Automatic Detection of Common Long-Term Monetary Policies on Global Exchange Market Using Gabor Analytic Phase Binary Encoder

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Abstract

An application of Signal Processing to time series data analysis is presented here. Gabor Analytic Phase Binary Encoder (GAPBE) is used to retrieve the phase information from the long time series of currency exchange rates. As a result, a binary code is generated for each currency. Then the (dis)similarity between the local trends of any two different currencies is expressed through Hamming distance. A common policy for two different currencies is found when the Hamming distance between the binary codes representing the two given currencies is sufficiently small, but exact interpretation of the similarity scores obtained is left to the specialists. And this is all from the economist's point of view.

On the other hand, those interested in iris recognition should read this paper because the same procedure can be used to encode images of human iris. In this case it is worth to give an example of cheating iris recognition by finding two different irides having too similar iris codes. From this perspective, we show here that the exchange market provide us with such an counter-example in which two different exchange rate variation curves are encoded as too similar binary codes.

1. Introduction

This paper aims to present an application of Signal Processing to time series data analysis. Even if the examples here are based on time series reflecting currency exchange rates, an informed reader will be able to replicate the results using other particular data sets. If someone is interested in automatic detection of (dis)similarity between the local trends of some time series, the approach presented here is suitable for achieving the goal, regardless the particular nature of the data. When the time series contain the currency exchange rates for a long period of time, the similarity between the local trends of two different currencies is called a *Common (Shared / Mimetic) Long-Term Monetary Policy* (CLTCP). This paper shows how to recognize automatically such a policy regardless if it happens intentionally or not.

Gabor Analytic Phase Binary Encoder (GAPBE) was originally introduced in [2] under the name of Gabor Analytic Iris Texture Binary Encoder (GAITBE) and used to encode images of human irides as binary iris codes. As is shown here, it can be also used to encode other signals (exchange rate time series in this case) very different from those for which it was originally designed. This is why, from now on, we will use the name of GAPBE without mentioning a particular type of signal (iris texture or something else). Some of our previously published papers [2-5] describe GAPBE and how it was initially used in iris recognition. Technical details and mathematical model of the encoder can be found in the references mentioned above, especially in [2]. For each currency, GAPBE is used here to retrieve the phase information from each exchange rate variation curve (Fig.1) as a binary code. Then the (dis)similarity between the local trends of any two different currencies is expressed using the Hamming distance between the corresponding binary codes generated for those currencies. A common policy for two different currencies is said to be found when the Hamming distance between the binary codes representing the variations of the two given currencies is sufficiently small, but the exact interpretation of the similarity scores obtained here will be left to be refined by the specialists.

