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Real-time change detection in time series based on Growing Feature Quantization

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***Abstract*—An unsupervised time series change detection method based on an extension of Vector Quantization (VQ) clustering is proposed. The method clusters the subsequences extracted with a sliding window in feature space. Changes can be defined as transition of subsequences from one cluster to another. The method can be used to achieve real time detection of the change points in a time series. Using data on road casualties in Great Britain, historical data on Nile river discharges, MODerate-resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index data and x simulated data. It is shown that the detected changes coincide with identifiable political, historical, environmental or simulated events that might have caused these changes. Further, the online method has the potential for revealing the insights into the nature of the changes and the transition behaviours of the system.**

***Index Terms*—Change Detection, Feature Space, Vector Quantization, Time Series**

I. Introduction

Time Series data are generated, maintained, and processed within a broad of application domains in different fields. Mining such time series data becomes vital as the applications demand for understanding of the underlying processes or phenomena that generate the data. A specific interesting mining task is to detect changes in a given time series. Early identification of changes in a time series is one of the most promising topics in statistics [1]–[4] and data mining [5]–[9] due to the numerous applications where early warning systems are needed. Also, known as change detection or sometimes event detection, this problem covers a broad range of areas of application including land cover change detection [1], [10], [11], early warning of pandemic outbreaks [12], signal segmentation in data streams [7], [8], fault detection in engineering systems [13], telecommunication network [14], economics [15] and business [9].

The aim of this paper is to propose a new method for real-time change detection, that generates insights into the transition behaviours of the system. Vector Quantization (VQ) is a popular and widely applied clustering algorithm [16], which moves clustering centres demoted as code-book vectors towards accumulation points in the data set. The algorithm will be described in section III-B. We propose a growing VQ approach using a set of features to characterise a time series subsequence and then introduced a user defined parameter to control the growth rate of the cluster formation. Then changes are defined as the transition of subsequences from one cluster to another. This method reveals transition migration of subsequences between existing clusters and helps find new states of the system.

The paper is organised as follows. Section II presents a brief review of relevant research. Section III-A represents the feature extraction of sliding windows. Section III-B presents vector quantization clustering and change detection based on a new algorithm which we call growing feature quantization (GFQ). Section III-C describes how to recognise changes and transitions between clusters. Section IV presents the results for three well-known datasets and two simulated time series. Section V presents the conclusions.

II. Related Work

A typical statistical formulation of change-point detection is to consider probability distributions from which data in the past and present intervals are generated, and regard the current time point as a change point if two distributions are significantly different [17]. Various other approaches have been investigated, such as the CUSUM (CUmulative SUM) [1], [2], direct density-ratio estimation [17] and unsupervised time series subsequence clustering [10]. CUSUM detects changes by investigating the sum of linear regression errors. When the errors exceed a threshold, we consider that the time series no longer fits the regression model and a change occurred. Direct density-ratio estimation is a non-parametric approach to estimate the ratio of probability densities. Whether there is a change point is decided by monitoring the logarithm of the likelihood ratio. The unsupervised time series subsequence clustering clusters the subsequences and defines the transition of the subsequence from one cluster to another as a change. However, those approaches only give indication if change has occurred rather than providing insights into the nature of the change and the transition behaviour of the system. In [10], the unsupervised clustering method to detect land cover change has the potential for revealing patterns in the system, but it could not be used to deal with recently acquired data.

Considering that a rapid response or early warning is crucial in many cases, this paper proposes a method for real time detection of the change points in time series. The proposed method is based on time series subsequence clustering. There are two main categories in time series clustering [18]. "Whole clustering" is similar to that of conventional clustering of discrete objects. The entire time series is taken as a discrete object. In contrast, "subsequence clustering" is performed on individual subsequences extracted with a sliding window. A subsequence $x_p(t)$ for a time series $x(t)$ with length m is

