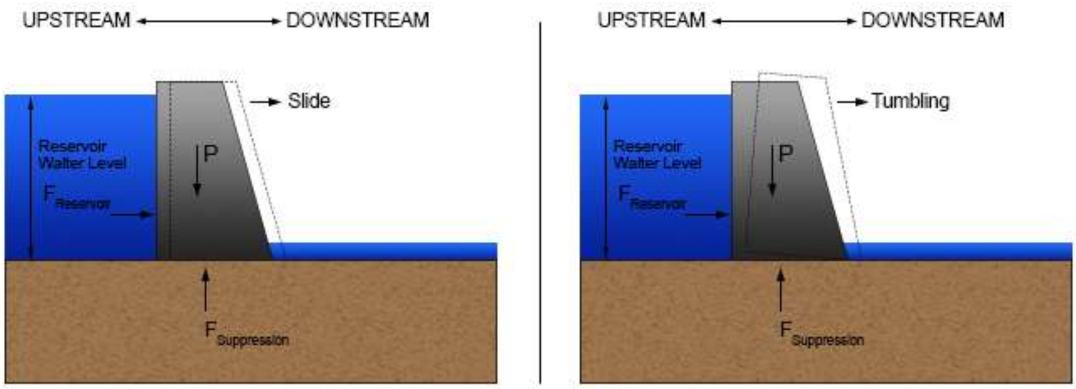

Figure1: Ways of dam destabilizing.

In order to monitor the stability of a structure regarding slide and tumbling it is necessary to install instrumentswhich are able to measure piezometric pressure levels in the rock-concrete interface as well as in existent sub horizontal discontinuities in the basement. Therefore, the measurement of the variable F sub pressure in dam concrete basements is extremely important to safety condition supervision and the piezometers are the required instruments to execute monitor [11].

III. Methodology

The methodology proposed in this article is anadaptation of the works[7], [8],[12]and [13], its main contribution is to present an approach which allows the detection of change points in time series without previous knowledge of deterministic or statistic models that describe data collection.

The method is divided into three steps: (1) Clustering of time series data through a self-organizing map of Kohonen; (2) Construction of a new time series by fuzzing the initial time series; (3) Use of Monte Carlo simulation via Metropolis-Hastings algorithm for determining the change point. These three steps are described in Figure 2and details are given next.

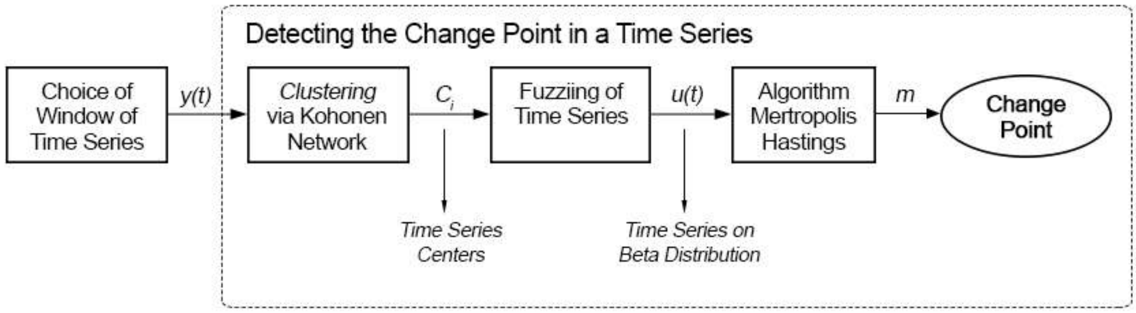

Figure2: Step of methodology for detection of change point of a time series.

Step 1: Clustering via Kohonen network.

The chosen methodology for the data clustering isbased on aKohonen self-organized RNA algorithm. The main reason for the choice of clustering of data via Kohonen network is because this method allows flexible grouping, thus determining besides centers, a proper quantity of groups ignoring unnecessary groups. This is a very important fact for the present work target because it enables the identification whether a change in the time series occurred or not.

