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Time series long-term forecasting model based on information granules and fuzzy clustering

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ABSTRACT

In spite of the impressive diversity of models of time series, there is still an acute need to develop constructs that are both accurate and transparent. Meanwhile, long-term time series prediction is challenging and of great interest to both practitioners and research community. The role of information granulation is to organize detailed numerical data into some meaningful, semantically sound entities. With this regard, the design of time series forecasting models used the information granulation is interpretable and easily comprehended by humans. In order to cluster information granules, a modified fuzzy c-means which does not require that data have the same dimensionality is proposed. Then, we develop forecasting model combining the modified fuzzy c-means and information granulation for solving the problem of time series long-term prediction. Synthetic time series, chaotic Mackey–Glass time series, power demand, daily temperatures, stock index, and wind speed are used in a series of experiments. The experimental results show that the proposed model produces better forecasting results than several existing models.

1. Introduction

The analysis of temporal data and the prediction of future values of time series are among the most important problems that data analysts have been facing in many fields, ranging from finance and economics (Bodyanskiy and Popov, 2006; Kang, 2003; Chen and Wang, 2010; Chen and Chen, 2011), to production operations management or telecommunications (Lendasse et al., 2002; Mastorocostas and Hilas, 2012). Different time series models have been proposed, including traditional and fuzzy methods. Traditional time series forecasting, such as statistics and neural networks, is usually highly dependent on historical data, which can be incomplete, imprecise and ambiguous. These uncertainties are likely to be widespread in real-world data and hinder forecasting accuracy, thus limiting the applicability of these models. Unlike traditional time series forecasting approaches, the fuzzy approach is capable of dealing with vague and incomplete time series data under uncertain circumstances. Castillo and Melin (2002) proposed the definition of fuzzy fractal dimension and developed hybrid intelligent systems combining neural networks, fuzzy logic, and the fractal dimension, for problem of time series prediction. Chen and Chang (2010) presented a method for multivariable fuzzy forecasting based on fuzzy clustering and fuzzy rule interpolation techniques. Song and Chissom (1993a, 1993b, 1994) pioneered the study of fuzzy time series(FTS), in which temporal data are represented as linguistic values rather than numeric ones. Since its emergence, numerous studies have been devoted to improving forecasting performance and efficiency following the steps of Song and Chissom's forecasting framework, and these have resulted insignificant achievements. Egrioglu et al. (2011) used an optimization technique with a single-variable constraint to determine an optimal interval length in high order fuzzy time series models. Chen and Chen (2011) proposed a new method to forecast the TAIEX based on fuzzy time series and fuzzy variation groups. Wang et al. (2013, 2014) used clustering and the concept of information granules to determine temporal intervals of unequal length in fuzzy time series model. Lu et al. (2014) proposed the modeling approach to realize interval prediction, in which the idea of information granules and granular computing is integrated with the classical Chen (1996)'s method.

Most of the above studies involve one-step-ahead forecasting models (single point prediction). Nevertheless, there is an increasing need for long-term forecasting going many time steps in advance, which is difficult to achieve because information is unavailable for the unknown future time steps (Simon et al., 2005). Meanwhile, in the plethora of currently available models

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of time series, their accuracy has been a holy grail of the overall modeling for a long time. With the emergence of more visible and well-justified need for interpretable models that are easily comprehended by humans, arose an important need to develop models that are not only accurate but transparent as well.

In order to satisfy the above-mentioned needs, a time series long-term forecasting model based on information granules and fuzzy clustering is proposed. The role of information granulation is in the organization of detailed numerical data into some meaningful and operationally viable abstract knowledge, which makes the interpretation of data easier and more transparent as well as becomes helpful navigate through various levels of abstraction/specificity by adjusting sizes of information granules used in the description (Pedrycz and Vukovich, 2001). Therefore, the design of time series forecasting models that used the information granulation is interpretable and easily comprehended by humans. The modified fuzzy c-means based on dynamic time warping is proposed to cluster the granules and extract the fuzzy logical rules. Then, we determine the weight of each fuzzy rule with respect to the input observation and use such weights to determine the predicted output based on the multiple fuzzy rules interpolation scheme. The advantages of the proposed model can be summarized as follows:

- Information granulation is used to design the time series forecasting model, which makes the model interpretable and easily comprehended by humans.
- Many well-known distance-based clustering algorithms (e.g., k-means, fuzzy c-means) require data of the same dimensionality. In order to avoid this drawback, a modified fuzzy c-means based on dynamic time warping is proposed.
- The predicted multiple values can be done in one step instead of iteratively predicting each value separately. The proposed model can simplify the forecasting problem and reduce computational overhead of modeling.