$$x_p(t) = (x(t_p), \cdots, x(t_{p+w-1})) \tag{1}$$

for $1 \leq p \leq m - w + 1$, where w is the length of the subsequence. The sequential subsequences in (1) are extracted using a sliding window with a length of w and position p, which is incremented with a natural number $\mathbb{N}$. Wide use of subsequence clustering has been made in different areas. However, the sliding window causes the clustering procedure to create meaningless results as it forms sine wave cluster centres regardless of the data set, which makes the clusters extracted by any clustering algorithm essentially random [18]. To address this problem, several solutions have been used. [18] demonstrated a meaningful motif-based-clustering method. [19] and [20] used alternative distance measures to make sequential time series clustering meaningful. In [21], global measures describing time series were proposed to capture the underlying characteristics: trend, seasonality, periodity, serial correlation, skewness, kurtosis, chaos, nonlinearity and self-similarity, and the clustering was performed on the subsequences defined by a feature vector of these measures. [10] demonstrated three different unsupervised clustering approaches that operate on short term Fourier transform coefficients computed over subsequences that are extracted with a temporal sliding window and created meaningful sequential time series. Here we borrow the idea of [10] and [21] and use a set of subsequence features to map the original subsequences into feature space before clustering subsequences meaningfully. However, changes are detected here in an online manner while [10] operates clustering off-line.

III. Proposed Methodology

A. Feature Extraction

It is claimed in [18] that non-overlapping sliding windows, with their positions incremented by exactly the periodic length, would produce valid clusters when applied to a periodic time series. However, using the magnitude of the first few Fast Fourier Transform (FFT) components of $x_p(t)$ to characterise the subsequences makes the sliding window position p not have to be shifted by a fixed amount, but can be incremented by any natural number $\mathbb{N}$ [10]. For each subsequence $x_p(t)$, the features $x_p(f)$ are computed as

$$X_p(f) = |\mathcal{F}(x_p(t))| \tag{2}$$

where $\mathcal{F}(\cdot)$ represents the Fourier transform. The window length w depends on the type of time series. For seasonal time series, w is always fixed at the number of samples corresponding to the length of the cycle.

Meanwhile, more features besides FFT components like chaotic properties, serial correlation and so on [21] could be calculated to characterize the time series subsequences.

B. Unsupervised Change Detection: Growing Feature Quantization

VQ clustering is a classical quantization technique to divide a large set of points (vectors) into groups. Each group is represented by its centroid point. Its goal is to discover structure in the data by finding how the data is clustered. In VQ, there is a codebook which is defined by a set of M prototype vectors. M is chosen by the user and the initial prototype vectors are chosen arbitrarily. An input belongs to cluster i if i is the index of the closest prototype. From the mathematical point of view, vector quantization is basically a simplified version of k-means [22]. The simple idea is in Algorithm 1.

Algorithm 1 VQ

1: Choose the number of clusters M
2: Initialize the prototypes $w_1, \cdots, w_m$
3: Randomly pick an input x
4: Find the winning cluster w^* by finding the prototype vector satisfying

$$|w^* - x| \leq |w_i - x|, i = 1, \cdots, M \tag{3}$$

5: Update the winning prototype weights according to

$$\bar{w^*}_{new} = \bar{w^*}_{old} + \eta * (x - \bar{w^*}_{old}) \tag{4}$$

where η is the adaptation value

Algorithm 1 can't be applied for data sets with an unknown number of clusters. Various clustering approaches have been presented in an incremental manner such as sequential k-means [23], dynamic Self Organised Maps (SOM) [24] and Growing Neural Gas [25], [26]. The GFQ clustering is proposed in this paper. The goal is to cluster the subsequence features incrementally, by which new clusters can be recognized in time and the number of clusters don't have to be known in advance. In some systems like infectious diseases the earliest possible warning of a change is required, while in other systems an early warning of changes costs a lot of energy, money and sometimes panic. To enable the sensitivity of the system to be controlled, a user defined single parameter R is used. For each incoming feature vector x, if this condition is fulfilled:

$$\text{distance}(x, w^*) \geq R \tag{5}$$

where w^* is the winning prototype, we create a new cluster, which x belongs to. Otherwise, x belongs to the winning cluster. The number of clusters will become smaller with the parameter R growing (Fig. 1). According to a number of experiments this parameter should be around $\sqrt{d}/3$, where d is the dimension of the feature space. Of course, this parameter can be flexibly tuned according to the real world context to reduce false alarms or increase early warnings. The whole process is summarized in Algorithm 2.

