

Dynamic Interaction Network to Model the Interactive Patterns of International Stock Markets

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Abstract—Studies in economics domain tried to reveal the correlation between stock markets. Since the globalization era, interdependence between stock markets becomes more obvious. The Dynamic Interaction Network (DIN) algorithm, which was inspired by a Gene Regulatory Network (GRN) extraction method in the bioinformatics field, is applied to reveal important and complex dynamic relationship between stock markets. We use the data of the stock market indices from eight countries around the world in this study. Our results conclude that DIN is able to reveal and model patterns of dynamic interaction from the observed variables (i.e. stock market indices). Furthermore, it is also found that the extracted network models can be utilized to predict movement of the stock market indices with a considerably good accuracy.

Keywords—complex dynamic relationship, dynamic interaction network, interactive stock markets, stock market interdependence.

I. INTRODUCTION

INTERACTION between stock markets has been researched in the past few years. Globalization has brought interdependence between stock markets around the world, in which a change in one stock market affects other stock markets. A study [1] stated that in 1990, the relationship between international stock markets is stronger than the preceding years, due to relaxation of foreign ownership restrictions. Some other researches [2]-[5] also showed that local stock markets are generally influenced by the major stock markets in the world (i.e. U.S., United Kingdom, and Japan). Several studies applied co-integration analysis method to find the correlation between the stock markets.

This study aims to employ and propose the use of a distinctive approach to find important and dynamic relationships between stock markets internationally. The technique Dynamic Interaction Network (DIN) originated in the bioinformatics field to construct gene regulatory network, and has been used to obtain dynamic relationships between

stock markets in Asia Pacific region [6]. It is applied in this study to simultaneously model multiple dynamic relationships between interactive stock markets. Working based on the Kalman filter algorithm, DIN not only extracts stock markets relationship, but also manages to predict future values of the stock market indices by using the interaction patterns.

Through DIN realization, we intend to acquire; (1) dynamic and complex relationship between global stock markets, and (2) future value prediction of each observed variables. In this study, we utilize the stock market indices data from countries around the world, which are; (1) DJA (U.S.), (2) FTSE (United Kingdom), (3) DAX (Germany), (4) JSE (South Africa), (5) SSE (China), (6) N225 (Japan), (7) JKSE (Indonesia), and (8) AORD (Australia).

II. DYNAMIC INTERACTION NETWORK - DIN

Construction of DIN was inspired by the Gene Regulatory Network (GRN) extraction method [7] in the bioinformatics field to extract gene regulatory networks from time-course gene expression data, where it was found that genetic network inference can be used successfully to reverse engineer the underlying regulatory interactions from the gene expression data. DIN has also successfully revealed important and complex relationship between stock markets in the Asia Pacific region and utilized the relationship to predict future value of the stock market indices [6]. In this study, we implement this Kalman filter based algorithm to extract dynamic relationship between stock markets which can be classified as complex dynamic systems (CDS) [8].

A. Pattern Extraction through DIN

DIN initially extracts transition matrix from the given data set. This is done using the Kalman filter algorithm. It estimates a process by using a form of feedback control: the filter estimates the process state at some timestamp and then obtains feedback in the form of noisy measurements. Thus, Kalman filter results in an $n \times n$ matrix, which relates the state at the time of $t+1$ to the state at t . After obtaining the transition matrix, the network diagram is constructed. The first step is to determine a threshold, which in the example in Figure 1 is set to 0.1. Therefore, it assigns the values (absolute value) greater than 0.1 as positive influence and values less than -0.1 as

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negative influence. The direction of influence is read from column to row. For example, in Figure 1a column 1 influences row 3, or SSX influences HSIX with positive value of 0.52.

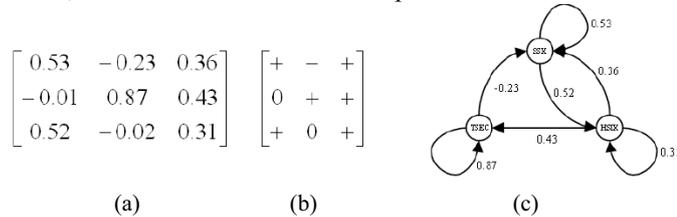


Fig. 1 Translating transition matrix into network model. (a) shows transition matrix. (b) shows the corresponding influence matrix. (c) shows the network diagram. SSX, TSEC and HSIX are stock market of Shanghai, Taiwan and Hong Kong respectively.