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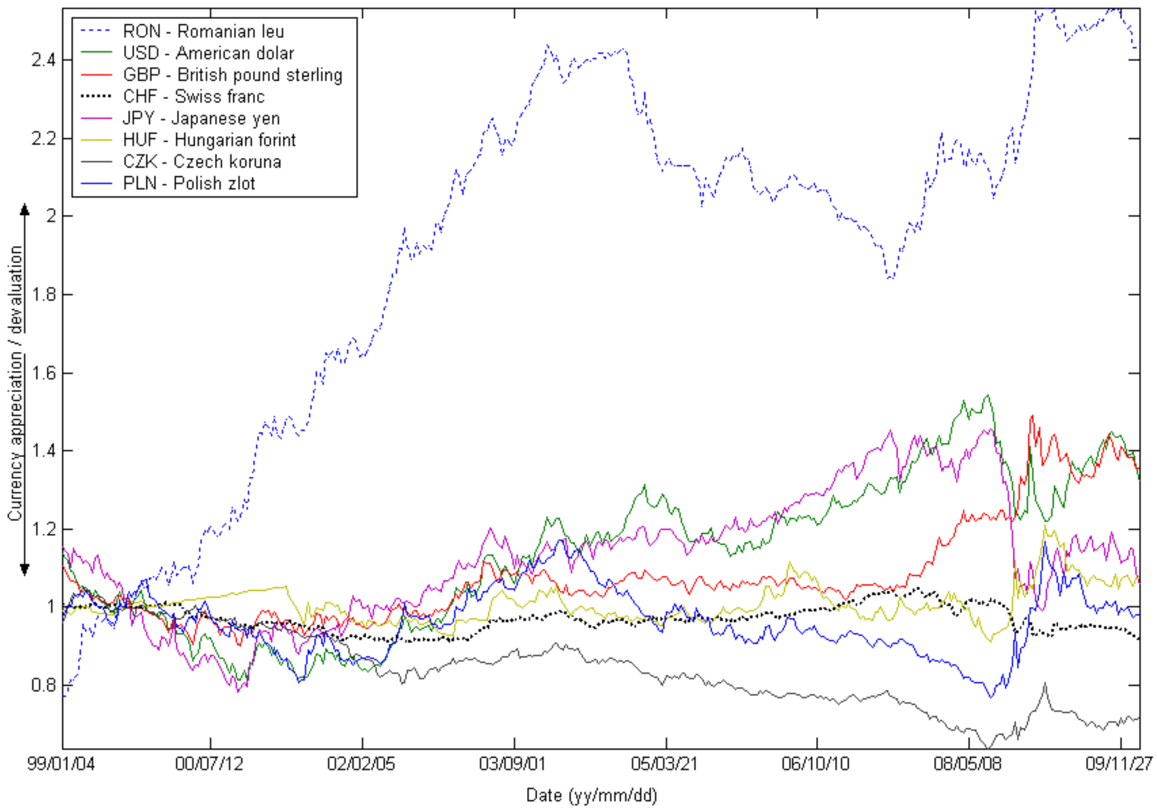

Fig.1. Currency exchange rate variation (appreciation/devaluation) curves for the last eleven years (1999-2010). The data originated from [1].

2. The test data set

The test data set used here comes from European Central Bank [1] and contains the exchange rates between euro and the other convertible currencies for a period of eleven years (1999-2010).

Just for unification, the old ROL currency is expressed as RON. The appreciation / devaluation curves in Fig.1 are obtained as follows:

- All currencies use EUR as reference (an imaginary horizontal line at the height of 1 should be interpreted as being the euro reference).
- The second reference value is computed for each currency as being the average currency-euro exchange rate on the first 1.4 years (between 1999/01/04 and 2000/06/01).

The two references defined above allow us to analyze exchange rate variations against the euro - as an external reference, and against a virtual auto-reference value computed for the early history of each currency. They also allow us to represent currency devaluation / appreciation curves in a horizontal narrow band around 1, regardless the big differences between the nominal values of different exchange rates (for example, see the following two average exchange rates: 0.6954 for GBP-EUR and 130.87 for JPY-EUR).

3. The phase of a time series

The concept of *phase* comes from Signal Processing where is generally used to express information about the local variations within a signal, where '*local*' means that the variations are measured within a neighborhood of the current point. The neighborhood is usually called a *window* and its extent is referred as the *scale* at which the signal is analyzed. And nothing changes if the analyzed signal is a time series of exchange rates.

When thinking about windows and scales, consider the following example: using a big window will enable us to find the roads within a satellite image but only a small window will allow the selection of a certain car from a certain road matching a given set of criteria. Here, the phase of a time series is computed as

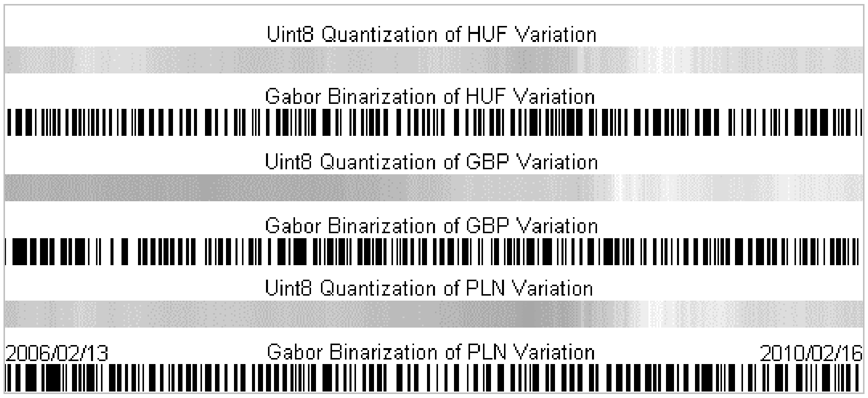

Fig.2. Uint8 quantization of three currency variation curves (HUF, GPB, PLN) and their corresponding binary codes (GAPBE).