A one-pass incremental and evolving variant of VQ were demonstrated in [22] by incorporating a vigilance parameter,

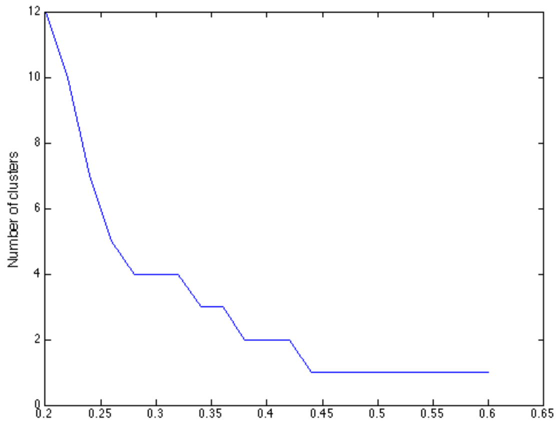

Fig. 1: How the choice of R influences the number of clusters

exploiting the idea in the adaptive resonance theory (ART) [27]. However the prototype vectors are not rescaled when the incoming input is outside the estimated range, which actually places the new input on a different scale to the prototype vectors.

C. Recognising changes and transition behaviours

Changes in time series are defined as the transition of the subsequence from one cluster to another within the feature space which characterise the time series subsequences. Thus the transition behaviours can be identified according to the memberships of the subsequences. It reveals whether the transition is between existing clusters or it changes to a new state. In this way, the states of the system can be both qualitatively and quantitatively described.

IV. Results

A. The seatbelt data

The seatbelt data is a monthly time series (from Jan 1969 to Dec 1984) of the number of car drivers in Great Britain killed or seriously injured in traffic accidents. There are two break-points in this time series, which are Oct 1973—associated with petrol rationing and the introduction of lower speed limits during the first oil crisis—and Jan 1983—associated with the seat belt law introduced in the UK on 1983-01-31 [28]. The sliding window length is fixed at $w = 12$ samples to correspond to the length of the annual cycle. We use magnitudes of the first four FFT components to characterize the sliding windows. Global features like chaotic properties are not used here because the short length of the subsequences and the short sliding step will not make those features of the subsequences well distinguished. In Fig. 2, the circles represent the ending points of the corresponding subsequences. Different colors means the subsequences are grouped into different clusters. From Fig. 2, using GFQ clustering, the transitions from one cluster to another can be seen both in end of 1973 and beginning of 1983.

Algorithm 2 GFQ

Initialize a threshold R, which gives a radius around a cluster prototype, in which feature vectors must lie to belong to the cluster
Initialize an adaptation value η, which depends on the number of inputs in the cluster
Collect a few data samples to obtain the estimated maximum and minimum for each feature component, and hence the estimated ranges of each feature
Initialize $C = 1$, where C is the current number of clusters; initialize a cluster prototype w_1, which is the first normalized input
Read the next incoming subsequence and calculate its feature vector x as the new input
if x is outside the estimated range **then**
    Update the ranges of each feature
    Rescale the current cluster prototypes using the updated ranges of each feature
else
    Use the current estimated ranges of each feature
Normalize the input to $[0, 1]^d$ according to the ranges, where d is the dimension of the feature space. Name the normalized input as $\hat{x}$
Find the winning cluster w^* by finding the prototype vector satisfying

$$|w^* - \hat{x}| \leq |w_i - \hat{x}|, i = 1, \cdots, C \qquad (6)$$

if distance$(\hat{x}, w^*) < R$ **then**
    Make $\hat{x}$ a member of w^*
    Let $C = C$
    Update the winning cluster center:

$$\bar{w^*}_{new} = \bar{w^*}_{old} + \eta * (\hat{x} - \bar{w^*}_{old}) \qquad (7)$$

    Update the adaptation rule:

$$\eta = 1/(\text{number of inputs in the cluster}) \qquad (8)$$

else
    Create a new cluster; make $\hat{x}$ a member (and the center) of the new cluster
    Let $C = C + 1$

To reveal the transition process in this system, denote the three clusters in this system as states $S1, S2, S3$. At the end of 1973, the system changed from $S1$ to $S2$, after which the system went back to state $S1$ from the beginning of 1976 till 1983. After that, there came a new state $S3$ in the beginning of 1983 because of the introduction of the seat belt law.