B. Multiple Time-Series Prediction with DIN

After acquiring the transition matrix, it can be applied to predict the future values of the observed variables. Referring to the given explanation in the previous section, by comprehending the matrix, the information of how strong one variable affects the others can be obtained. In Figure 1, it is shown that the value of SSX is influenced by itself, HSIX, and TSEC. From translating the transition matrix, we are able to write a formula to predict the future value (at state $t+1$) of SSX:

$$SSX_{t+1} = 0.53SSX_t - 0.23TSEC_t + 0.36HSIX_t$$

There are two different approaches for the prediction part, which are static and on-line learning. In static approach, the transition matrix is used to build a network to predict the future values. The matrix itself remains constant during the prediction as shown in Figure 2. It only relates itself to the values at state t and is used to predict the values at state $t+1$. For on-line learning approach, the transition matrix is updated after it predicts every $t+1$ state during the prediction. After the matrix is obtained from training data, every time the state move forward for $t+1$ it will update the matrix, so the matrix is constantly changing. This approach is also referred as evolving system, which can be implemented using real-time data. The illustration for on-line learning approach is in Figure 3.

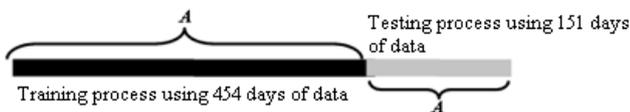


Fig. 2 Prediction with static approach. Transition matrix A remains constant

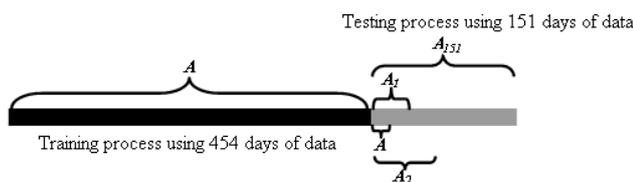


Fig. 3 Prediction with on-line learning approach. Transition matrix A is updated continuously

III. EXPERIMENTS AND RESULTS

To model the pattern between global stock markets, we use the data of stock market indices from eight countries around the world, which are (1) DJA (U.S.), (2) FTSE (United Kingdom), (3) DAX (Germany), (4) JSE (South Africa), (5) SSE (China), (6) N225 (Japan), (7) JKSE (Indonesia), and (8) AORD (Australia). Data sample span from September 2006 until June 2009. They have undergone preprocessing step, which are data trend removal, linear normalization and data smoothing. Figure 4 illustrates trajectories of the stock market indices data which are used in this study. Furthermore, we have used the DIN Extraction Software (DREST) [6] to work on the data.

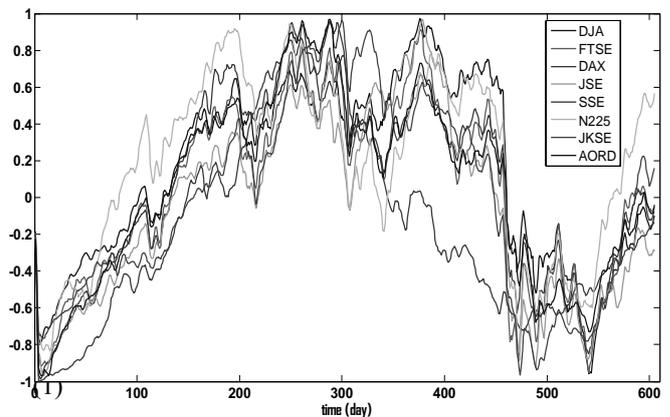


Fig. 4 Movement of the observed stock market indices from eight countries which span from September 2006 to June 2009 (data have undergone trend removal, normalization, and smoothing process)