follows: for a given signal **v**, the corresponding strong analytic signal is computed:

$$a = v + jH(v),$$

where **H** denotes the Hilbert transform [6] computed using a certain window of size **s** (here we will use windows of one, two, or four weeks) and **j** is the complex unit.

Then the phase information contained in **v** is retrieved as the instant phase of the complex signal **a**:

$$P = \mathit{atan}(\ \mathit{imag}(a)\ ./\ \mathit{real}(a)\ ),$$

where the division by zero is considered a legal operation and the notation './' indicates component-to-component division.

Gabor binarization (Fig.2) of initial signal **v** is then defined as being the logical index (binary code):

$$B = \mathit{logical}(\ P>0\ ),$$

also regarded as a relation between the components of **B** and **P**, respectively.

In short, the above three operations define what we called Gabor Analytic Phase Binary Encoder (GAPBE). More details about the encoder can be found in [2]. Also, a demo program will be available for download as soon as possible [7].

In Fig.2, three variation curves from Fig.1 (HUF, GBP and PLN) are quantized as uint8 (unsigned 8-bit integer) line vectors and replicated (32 times each) to form a visible image. The same type of replication is done with Gabor binarization codes in order to obtain big enough images illustrating exchange rate variations in 8-bit and 1-bit domains.

4. Gabor-Hamming indicators

Let us consider **n** currencies $\mathbf{C_1},\ldots,\mathbf{C_n}$ and their Gabor binarization codes $\mathbf{B_1},\ldots,\mathbf{B_n}$. Hamming similarity between two binary codes $\mathbf{B_i}$ and $\mathbf{B_j}$, denoted $\mathbf{h_{ij}}$, is the ratio between the number of the corresponding bits that agree and the common length of the codes:

$$h_{ij} = \mathit{sum}(\ \mathit{logical}(B_i == B_j\ )\ )\ /\ \mathit{length}(B_i)$$

Such similarity coefficients computed for eight currencies are presented below, in Table 1 and Table 2, as percents.

Gabor-Hamming indicators of common long-term monetary policy for a certain set of **n** currencies are defined here as being the biggest values found within the lines and columns of $\mathbf{h_{ij}}$ matrix, excepting the components of the first diagonal. In Tables 1 and 2, *Gabor-Hamming indicators* are marked in bold. The coefficients marked with gray background tell us that the compression practiced by applying GAPBE can lose enough information such that the similarity between two very different variation curves (Fig.1 RON-HUF, RON-PLN) to be scored almost identical or even better than the similarity between two curves that really look alike (Fig.1, CZK, HUF, PLN).

Table 3 shows the correlation coefficients $\mathbf{c_{ij}}$ computed for all pairs of currencies (i,j). *Correlation-based indicators* of common long-term monetary policies are defined here as being the most extreme values found within the lines and columns of $\mathbf{c_{ij}}$ matrix.

From all *Gabor-Hamming indicators* (Tables 1 and 2), those marked in red have the highest level of confidence because they are also confirmed by the *correlation-based indicators*.

Table.1. *Gabor-Hamming indicators* of common long-term (2006/02/13 - 2010/02/16) monetary policies computed using a window of two weeks.

%	USD	GBP	JPY	CHF	CZK	HUF	PLN	RON
USD	-	**58**	**66**	54	45	38	39	44
GBP	**58**	-	50	48	47	52	51	52
JPY	**66**	50	-	**67**	47	36	38	40
CHF	54	48	**67**	-	44	39	39	40
CZK	45	47	47	44	-	63	**67**	57
HUF	38	52	36	39	63	-	**77**	**67**
PLN	39	51	38	39	**67**	**77**	-	65
RON	44	52	40	40	57	**67**	65	-

Table 2. *Gabor-Hamming indicators* of common long-term (2006/02/13 - 2010/02/16) monetary policies computed using one-week, two-weeks and four-weeks windows.