To make comparisons, Fig. 3 gives the clustering results using growing vector quantization based on raw data (but not features). The results are in line with the "meaningless " interpretation reported in [18]. On the other hand, Fig. 2 indicates the meaningful subsequence clustering based on features. Fig. 4 gives the clustering results using k-means based on features. The two main changes identified using GFQ

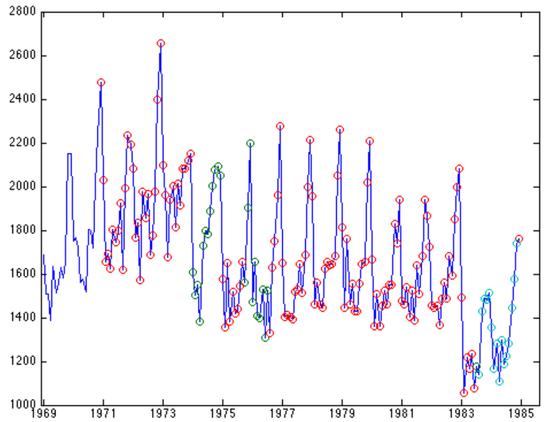

Fig. 2: SeatBelt time series

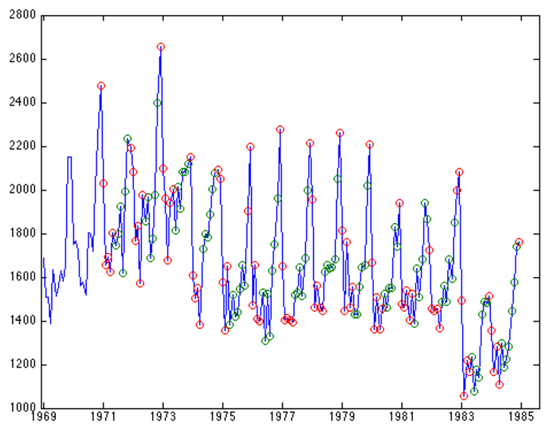

Fig. 3: SeatBelt time series subsequence clustering using growing vector quantization based on raw data

are roughly in accordance with the changes detected using k-means. This indicates that GFQ can obtain similar quality results as k-means but GFQ clustering is a real-time method, in which the number of clusters don't have to be known in advance.

B. The Nile data

The Nile data is a time series of the annual flow of the river Nile at Aswan from 1871 to 1970 [2], [29]. It measures annual discharge at Aswan in $10^8 m^3$. From Fig. 5, we can see that there is a change around 1900. The obvious reason is the Aswan dam that was built in 1898. Fig. 6 shows the distance from the data points to the winning prototype. From 1871, the data points are moving further from the first prototype until a new cluster is created around 1900 when the distance of the incoming data points to the original prototype exceeds the pre-defined threshold R.

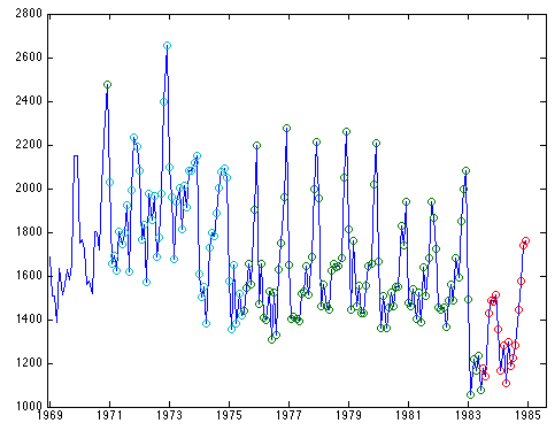

Fig. 4: SeatBelt time series subsequence clustering using k-means based on features