As in this study the interest is only for one dimension time series the doors for this network is a unique variable, which are the measurements given by the dam monitor instrument. Since the target is to identify just one time series change, the network starts with only two neurons, whose initial values are defined by: time series minimum value(w_1) and half of the subtraction between the minimum and maximum values of the time series (w_2). This choice ensures that the second neuron only has anassociation with data if, in fact , a behavior change in the time series happened and this is what enables the method to claim for the occurrence or not of the change.

Yet, in the beginning of the process a maximum limit of 1000 iterations is defined, a learning rate $\alpha = 0{,}1$ for the first part of the method and neighboring radius equal 1. As only a unique neuron wins each iteration it is not necessary to use the neighboring radius.

The second part of the algorithm consists of an unsupervised and competitive training of neural network [14]. Hence, for each iteration (i), the time series values are covered, adding for each value the Euclidian distance between the value and each of the neurons. The neuron which gets the shortest distance is considered the winner. Afterwards, the learning rate α is linearly updated by the equation$\alpha = 0{,}1 - (9 \times 10^{-5})i$. This process is repeated until the quantity of chosen iteration is finished.

Finally, the algorithm uses a low performance elimination criteria process, so a performance index which quantifies the association numberof each neuron and doors is defined. If one of the neurons has no association, or rather, the performance index is void, the algorithm shows that the time series had no behavior change. Otherwise the value of the two neurons is defined as cluster centers so that they can be used in the next step of the method.

Thus, this first methodology step, given by the data clustering algorithm via Kohonen network enables the detection of an existing change point in the time series. In case such existence is confirmed , the nest steps are developed to show the moment this change occurred.

Step 2: Fuzzying of the time series.

The classic grouping methods divide data in categories, however, in many cases, some elements cannot belong to a specific category because they belong to two or more categories simultaneously. The use of fuzzy sets as grouping methods is a good alternative to solve such problem, because this way an element can belong to more than one category simultaneously[15].

For this work, it has been used a fuzzy grouping method to generate a new time series based on cluster centers calculated by the Kohonen network developed in the previous step.

This way, given a time series $y(t)$ with n points, the cluster centers found previously are the values $C_1$and C_2 which solve the following minimizing problem.

$$\min \sum_{i=1}^{2} \sum_{t=1}^{n} \|y(t) - C_i\|^2. \quad (1)$$

This way, the function defined by,

$$\mu(t) = \left[\sum_{j=1}^{k} \frac{\|y(t)-C_1\|^2}{\|y(t)-C_j\|^2}\right]^{-1}, \quad (2)$$

has its image contained within the gap $[0,1]$ and thus, it is possible to consider $\mu(t)$ as being a fuzzy set which describes the pertinence degree of the point $y(t)$ in cluster relation of center C_1.

The most important for this study is the fact that using statistic tests[12] it is possible to conclude that the function can be approximated by a beta distribution function with different entrance parameters, or rather, a beta distribution $(a,b)$to $t \leq m$ and a beta distribution (c,d) to $t > m$,or rather, the probability distribution of variables $\mu(t)$ depends on five parameters (a,b,c,d,m) and has approximation

$$f(\mu|a,b,c,d,m) \sim \prod_{i=1}^{m} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \mu(i)^{a-1}\left(1-\mu(i)\right)^{b-1} \prod_{i=m+1}^{n} \frac{\Gamma(c+d)}{\Gamma(c)\Gamma(d)} \mu(i)^{c-1}\left(1-\mu(i)\right)^{d-1}, \quad (3)$$

being $\Gamma(x) = \int_0^\infty u^{x-1}e^{-u}du$ the function gamma.

