Competitive Benchmarking Using Self-Organizing Neural Networks

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ABSTRACT

A huge amount of financial information in large databases makes performance comparisons among organizations difficult or at least very time-consuming. This paper investigates whether neural networks in the form of self-organizing maps can be effectively employed to perform a competitive benchmarking in large databases. By using self-organizing maps, we expect to overcome problems associated with finding appropriate underlying distributions and functional forms of underlying data. The method also offers a way of visualizing the results. The database in this study consists of annual financial reports of 100 biggest Korean companies over the years 1998, 1999, and 2000.

Keywords: self-organizing neural networks, self-organizing maps, competitive benchmarking

1. Introduction

Competitive benchmarking is a strategically important internal process, by which the functions and performance of one company are compared with those of other companies. Financial competitive benchmarking uses financial information in the form of ratios most often to perform these comparisons, and it is utilized, among other things, as a communication tool in strategic management, for example in situations where company management must gain approval, from internal and external interest groups alike, for new functional objectives for the company.

Previously, multivariate statistical methods have been used as a primary tool for performance analyses, bankruptcy predictions, stock market predictions, to name a few, in most research contexts, however, many problems have been reported concerning these methods. The most serious problems with these methods are the assumption on normality in the underlying distributions and difficulties in finding an appropriate functional form for the distributions. Moreover, results of the analyses are difficult to visualize when there are several explanatory variables.

Many researchers have addressed these problems, for example, Trigueeros [1995] reported on several studies that have shown the existence of positive or negative skewness in the ratios and suggests the remedies to overcome these difficulties, respectively. He also explained the existence of symmetrical and negatively skewed ratios and offered guidelines for achieving higher precision when using ratios in statistical context. Fernandez-Castro & Smith [1994] used a non-parametric model of corporate performance to overcome the need for specification of statistical distributions or functional forms. Vermeulen et al. [1994] presented a way to visualize the results with inter-firm comparisons when the explanatory variable was expressed by more than one characteristic [Back at al., 1995].

Vanharanta [1995] has used a modern computer technology and built a hyperknowledge-based system for financial benchmarking. The system contains a database with financial data on more than 160 pulp and paper companies worldwide. The amount of financial information in this system is, however, so large that it makes comparisons between companies very difficult.

The field of artificial neural networks is a promising new paradigm in information processing. Originally, they were developed as computer analogues for the human brain [Hecht-Nielsen, 1991]. Artificial neural networks enables us to learn the pattern of a system from a given set of examples, which makes them very attractive. They are applicable to such processes as classification, prediction, control, and inference [Rumelhart et al., 1986].

Back et al. [1996] investigated the potential of self-organizing maps for pre-processing 120 world wide forest companies' financial databases and presented an approximate position of each company's financial performance compared to those of other companies. The results were promising. By using self-organizing maps, they could overcome the problems associated with finding the appropriate underlying distribution and the functional form of the financial indicators. In addition, the visualization capabilities of self-organizing maps provide a good way of presenting and analyzing the

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results.

Neural networks have been suggested by Trigueiros [1995] for use with computerized accounting reports databases, and by Chen et al. [1995] to define cluster structures in large databases. Martin-del-Brio & Serrano-Cinca [1995] used self-organizing maps for analyzing the financial states of Spanish companies.

In this paper, we use the self-organizing maps to structure the financial information of 100 biggest Korean companies listed in National Information & Credit Evaluation's database. Specifically, they are clustered based on the underlying weight maps. Each group is then named according to the financial characteristics inherent in the group. We analyze the financial performance of the Korean companies in these maps over the years 1998, 1999, and 2000. Even though we take a closer look only at these companies in this paper, any individual company or group of companies can be the focus of interest.

We anticipate that neural networks can be successfully used for benchmarking purposes to help executives find their respective company's characteristics that will lead to sustainable excellence of the company. In other words, we attempt to answer the following question: What are the key factors that lead a company towards long-lasting good performer in the market? Some company characteristics seem to provide good overall company performance, sustainable profitability, increasing productivity and continuous growth.