%	USD	GBP	JPY	CHF	CZK	HUF	PLN	RON
USD	-	**60**	**67**	53	45	39	39	46
GBP	**60**	-	52	50	51	51	52	53
JPY	**67**	52	-	**67**	47	37	38	41
CHF	53	50	**67**	-	46	40	42	42
CZK	45	51	47	46	-	65	**67**	58
HUF	39	51	37	40	65	-	**75**	**68**
PLN	39	52	38	42	**67**	**75**	-	65
RON	46	53	41	42	58	**68**	65	-

Table 3. *Correlation-based indicators* of common long-term (2006/02/13 - 2010/02/16) monetary policies.

%	USD	GBP	JPY	CHF	CZK	HUF	PLN	RON
USD	-	**36**	**36**	16	**-78**	-38	-42	19
GBP	**36**	-	-69	**-75**	-56	50	47	**92**
JPY	**36**	-69	-	**93**	1	**-78**	**-74**	**-80**
CHF	16	-75	**93**	-	17	-73	-67	**-86**
CZK	**-78**	-56	1	17	-	26	**39**	-38
HUF	-38	50	**-78**	-73	26	-	**88**	69
PLN	-42	47	**-74**	-67	**39**	**88**	-	65
RON	19	**92**	**-80**	**-86**	-38	69	65	-

5. Conclusion

From the economist's point of view, the facts presented above tell that *Gabor-Hamming indicators* of common long-term monetary policy are suitable tools for economical analysis but they should be used in conjunction with other indicators of other type (*correlation-based indicators*, for example). The same recommendation is theoretically advisable when using GAPBE in iris recognition, but unfortunately it is unpractical because, in iris recognition, supervising Hamming similarity with other parameters inevitably leads to a loss of speed.

The automatic analysis of the sub-market containing those eight currencies considered in Fig.1 and Tables 1-3 reveals a cluster of three Central and South-East European currencies which behave unitary, as a single currency (CZK, HUF and PLN).

It can be also seen that RON currency is the big looser on this sub-market because, excepting a positive trend in between 2005-2007, it always failed to integrate with the common regional monetary policy of its stable neighbors.

REFERENCES

[1] European Central Bank, *1999-2010 XML Data Archive of Euro Foreign Exchange Reference Rates*, http://www.ecb.int/stats/exchange/eurofxref/html/index.en.html, retrieved on February 16, 2010.

[2] N. Popescu-Bodorin, *Gabor Analytic Iris Texture Binary Encoder*, Proc. of the 4th Annual South East European Doctoral Student Conference, vol. 1, pp. 505-513, South-East European Research Centre (SEERC), July 2009.

[3] N. Popescu-Bodorin, *Exploring New Directions in Iris Recognition*, Post-Proc. of the 11th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing, Conference Publishing Services of IEEE Computer Society, in print (December 2009).

[4] N. Popescu-Bodorin, *'Fragile Bits' vs. Multi-Enrollment - A Case Study of Iris Recognition on Bath University Iris Database*, ROMAI Journal, Nr.5, vol. 2/2009, pp. 127-144, February 2010.

[5] N. Popescu-Bodorin, *Computational Intelligence Challenges in Iris Recognition. Processing Tools for the University of Bath Iris Image Database*, submitted to 2010 IEEE Congress on Evolutionary Computation (IEEE CEC 2010), February 2010.

[6] F. R. Kschischang, *The Hilbert Transform*, Department of Electrical and Computer Engineering, University of Toronto, *http://www.comm.toronto.edu/frank/papers/hilbert.pdf* retrieved on February 20, 2010

[7] N. Popescu-Bodorin, *List of Demo Programs*, *http://fmi.spiruharet.ro/bodorin/demos/*, 2010