A. Important and Complex Variables Relationship Analysis

From the transition matrix and network model in Figure 5 (as results from DIN modeling) it can be seen that DJA (U.S.) is mainly influenced by itself (the previous value) and significantly by some other countries (United Kingdom, Germany, China, and South Africa). This finding falls in with results from research conducted by Bessler [9], where it was concluded that U.S. stock is strongly influenced by itself and significantly influenced by United Kingdom and Germany. It also illustrates that the other stocks are significantly influenced by stock markets in U.S. and United Kingdom. This finding confirms outcome of research conducted in Greece [2], where they concluded that in developing countries there is no strong relationship between stock market and macroeconomics factors. JKSE (Indonesia) is shown to have the weakest influence compared to other stock markets, since it only significantly influences itself. Moreover, the extracted network model also shows that there is interdependence between U.S. and South Africa stock markets [5].

1.2971	0.4980	-0.6300	-0.3195	0.1886	0.0960	0.0466	-0.0730
0.4279	1.6574	-0.8878	-0.4388	0.2706	0.1426	0.0644	-0.0899
0.5072	0.8404	-0.0917	-0.5547	0.3141	0.1869	0.0920	-0.1094
0.3968	0.6493	-0.8167	0.5714	0.2514	0.1226	0.0609	-0.0985
0.1218	0.2233	-0.2844	-0.1540	1.0825	0.0639	0.0178	-0.0254
0.4354	0.7297	-0.9259	-0.4569	0.2702	0.9857	0.0640	-0.1031
0.2387	0.4215	-0.5388	-0.2746	0.1567	1.1397	1.0242	-0.0190
0.4454	0.7213	-0.9201	-0.4673	0.2837	0.1526	0.0631	0.8777

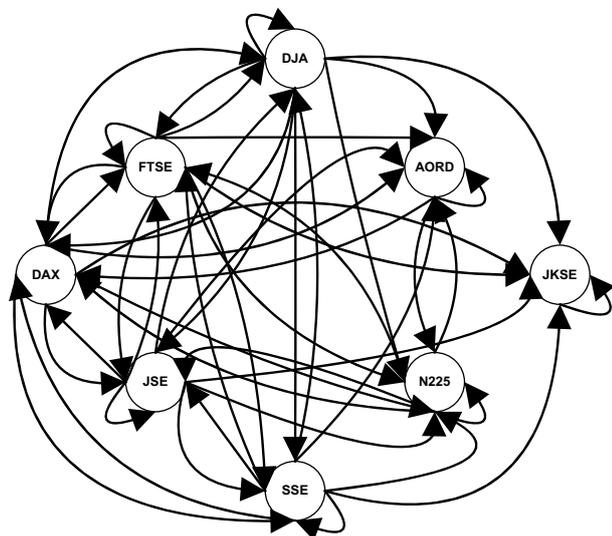


Fig. 5 Transition matrix and network diagram generated from data spanning from September 2006 to September 2008

After extracting the matrix, we employed the on-line learning method on the test data set spanning from September 2008 to June 2009. As results to this, the transition matrix and network model in Figure 6 are obtained. The figure shows that after 10 months, relationship among the economic variables has changed compared to the transition matrix and network model extracted in earlier time as shown in Figure 4. Extracted network model shows that DJA (U.S.) is now being influenced strongly by SSE (China) and significantly by the rest of the countries. China also becomes the most influencing stock market among the other countries. AORD (Australia) is shown to have interdependence with the other countries (except United Kingdom and South Africa). This finding complies with theory supported by Drew and Chong [4]. The result is also in line with the study done by Beelders [5], since there is also interaction between South Africa stock market and other countries.

In Figure 5 and 6, we can see the network models as a form to represent the interaction between stock market indices internationally. Comparing both figures, we can see that the network model is adjusted over time. Using static approach, U.S. stock market is strongly influenced by itself. Yet, after on-line learning is applied, U.S. stock market now becomes mainly influenced by China. JKSE (Indonesia), which in static approach has the weakest influence, is updated after on-line learning to show more significant influence to other stock markets. Additionally, as it is expected, DIN is able to show that interactions between the stock market indices internationally can be categorized as a complex dynamic system. This has been proven by conducting an on-line

learning process in which DIN extracts various network models across time, in order to obtain the most updated patterns of the observed variables.