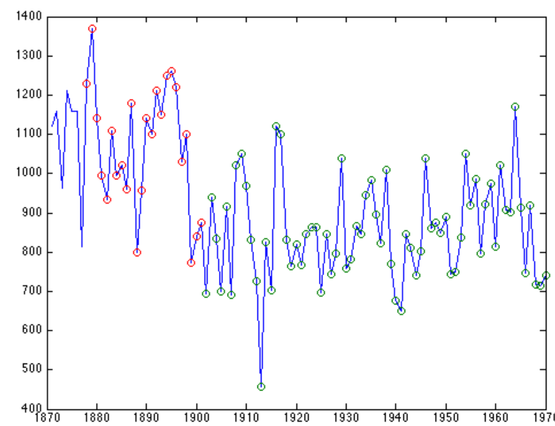

Fig. 5: Nile time series with changes using GFQ

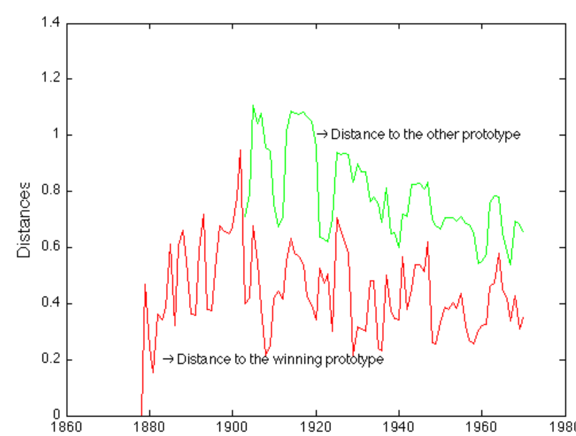

Fig. 6: Distances to prototypes

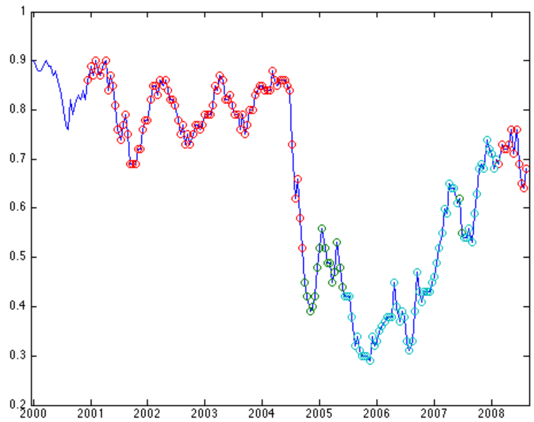

Fig. 7: MODIS time series

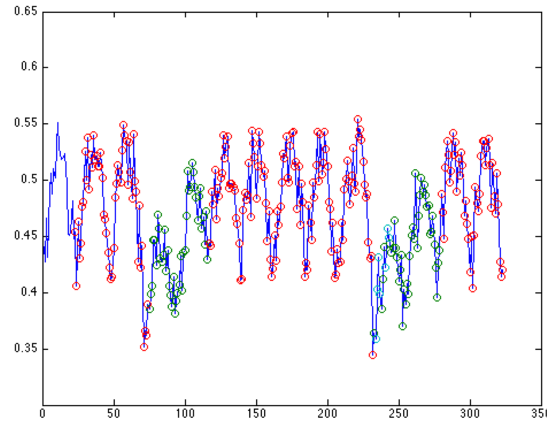

Fig. 8: Simulated time series

C. The MODIS NDVI data

The MODIS NDVI data is an NDVI time series of a *pinus radiata* plantation [1]. The transition of clusters can be seen in Fig. 7 around the year 2004, which is the known harvest year.

D. Simulated time series

Simulated time series are generated by summing individually simulated seasonal, noise and trend components [1]. The seasonal component is created using an asymmetric Gaussian function for each season, which has been shown to perform well when used to extract seasonality [30]. The noise component is generated using a random number generator that follows a normal distribution. The trend component was generated by selecting a constant. Two drops and linear recovery phases in trend component are simulated in Fig. 8. An additional change in seasonal component is simulated in Fig. 9. From the transition of the subsequence membership, the simulated changes are detected easily.