The rest of the paper is organized as follows. Section 2 describes the methodology used, the network structure, the database, the list of companies in the study, and the choice of financial ratios. Section 3 presents the results of applying neural networks to the problem and section 4 describes the empirical finding. The conclusions of this study are presented in Section 5.

2. Theoretical Background

2.1 Competitive benchmarking

Competitive benchmarking is a company-internal process in which the activities of a given company are measured against the practices of best-in-class companies. In the process of competitive benchmarking, internal functions are measured and analyzed using financial (quantitative) and/or non-financial (qualitative) yardsticks, and they are compared with similar functions of leading competitors, or with the best practices in other industries. The performance differences between compared functions are then measured. The overall management goal of competitive benchmarking within a given company is to close the measured gap by changing their characteristics in order to improve their performance.

The generic benchmarking process consists of planning phase, analysis phase, and integration and action phase. The specific activity of financial competitive benchmarking is an integral part of the generic benchmarking process. In financial benchmarking, the aim is to compare one company with its competitors using financial information and yardsticks available. At the beginning of a benchmarking process, (in its planning phase), financial benchmarking plays an important role in the identification and selection of the right competitors and/or good performers as they will act as the benchmarking points in non-financial benchmarking to be done later in the generic process. Financial benchmarking is important in the analysis phase as well where performance gaps are measured and future performance levels are projected. In the integration and action phase, financial benchmarking is also useful to monitor and track progress, and to recalibrate the benchmarking points. Financial benchmarking, however, has its greatest potential as a communications tool when company's management must gain approval, from internal as well as external interest groups, for new strategic objectives of the company.

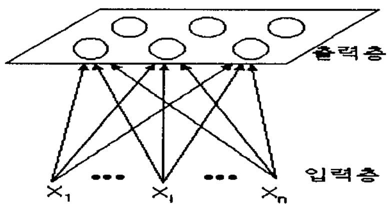
The financial information needed for financial benchmarking is, however, difficult to collect as it is invariably available only from large commercial databases or from specialized reports and publications, and it must be gleaned with care form these sources. Such information is thus far removed from its active users. If the financial information needed is to be brought closer to the active users, it must be pre-processed, i.e. refined and classified. The overall objective of this study is to pre-process, with the help of neural networks, the data and information required for financial benchmarking. Pre-processed information can then be used in computerized benchmarking systems and executive support systems, and to make the task of competitive financial benchmarking easier and more effective.

2.2 Neural networks

A neural network is a computing device that enables to learn from examples. It consists of a set of simple processing units, neurons, which are connected each other to form a network topology. A neural network compares input data with output data, and tries to approximate some complicated, and unknown functionality between them. The first step of developing a neural network is to find a suitable topology for the network and thereafter train it so that it can gradually learn the desired input/output functionality. There are two ways to train a network: supervised and unsupervised. In supervised learning, the network is presented with examples of known input-output data pairs, after which it starts to mimic the presented input-output behavior. The network is then tested to see whether it is able to produce correct output when only input is presented to it. In unsupervised learning, on the other hand, the output data is not available and usually not even known beforehand. Instead, the network tries to find similarities between input data samples. Similar samples form clusters that constitute the output of the network. The user is responsible for providing an interpretation of each cluster.

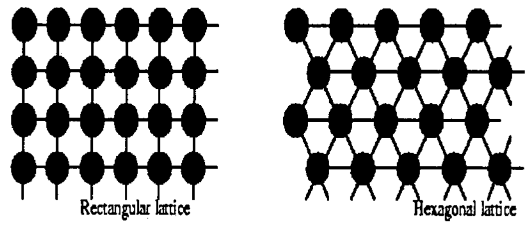
The Kohonen network [Kohonen, 1998] is the most common network model based on unsupervised learning. The Kohonen network usually consists of two layers of neurons: an input layer and an output layer. The input layer neurons present an input pattern to each of the output neurons. The neurons in the output layer are usually arranged in a grid, and are influenced by their neighbors in this grid. The goal is to cluster the input patterns in such a way that similar patterns are represented by the same output neuron, or by one of its neighbors. Every output neuron has an associated weight vector. The neighborhood structure of the output layer will cause neighboring neurons in it [the output layer] to have similar weight vectors. These vectors should represent some subclasses of the input patterns, thus forming a map of the input space, a self-organizing map (SOM).