0.7336	0.5048	-0.8710	-0.5780	-2.1316	0.9059	0.2638	-0.9789
-0.0766	1.7406	-0.1598	-0.3427	-1.1231	-0.2694	1.0057	-1.4790
-0.2667	0.2754	0.8876	-0.3173	-1.5174	0.5787	0.3064	-1.0279
0.2338	0.8086	-1.0987	0.5453	-0.8955	-0.1110	0.5688	-0.5752
-0.1205	-0.1967	0.9983	0.2161	1.3520	-0.2603	0.1527	-0.3730
0.2686	0.8261	0.6364	0.0482	-0.0403	-0.3261	1.5376	-1.7096
0.0325	0.3180	0.7037	0.1476	0.1181	-0.7117	1.7588	-0.9404
-0.5413	-0.0569	1.0421	-0.0911	-1.4416	0.6196	0.3229	-0.5031

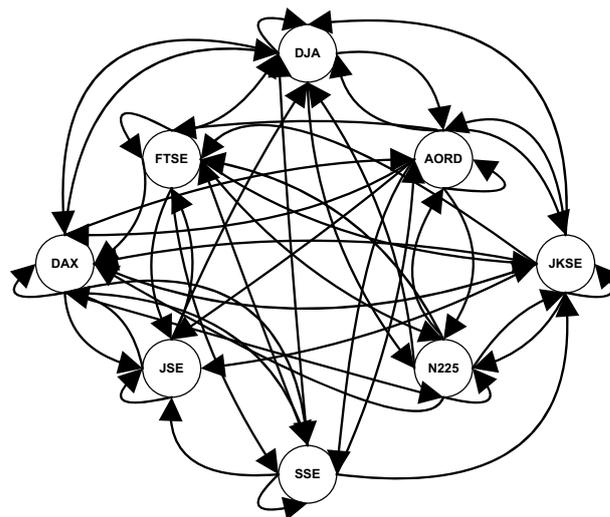


Fig. 6 Transition matrix and network diagram generated using data from September 2008 until June 2009, 10 months after the previous model in Figure 5 was generated

B. Prediction of Stock Market Index and Macroeconomics Factors with DIN

Two different approaches are employed for the prediction, namely off-line (static) learning and on-line (incremental) learning. In the off-line learning, the transition matrix is used to build a network to predict the future values. The matrix itself remains constant during the prediction. As for the on-line learning, the transition matrix is updated after it predicts every $t+1$ state during the prediction (using new data).

TABLE I
 RMSE BETWEEN PREDICTED AND ACTUAL VALUE WITH THE STATIC APPROACH FOR OBSERVED VARIABLES

Observed Variables	Period	RMSE (static)
DJA	Sept 2008 – June 2009	0.10839
FTSE	Sept 2008 – June 2009	0.10889
DAX	Sept 2008 – June 2009	0.2269
JSE	Sept 2008 – June 2009	0.14564
SSE	Sept 2008 – June 2009	0.051934
N225	Sept 2008 – June 2009	0.12869
JKSE	Sept 2008 – June 2009	0.07418
AORD	Sept 2008 – June 2009	0.14367