An illustrative example for forecasting a synthetic time series is used to verify the effectiveness of the proposed model. Moreover, we conduct the experiments on the chaotic Mackey–Glass time series, power demand, daily temperatures, stock index, and wind speed. The experimental results show that the proposed model produces better forecasting results than those provided by several existing models.

The paper is organized as follows: Section 2 introduces the principle of justifiable granularity and presents a formation of information granules for given time series. Section 3 proposes a new fuzzy clustering algorithm by combining fuzzy c-means clustering and dynamic time warping. Section 4 proposes a time series long-term forecasting model based on information granules and fuzzy clustering. In Section 5 we compare the forecasting results of the proposed model with the results of the existing models. The conclusions are covered in Section 6.

2. Granular time series

The concept of information granule is first proposed by Zadeh (1979). Pedrycz and Vukovich (2001) introduced a model of generalization and specialization of information granules. Information granulation can split the problem into several manageable subproblems for which we are in a position to produce effective solutions. The formation of the information granules is realized as a compromise between two intuitively compelling requirements–*Justifiable granularity* and *Semantic meaningfulness*. For numeric data, the requirement of *Justifiable granularity* is quantified by counting the number of data falling within the bounds of the granule, and the requirement of *Semantic meaningfulness* is quantified by the length of the granule.

Information granulation play a pivotal role and give rise to granular models of time series or granular time series. Granular time series models offer a new, highly user-centric perspective at description of temporal data. Information granules are tangible and easily interpretable entities, which help perceive, quantify and interpret the data.

Consider a time series $\{x_1, x_2, \ldots, x_N\}$ shown in Fig. 1. A convincing description is realized as a sequence of information granules of magnitude of the time series where each information granule spreads over some time interval (time slice) $T_1, T_2, \ldots, T_p$ where "p" denotes a number of time slices predefined in advance. For all samples of the time series falling within the temporal window T_i, an information granule of the magnitudes of the time series is formed by invoking the principle of justifiable granularity, see Fig. 2. More formally, the principle of the justifiable granularity G is applied to the finite set of data $\{x_1, x_2, \ldots, x_N\}$ and the information granule $\Omega_\alpha^i = G(\{x_1, x_2, \ldots, x_N\}, T_i, \alpha)$ is realized for a certain predefined value of α.

For each temporal window T_i, the volume of the associated information granule $\mathrm{Vol}(\Omega_i)$ is computed by taking a product of the integral of Ω_i (its sigma count) and the length of the temporal window, that is

$$\mathrm{Vol}(\Omega_i) = T_i \int_{x_{min}}^{x_{max}} \Omega_i(z)\, dz, \tag{1}$$

where the bounds of the integration x_{min} and x_{max} are, respectively, minimal and maximal values of the amplitudes of the time series recorded in the temporal window T_i.

The intent is to arrive at information granules $\Omega_1, \Omega_2, \ldots, \Omega_p$ that are the most "*informative*" (compact) so that they carry a clearly articulated semantics. This gives rise to the optimization problem of

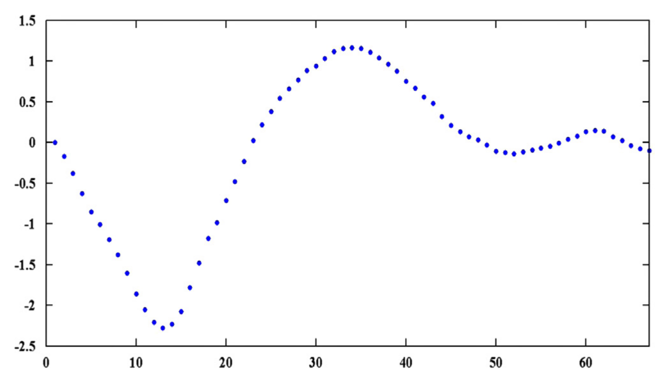

Fig. 1. A discrete time series.

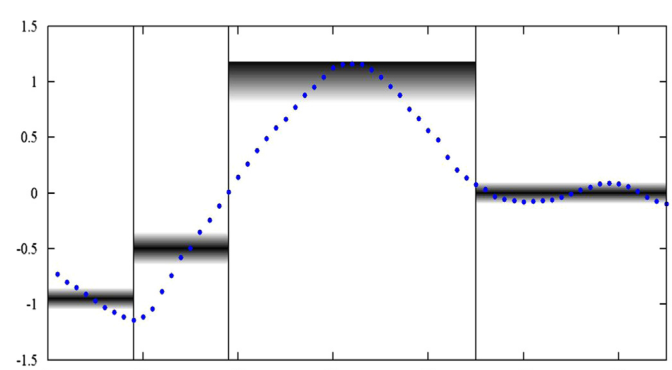

Fig. 2. The description of the time series as a sequence of information granules of magnitude formed over temporal windows.