Therefore, this methodology step proposal, through the fuzzy set (Equation 2), intends to transform data set into a time series without any previous knowledge in a time series with statistic information enough for the application of bayesian inference methods, enabling to estimate beta distribution parameters (Equation 3). Particularly, the parameter m which is the moment that the behavior change in the time series $y(t)$ occurs.

Step 3: Metropolis-Hastings algorithm.

Once the previous steps transformed the original time series, with a distribution of any probability, into a new time series $\mu(t)$ with a function of beta probability distribution, so, the new statistic model is set and considered in a bayesian formulation in order to estimate beta distribution parameters which come forward the new time series and thus, enabling to estimate the parameter m[12]. In this step, the Metropolis-Hastings algorithm is used to execute the Monte Carlo simulation via Markov chains with the aim at estimating parameters.

The definition of a Markov chains is given as: Given a random vector $\theta_i = (a_i, b_i, c_i, d_i, m_i)$, it is chosen a candidate value $\theta = (a,b,c,d,m)$ of a distribution with density $f_{\theta|\theta_i}(\mu) = q(\theta_i;\theta)$. The function q is known as chain transition nucleus. It is a function that depends on two variables the current estate of the chain θ_i and the candidate value θ.

The candidate value θ is accepted or rejected depending on the probability value of acceptance given by

$$\alpha(\theta_i,\theta) = \min\left(1, \frac{\pi(\theta)q(\theta;\theta_i)}{\pi(\theta_i)q(\theta_i;\theta)}\right). \quad (4)$$

If the candidate value is accepted so $\theta_{i+1} = \theta$, on the contrary $\theta_{i+1} = \theta_i$. This way, if the candidate value is rejected, the Markov chain has a sequence reiteration. Therefore, the sequence $\theta_0, \theta_1, \theta_2, \ldots$ makes a Markov chain with balanced distribution π.

In practical terms the Metropolis-Hastings algorithm presented is specified over the fact that steps prior to the transformed time series $\mu(t)$ follows the given distributions:$\mu(t) \sim beta(a,b)$to$t = 1, \ldots, m$ and $\mu(t) \sim beta(c,d)$ to $= m+1, \ldots, n$. This way the parameters which must be estimated by the algorithm are a, b, c, d and the change point m.

As the values a, b, c and d must be parameters of a beta distribution, so they must be considered positivereal numbers, this way the proposed distribution $q(.)$ Is used to generate candidates to these parameters, the gamma distribution $(0{,}1\ , 0{,}1)$.Whereas, in the case of the value m which should belong to the discreet set$\{1,2,\ldots,n\}$, the proposed distribution$q(.)$To generate candidates to value m is given by the standard distribution$U\{1,2,\ldots,n\}$. This way a vector $\theta' = (a', b', c', d', m')$generated bythe proposed distribution $q(.)$ has $a', b', c', d' \sim Gama(0{,}1\ , 0{,}1)$and $m' \sim U\{1,2,\ldots,n\}$.

For the interest distribution $\pi(\theta)$,is adopted the later distribution of θ determined by the time series $\mu(t)$, or rather, $p(\mu|\theta)$ Thus, the function of likelihood$l(\mu;\theta)$is given by the function $f(\mu|a,b,c,d,m)$ in Equation 3 and the previous distributions $\theta = (a,b,c,d,m)$ is the gamma distribution $(0{,}1\ , 0{,}1)$ for the parameters a, b, c and d and $U\{1,2,\ldots,n\}$ for the parameter m. Then the probabilities are calculated by

$$p(x) = \frac{0{,}1^{0{,}1} x^{0{,}1-1} e^{-0{,}1x}}{\Gamma(0{,}1)}, \quad (5)$$

to $x = a, b, c$ or $d$and

$$p(m) = 1/n. \quad (6)$$

This way, if the chain is in the state $\theta_i = (a_i, b_i, c_i, d_i, m_i)$, the acceptanceprobability (Equation 4)for each new value parameter $\theta' = (a', b', c', d', m')$ generated by $q(.)$.