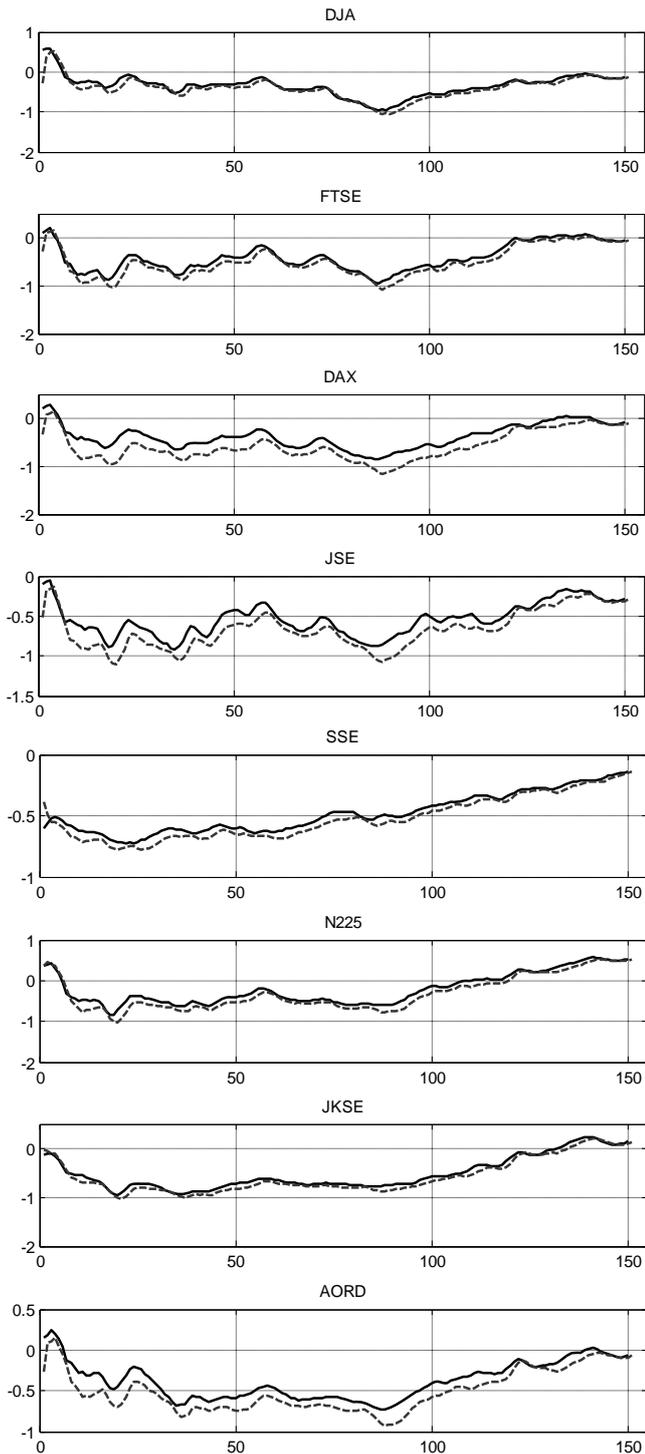


Fig. 7 Actual value (solid line) and predicted values (dashed line) in comparison using the static approach

The off-line learning approach has a major drawback since economic variables are changing over time. Static model is not sufficient to predict the movement of the observed variables in the distant future, given that the interaction between the variables is subjected to change. Additionally, using the off-line learning we would not be able to capture adjustments in pattern of relationship between observed variables over time.

The prediction result using static approach is shown in Figure 7. The root mean squared error (RMSE) for prediction result using static approach is shown in Table I.