The SOM is divided into 1-dimensional array and 2-dimensional array of output layer neuron. Usually, the form of 2-D as <Figure 1> is preferred.



<Figure 1> 2-D array of SOM

The Kohonen network topology can be described by the number of output neurons present in the network and by the way in which the output neurons are interconnected, i.e. by describing which neurons in the output array are mutual neighbors. Usually, neurons on the output layer are arranged in either a rectangular or a hexagonal grid (See <Figure 2>). In a rectangular grid, each neuron is connected to four neighbors, except for the ones at the edge of the grid. The output neurons, on the other hand, are arranged in a hexagonal lattice structure. This means that every neuron is connected to exactly six neighbors, except for the ones at the edge of the grid. Usually, the latter is preferred.



<Figure 1> Network topology

As previously stated, the Kohonen network is trained using unsupervised learning. During the training process the network has no knowledge about the desired outputs. The training process is characterized by a competition between the output neurons. The input patterns are presented to the network one by one, in random order. The output neurons compete for each and every pattern. The output neuron with a weight vector that is closest to the input vector is called the winner. To express the similarity between two vectors, we use the Euclidean distance between two vectors. The weight vector of the winner is adjusted in the direction of the input vector, and so are the weight vectors of the surrounding neurons in the output array. The size of adjustment in the weight vectors of the neighboring neurons is dependent on the distance of that neuron from the winner in the output array. The training algorithm of the SOM is described as follows.

Step 1 : Initialize weights
    w ← random value
Step 2 : Set topological neighborhood and learning rate
    r ← integer
    α ← small number (0 < α < 1)
Step 3 : While stop condition is not satisfied,
    do Step 4 - 8
    *Step 4 : For each input **x***
        do Step 5 - 8
        Step 5 : Compute distance

$$D(j) = \sum_i (w_{ji} - x_i)^2$$

        Step 6 : Find winner neuron y_j
        Step 7 : Update weights within radius

$$w_{ji}^{k+1} = w_{ji}^{k} + \alpha[x_i - w_{jk}^{k}]$$

        Step 8 : Reduce learning rate and radius
        Step 9 : Test stop condition

<Figure 3> The training algorithm of the SOM

3. Case Analysis

3.1 Research model

Since companies [in the database] do not have predefined labels describing their financial status, a network intended for pre-processing their data can have no pre-desired outputs. For this reason, we utilize an unsupervised learning method. Specifically, the Kohonen network [Kohonen, 1998], the most common network model based on unsupervised learning, is used in this study.

We use two learning parameters: the learning rate and the neighborhood width. The learning rate influences the size of the weight vector adjustments after each training step, whereas the neighborhood width determines to what extent the surrounding neurons, the neighbors, are affected by the winner. An additional parameter is the training length, which measures the processing time, i.e. the number of iterations through the training data.

Our criterion for the quality of a good map was the average quantization error, which is the average of the Euclidean distances of each input vector and its best matching reference vector in the SOM.

3.2 Database and selection of companies

The commercial database of National Information & Credit Evaluation is used as the experimental financial knowledge base for the neural network tests. It provides standardized income statement, balance sheets, and cash flow statements of listed companies in Korea stock market. The database also consists of specific financial ratios calculated using information from the standardized reports. In this paper, we extract 100 biggest companies and use 6 financial ratios from the database. These companies are listed in <Table 1>.