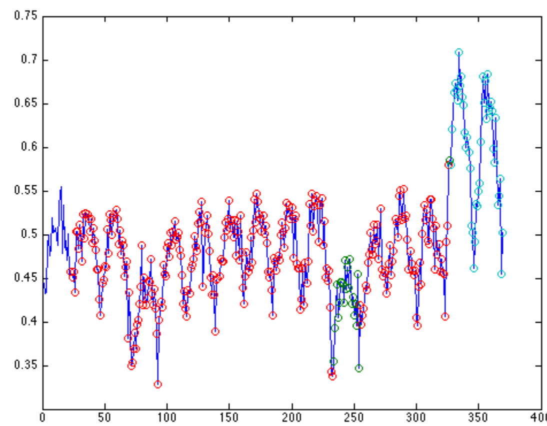

Fig. 9: Simulated time series

V. Conclusion

In this paper, a method for real-time time series change detection is proposed. It is based on an extension of VQ—known as growing feature quantization (GFQ) clustering, which provides insights into the transitions of the time series subsequence states. In order to avoid the meaninglessness limitation pointed out in [18], the method uses features instead of raw data to characterise the time series subsequences. According to the experiments on three frequently used time series as well as two simulated data, the proposed approach performs as well as k-means, but it can be used to detect changes in a real-time manner and the number of clusters don't have to be known in advance. Besides, the method can reveal the transitions among the system, provide insights into the nature of the pattern changes and find new states coming in the current system.

Further research is necessary to study the choice of subsequence features. Extension of features to a more comprehensive feature set will be studied. Future work also involves the choice of the threshold R. This parameter can be flexibly tuned according to the real world context to reduce false alarms or increase early warnings. That means it depends on trade-off between the benefits of early warning and the misclassification costs in the system. It is necessary to find an optimal threshold R^* to detect changes reasonably for a specified system. Besides, larger datasets in more fields of application such as sleep staging [31]–[34] will be tested using GFQ change detection approach.

References

[1] J. Verbesselt, R. Hyndman, G. Newnham, and D. Culvenor, "Detecting trend and seasonal changes in satellite image time series," *Remote Sensing of Environment*, vol. 114, no. 1, pp. 106 – 115, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S003442570900265X

[2] A. Zeileis, C. Kleiber, W. Krämer, and K. Hornik, "Testing and dating of structural changes in practice," *Computational Statistics & Data Analysis*, vol. 44, no. 1-2, pp. 109–123, Oct. 2003. [Online]. Available: http://www.sciencedirect.com/science/article/B6V8V-485X6V4-6/1/feb5424458e8a479d4ce3eb821cefc45

[3] J. Bai and P. Perron, "Computation and analysis of multiple structural change models," *Journal of Applied Econometrics*, vol. 18, no. 1, pp. 1–22, 2003. [Online]. Available: http://dx.doi.org/10.1002/jae.659

[4] J. Verbesselt, R. Hyndman, A. Zeileis, and D. Culvenor, "Phenological change detection while accounting for abrupt and gradual trends in satellite image time series," *Remote Sensing of Environment*, vol. 114, no. 12, pp. 2970 – 2980, 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0034425710002336

[5] M. Sharifzadeh, F. Azmoodeh, and C. Shahabi, "Change detection in time series data using wavelet footprints." in *SSTD*, ser. Lecture Notes in Computer Science, C. B. Medeiros, M. J. Egenhofer, and E. Bertino, Eds., vol. 3633. Springer, 2005, pp. 127–144. [Online]. Available: http://dblp.uni-trier.de/db/conf/ssd/sstd2005.html#SharifzadehAS05

[6] D. Kifer, S. Ben-David, and J. Gehrke, "Detecting change in data streams," in *VLDB 04: Proceedings of the 30th International Conference on Very Large Data Bases*. Morgan Kaufmann Publishers Inc., 2004, pp. 180–191.