After calculating acceptance probabilities of each parameter, a value u is drawn from the distribution $U(0,1)$ and each new vector parameter $\theta_{i+1} = (a_{i+1}, b_{i+1}, c_{i+1}, d_{i+1}, m_{i+1})$ is built through the rule: If $u < \alpha(x_i, x')$,so accepting the new value and do $x_{i+1} = x'$, otherwise , reject and do$x_{i+1} = x_i$, with $x = a, b, c, d$ and m.

Afterwards, the iteration value i is adjusted to $i+1$, a new vector $\theta'$is generated by $q(.)$ and the process is repeated. For this work 1000 iteration were chosen which generate a Markov chain of 1000 estimative for the vector$\theta = (a,b,c,d,m)$.

Since the target of this step is to determine the best estimative of the parameter m the method is finished with the choice of value which happens with larger frequency amongst the 1000 estimate for m because this is value , amongst the estimate ones, that has the biggest probability of being parameter $m$of beta distribution which gets closer to data distribution in a time series$\mu(t)$, and consequently is the moment of change behavior of the time series $y(t)$.

IV. Aplication: Itaipu Hydroelectric Power Plant

Itaipu isregarded as one of the greatest hydroelectric projects in the world. It is the result of the efforts and commitment of two neighbor countries Brazil and Paraguay. The dam is located in the Parana river where the countries are bordered, 14 kilometers upstream from the international bridge which connects the city of Foz do Iguassu, in Brazil to Ciudad del Este, in Paraguay[16].

Due to its giant size, Itaipu hydroelectric power plant has kept since its project, constant attention regarding the structural safety of its dam. Itaipu currently has about 2792 installed instruments and 10 percent of them are equipped with an automatic system of data acquisition which aims to monitor the dam structural behavior through measurements related to stress, deformation, misplacement, pressure, water infiltration, downstream and upstream river levels, temperature and rainfall. These instruments enable the obtain scans at a controllable frequency from 5to 30 minutes. The information is processed, stored and sent to a central station which is responsible for processing, analyzing and comparing data and trigger alarms[11].

Amongst the phenomena which Itaipu monitors, earthquakes both of little or large magnitudes deserve a lot of attention, because some of these tremors even located distantly from the dam, they have been registered by the seismographic network of Itaipu and accused temporary change in some of the instruments installed.

According to [17] the earthquake Maule in Chile is especially very important for the context of this work because besides being detected by the seismographic network, it has also been shown by some instruments from Itaipu auscultation system, since it was a large magnitude earthquake, above 8.0 (Richter scale). At the time, it was possible to verify that some monitor system instruments from Itaipu dam would register brief changes in standard behavior which can be related to this event.

In order to show the efficiency of neuro/fuzzy/ bayesian approach in the detection of change points in time series applied to real problems, it was chosen, for this study, the time series generated by the piezometer named PS-D-21, which is responsible for monitoring the contact between the rock mass and the concrete wall of Itaipu Hydroelectric power plant.

The mentioned piezometer is an automatic instrument, which registered, through a visual analysis of its time series, a little behavior change after the occurrence of the earthquake in Maule-Chile (8.8mb). The data collection from the instrument has 48 points related to measurements done every 30 minutes on February 27th 2010, when the quake occurred (Figure 3).