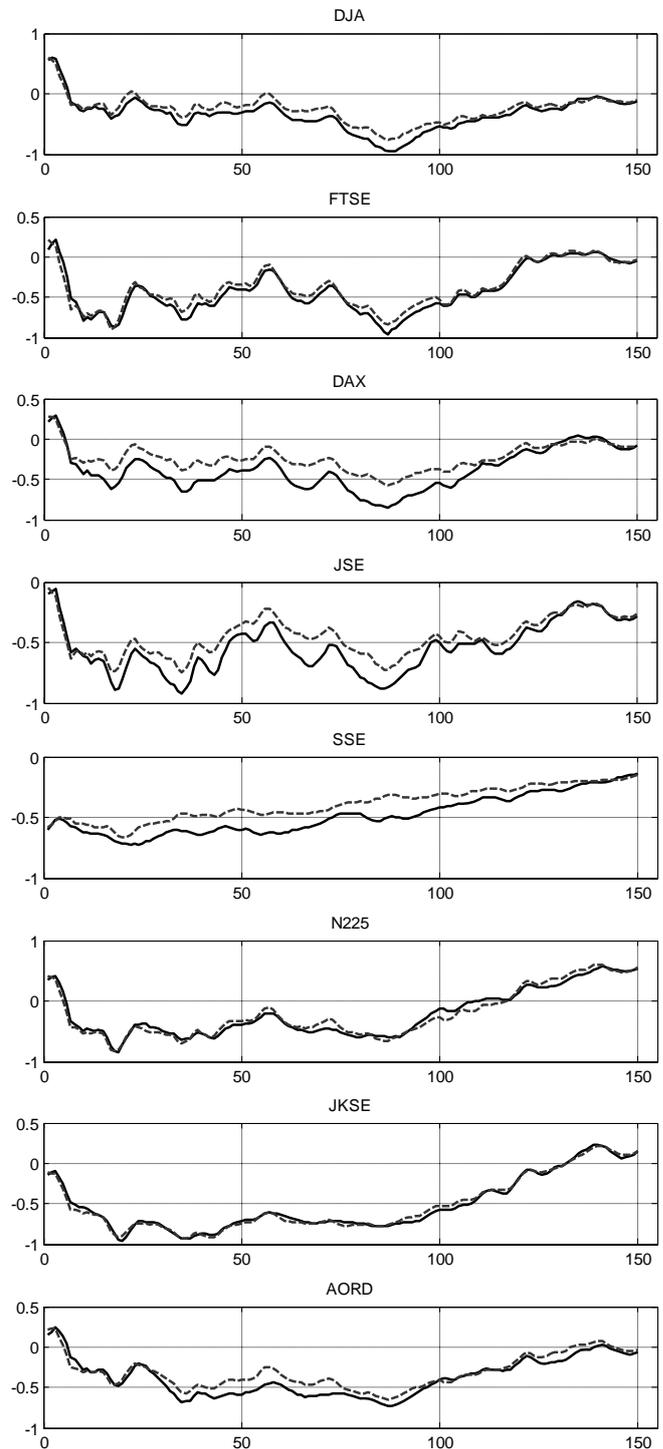


Fig. 8 Actual (solid line) vs. predicted (dashed line) values using the on-line learning approach

The on-line learning approach involves the transition matrix to alter itself over time during the prediction timeline (the result is displayed in Figure 8). This method increases the

TABLE II
 RMSE BETWEEN PREDICTED AND ACTUAL VALUE WITH ON-LINE
 LEARNING APPROACH FOR OBSERVED VARIABLES

Observed Variables	Period	RMSE (on-line)
DJA	Sept 2008 – June 2009	0.11366
FTSE	Sept 2008 – June 2009	0.064351
DAX	Sept 2008 – June 2009	0.18052
JSE	Sept 2008 – June 2009	0.11763
SSE	Sept 2008 – June 2009	0.1055
N225	Sept 2008 – June 2009	0.074479
JKSE	Sept 2008 – June 2009	0.034345
AORD	Sept 2008 – June 2009	0.093822

prediction accuracy since the model keeps changing to adjust itself to current state relationship between observed variables, which tend to change over the period of time. Thus, it results in more updated model for the relationship pattern between stock market indices. In spite of that, it can be observed from Table II that RMSE for prediction of DJA and SSE are slightly higher (less accurate) with the off-line learning mode (in comparison with RMSE result in Table I). This result is somewhat unusual compared to the results from a study conducted by Widiputra et al [6] in which by implementing the on-line learning, accuracy of prediction for all data series were increased significantly.

IV. CONCLUSION

In this study we find through extracted model, the important and complex relationship between the stock market indices globally, which points out the interdependence between stock market indices. This finding agrees with outcome of previous researches, showing that stock markets are interlinked, particularly after the globalization took place. Our extracted network model manages to show the interactive patterns between the stock markets.

Nevertheless, extracted network model reveals dynamic changes in pattern of interaction among the stock markets over time and it has been proven that extracted transition matrix can be used to predict movement of multiple economic variables with a reasonable degree of accuracy.

As for our future works, we intend to conduct a further study to reveal significant relationship among the other economic variables across various countries in the world. Additionally, we seek to extend the algorithm so it would be able to reveal not only linear but also non-linear relationship among observed variables.

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