[7] L. Firoiu and P. R. Cohen, "Segmenting time series with a hybrid neural networks - hidden markov model." in *AAAI/IAAI*, 2002, pp. 247–252. [Online]. Available: http://dblp.uni-trier.de/db/conf/aaai/aaai2002.html#FiroiuC02

[8] E. J. Keogh, S. Chu, D. Hart, and M. J. Pazzani, "An online algorithm for segmenting time series." in *ICDM*, N. Cercone, T. Y. Lin, and X. Wu, Eds. IEEE Computer Society, 2001, pp. 289–296. [Online]. Available: http://dblp.uni-trier.de/db/conf/icdm/icdm2001.html#KeoghCHP01

[9] C.-Y. Tsai and Y.-C. Shieh, "A change detection method for sequential patterns," *Decision Support Systems*, vol. 46, no. 2, pp. 501 – 511, 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167923608001449

[10] B. Salmon, J. Olivier, K. Wessels, W. Kleynhans, F. van den Bergh, and K. Steenkamp, "Unsupervised land cover change detection: Meaningful sequential time series analysis," *Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of*, vol. 4, no. 2, pp. 327 –335, june 2011.

[11] R. S. Lunetta, J. F. Knight, J. Ediriwickrema, J. G. Lyon, and L. D. Worthy, "Land-cover change detection using multi-temporal modis ndvi data," *Remote Sensing of Environment*, vol. 105, no. 2, pp. 142 – 154, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0034425706002549

[12] A. Culotta, "Detecting influenza outbreaks by analyzing twitter messages," *CoRR*, vol. abs/1007.4748, 2010. [Online]. Available: http://dblp.uni-trier.de/db/journals/corr/corr1007.html#abs-1007-4748

[13] R. Fujimaki, T. Yairi, and K. Machida, "An approach to spacecraft anomaly detection problem using kernel feature space." in *KDD*, R. Grossman, R. Bayardo, and K. P. Bennett, Eds. ACM, 2005, pp. 401–410. [Online]. Available: http://dblp.uni-trier.de/db/conf/kdd/kdd2005.html#FujimakiYM05

[14] P. Burge, J. Shawe-Taylor, C. Cooke, Y. Moreau, B. Preneel, and C. Stoermann, "Fraud detection and management in mobile telecommunications networks," in *Security and Detection, 1997. ECOS 97., European Conference on*, apr 1997, pp. 91 –96.

[15] J. Jouini and M. Boutahar, "Evidence on structural changes in u.s. time series," *Economic Modelling*, vol. 22, no. 3, pp. 391 – 422, 2005. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0264999304000483

[16] R. Gray, "Vector quantization," *ASSP Magazine, IEEE*, vol. 1, no. 2, pp. 4 –29, april 1984.

[17] Y. Kawahara and M. Sugiyama, "Change-point detection in time-series data by direct density-ratio estimation." in *SDM*. SIAM, 2009, pp. 389–400. [Online]. Available: http://dblp.uni-trier.de/db/conf/sdm/sdm2009.html#KawaharaS09

[18] E. J. Keogh and J. Lin, "Clustering of time-series subsequences is meaningless: implications for previous and future research." *Knowl. Inf. Syst.*, vol. 8, no. 2, pp. 154–177, 2005. [Online]. Available: http://dblp.uni-trier.de/db/journals/kais/kais8.html#KeoghL05

[19] J. R. Chen, "Making subsequence time series clustering meaningful." in *ICDM*. IEEE Computer Society, 2005, pp. 114–121. [Online]. Available: http://dblp.uni-trier.de/db/conf/icdm/icdm2005.html#Chen05

[20] D. Q. Goldin, R. Mardales, and G. Nagy, "In search of meaning for time series subsequence clustering: matching algorithms based on a new distance measure." in *CIKM*, P. S. Yu, V. J. Tsotras, E. A. Fox, and B. Liu, Eds. ACM, 2006, pp. 347–356. [Online]. Available: http://dblp.uni-trier.de/db/conf/cikm/cikm2006.html#GoldinMN06