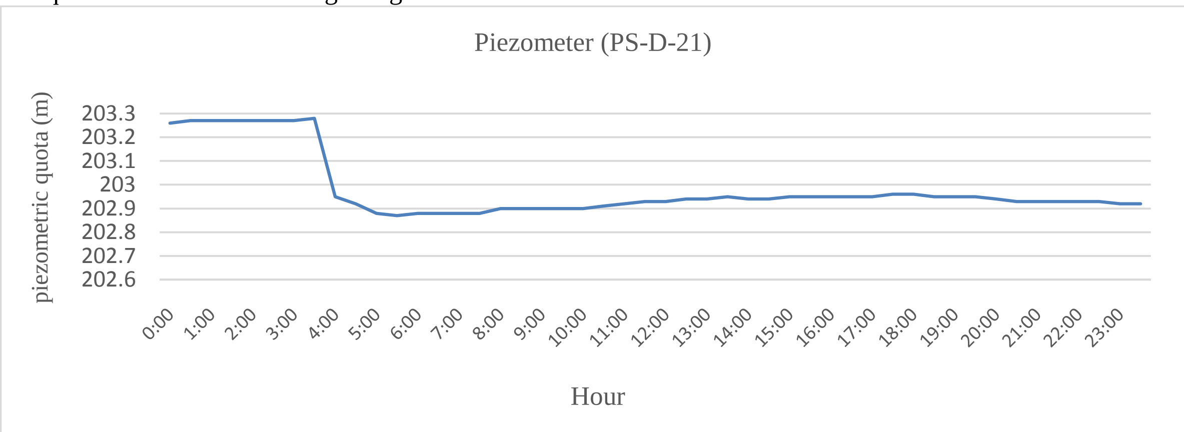

Figure3: Piezometer PS-D-21 automatic readings (rock/concrete interface) – Earthquake in Chile(02/27/2010).

The earthquake in Chile in 2010, happened at 03:34:08, local time, in the same time zone where Itaipu is located (UTC-03). It is possible to see in the above graphic, that the behavior change in the time series also occurred by that time (between 03:30 and 04:00), which enabled to related the behavior change data with the occurrence of the earthquake.

As earlier shown, the target of this study, does not aim at the detection of occurrence of an earthquake, but to identify, automatically, which monitor instruments had behavior changes after the occurrence of the phenomenon already detected. Therefore, an algorithm has been installed in the software MATLAB R2011 based on the earlier presented methodology (Section 3) and applying it to the time series (Figure 3).

V. Results and Discussions

The graphic result are shown in Figure 4 and present the following interpretation: Figure 4a represents the first phase of the algorithm given by clustering via Kohonen network (Step 1 of Section 3) applied to the time series of the chosen piezometer. Two cluster centers have been found C_1e C_2confirming the change point existence in the time series which enabled the methodology next step.

During the second phase of the algorithm, the fuzzying of the time series is done (Step 2 in section 3) defining a new time series. The Figure 2b presents the transformed time series, represented by $\mu(t)$ which, according to the theory exposed in this article has distribution that can be described by on e of the beta distributions with parameters (a, b, c, d, m). Thus, the next step of the method is responsible for estimating the parameter m through a Monte Carlo simulation.

Afterwards, the Metropolis-Hastings algorithm, described in Step 3, is applied in the time series transformed in the previous step, building Markov chains with 1000 estimate values for each parameter (a, b, c, d, m) of the possible beta distribution. Since the final target is to obtain only parameter m of each time series, the Figura4c shows the sequence of 1000 estimate values for m of the time series evaluated.