[21] X. Wang, K. A. Smith, and R. J. Hyndman, "Characteristic-based clustering for time series data." *Data Min. Knowl. Discov.*, vol. 13, no. 3, pp. 335–364, 2006. [Online]. Available: http://dblp.uni-trier.de/db/journals/datamine/datamine13.html#WangSH06

[22] E. Lughofer, "Extensions of vector quantization for incremental clustering." *Pattern Recognition*, vol. 41, no. 3, pp. 995–1011, 2008. [Online]. Available: http://dblp.uni-trier.de/db/journals/pr/pr41.html#Lughofer08

[23] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification (2nd Edition)*, 2nd ed. Wiley-Interscience, Nov. 2001. [Online]. Available: http://www.amazon.com/exec/obidos/redirect?tag=citeulike07-20\&path=ASIN/0471056693

[24] D. Alahakoon, S. Halgamuge, and B. Srinivasan, "Dynamic self-organizing maps with controlled growth for knowledge discovery," *Neural Networks, IEEE Transactions on*, vol. 11, no. 3, pp. 601 –614, may 2000.

[25] A. Jirayusakul and S. Auwatanamongkol, "A supervised growing neural gas algorithm for cluster analysis." *Int. J. Hybrid Intell. Syst.*, vol. 4, no. 2, pp. 129–141, 2007. [Online]. Available: http://dblp.uni-trier.de/db/journals/ijhis/ijhis4.html#JirayusakulA07

[26] I. Sledge and J. Keller, "Growing neural gas for temporal clustering," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*, dec. 2008, pp. 1 –4.

[27] G. A. Carpenter and S. Grossberg, "Adaptive resonance theory." in *Encyclopedia of Machine Learning*, C. Sammut and G. I. Webb, Eds. Springer, 2010, pp. 22–35. [Online]. Available: http://dblp.uni-trier.de/db/reference/ml/ml2010.html#CarpenterG10

[28] A.C. and Harvey, "The effects of seat belt legislation on british road casualities: A case study in structural modelling: A.c. harvey and j. durbing, journal of the royal statistical society, series a 149 (1986) (in press)," *International Journal of Forecasting*, vol. 2, no. 4, pp. 496 – 497, 1986. [Online]. Available: http://www.sciencedirect.com/science/article/pii/016920708690097X

[29] G. W. Cobb, "The problem of the nile: Conditional solution to a changepoint problem," *Biometrika*, vol. 65, no. 2, pp. pp. 243–251, 1978. [Online]. Available: http://www.jstor.org/stable/2335202

[30] P. Jonsson and L. Eklundh, "Seasonality extraction by function fitting to time-series of satellite sensor data," *Geoscience and Remote Sensing, IEEE Transactions on*, vol. 40, no. 8, pp. 1824 – 1832, aug 2002.

[31] E. Stanus, "Computerized sleep stages analysis," *Signal Processing*, vol. 10, no. 1, pp. 101–102, Jan. 1986. [Online]. Available: http://www.sciencedirect.com/science/article/B6V18-499905M-F/1/8dcc64245b115cbb2314b90f99a20b44

[32] U. R. Acharya, E. C.-P. Chua, K. C. Chua, L. C. Min, and T. Tamura, "Analysis and automatic identification of sleep stages using higher order spectra." *Int. J. Neural Syst.*, vol. 20, no. 6, pp. 509–521, 2010. [Online]. Available: http://dblp.uni-trier.de/db/journals/ijns/ijns20.html#AcharyaCCMT10

[33] Y.-H. Lee, Y.-S. Chen, and L.-F. Chen, "Automated sleep staging using single eeg channel for rem sleep deprivation," in *Bioinformatics and BioEngineering, 2009. BIBE '09. Ninth IEEE International Conference on*, june 2009, pp. 439 –442.

[34] S. Gnes, K. Polat, and S. Yosunkaya, "Efficient sleep stage recognition system based on eeg signal using k-means clustering based feature weighting." *Expert Syst. Appl.*, vol. 37, no. 12, pp. 7922–7928, 2010. [Online]. Available: http://dblp.uni-trier.de/db/journals/eswa/eswa37.html#GunesPY10a