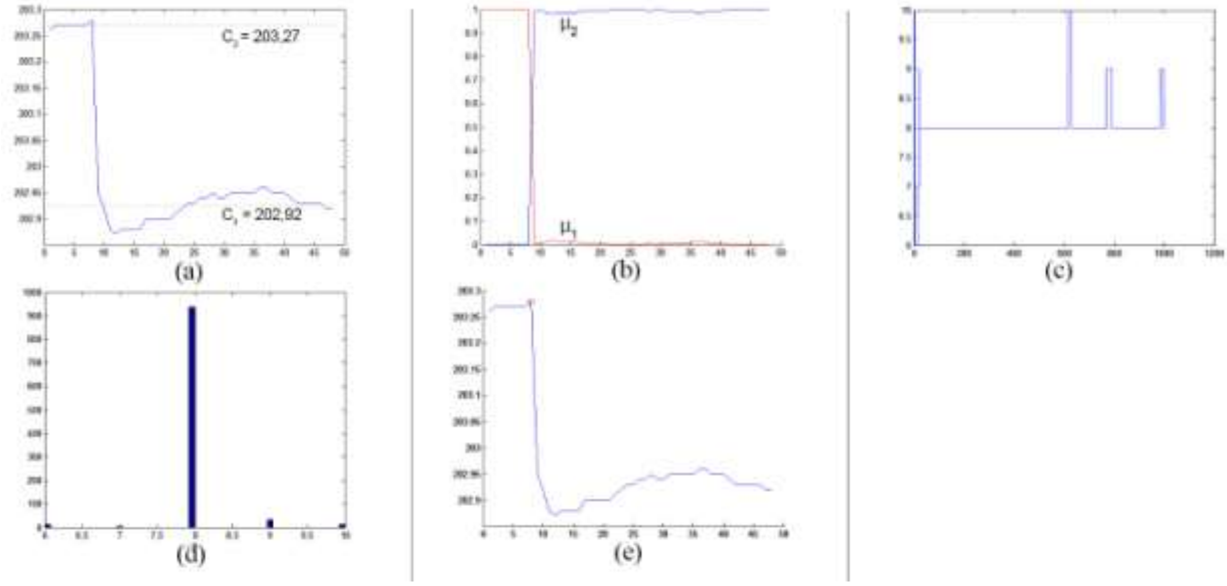

Figure4: Graphical results of the proposed methodology

The Metropolis-Hastings algorithm builds a Markov chains, accepting as a new value only the ones with great probability of satisfying the *posteriori* data distribution. So, the term which occurs more frequently in the value sequence is considered the best estimate to be the desired parameter m. According to the histograms presented in Figure4d, it is claimed that the series PS-D-21, the value $m = 8$ occurred with the larges frequency ,or rather, around 910 times among the 1000 simulated values, thus, $m = 8$ is considered the change point of the time series generated by the piezometer PS-D-21.

At last, the picture 10 presents graphics of original time series plotted with their respective change points detected by the proposed method.

Therefore, it is claimed that the proposed methodology detected that the time series PS-D-21 suffered behavior change right after the instant 8 (eight) (Figure 4e). As each time series input represent measurements done from 12:00 am on February 27th 2010 verified every 30 minutes, the detected point 8 (eight), is related to the measure performed at 03:30 that day. It implies that the identified change occurred between the measures made at 03:30 and 04:00, the same time of the earthquake occurrence, at 03:34:08. This fact indicates the relation between of the detected change to the earthquake, which corroborates the result obtained by the method.

VI. Conclusion

In this article, it is proposed a behavior change in time series detection method by monitor instruments used in dam safety management. The method brings concepts of artificial neuro networks, fuzzy sets theory and bayesian inference and has as its main factor the identification of change points in time series without the need of a priori knowledge of data set, besides enabling the detection of changes which vary more slowly regarding time.

The method efficiency has been tested through the application in real time series used in Itaipu dam monitor, on which it has been detected, through manual analysis little behavior changes after the occurrence of an earthquake. The results obtained through the method showed themselves coherent with the analysis manually made, in which all the changes have been detected automatically and the estimate value for the moment of the occurrence was exactly the moment of the occurrence of the earthquake, which is responsible for the detected changes.

The importance of the methodology is due to the fact that in large dams such as Itaipu, in every earthquake event, the company needs to manually review the behavior change in a large number of instruments, therefore the use of the methodology is of enormous interest because it would speed the decisions taking, thus improving the dam safety management.

Therefore, the application of the proposed method in real data involved with Itaipu dam safety monitor, sustains the importance of a tool to automatically evaluate behavior changesin measurements performed by monitor instruments and guarantee the method efficiency, which besides detecting all foreseen changes, it also determines likely estimate for the change occurrence moment thus relating the behavior change to its possible cause.

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