<Table 1> Company list

Company	No.	Company	No.
고려아연	F1	인천정유	F51
고려화학	F2	인천제철	F52
국도화학	F3	자화전자	F53
금강	F4	제일모직	F54
금호산업	F5	제일제당	F55
금호석유화학	F6	KDS	F56
남해화학	F7	코오롱	F57
녹십자	F8	코오롱건설	F58
농심	F9	코오롱상사	F59
다우기술	F10	콤텍시스템	F60
대덕전자	F11	태광산업	F61
대림산업	F12	팬택	F62
대상	F13	포항종합제철	F63
대한알루미늄공업	F14	하이트맥주	F64
대한전선	F15	한국타이어	F65
대한통운	F16	한라공조	F66
대한항공	F17	한솔제지	F67
대한해운	F18	한솔CSN	F68
데이콤	F19	한진	F69
동국제강	F20	한진중공업	F70

<Table 1> Continued

Company	No.	Company	No.
동부건설	F21	한진해운	F71
동부제강	F22	한화	F72
동아건설산업	F23	한화석유화학	F73
동양시멘트	F24	현대강관	F74
두산	F25	현대건설	F75
두산건설	F26	현대미포조선	F76
롯데삼강	F27	현대산업개발	F77
롯데제과	F28	현대상선	F78
롯데칠성음료	F29	현대엘리베이터	F79
메디슨	F30	현대자동차	F80
미래산업	F31	현대전자산업	F81
미래와사람	F32	현대정공	F82
삼보컴퓨터	F33	현대종합상사	F83
삼성물산	F34	현대중공업	F84
삼성엔지니어링	F35	호남석유화학	F85
삼성전기	F36	호텔신라	F86
삼성전자	F37	효성	F87
삼성정밀화학	F38	LG건설	F88
삼성중공업	F39	LG산전	F89
삼성테크윈	F40	LG상사	F90
삼성SDI	F41	LG전선	F91
삼양사	F42	LG전자	F92
삼영전자공업	F43	LG정보통신	F93
삼진제약	F44	LG화학	F94
새한	F45	LG-Caltex가스	F95
성미전자	F46	SK	F96
쌍용	F47	SK상사	F97
쌍용양회공업	F48	SK케미칼	F98
쌍용정유	F49	SK텔레콤	F99
아남반도체	F50	SKC	F100

3.3 Choice of financial data

The population consists of 13 financial ratios, 4 internal value indexes, 4 stock price related indexes, balance sheets, income statements, and cash flow tables in the benchmarking system.

The choice of financial data in this study was based on balancing following categories: "Profitability", "Indebtedness", and "Debt coverage". The 6 financial data that were finally selected is summarized in <Table 2>.

<Table 2> Financial Data

	Financial Ratio	Formular
Debt Coverage	Interest Cost	(Interest Cost ÷ Sales) × 100
	Interest Coverage Ratio	(EBIT+Interest Cost) ÷ Interest Cost
Profitability	Operating Income	(Operating Income ÷ Sales) × 100
	Ordinary Income	(Ordinary Income ÷ Total Assets) × 100
Indebtedness	Short-term Debt	(Short-term Debt ÷ Total Debt) × 100
	Total Liabilities	(Total Debts ÷ Total Equity) × 100

Source: Maeil Business Newspaper 26/9/2000 Sec. 3.

Financial ratios to evaluate the corporate financial structure are various. In this paper, however, only 6 financial ratios is used to conduct competitive benchmarking between individual companies in which Financial Supervisory Commission's the 2nd round financial restructuring plan.

3.4 Training and testing the network

In this section, we give a description of the construction process in developing the self-organizing maps. The actual construction work was performed using *The Self-Organizing Map Program Package version 3.1* and *Nenet version 1.1* prepared by the SOM Programming Team of the Helsinki University of Technology.

We started by standardizing the ratios in the database using standard normalization in order to smooth different scales, to ease the SOM's learning process, and to improve its performance [Martin-del-Brio & Serrano-Cinca, 1995].

All the maps were trained in two phases. The purpose of the first training phase was to order the randomly initialized reference vectors of the maps according to their approximately correct values. During the second phase the maps are fine-tuned, i.e. final ordering of the reference vectors takes place.

Training process of maps in this study is somewhat slow due to the very large amount of training data employed; but we can manage to make comparisons between the financial situations of companies with the help of our maps. This approach, however, does include the presumption that the input space for each year contains an adequately comprehensive description of the whole possible input space, i.e. all the realistically possible combinations of financial ratios.

We constructed the maps over the years 1998, 1999, and 2000. The network topology chosen was hexagonal with 15*15 neurons in all cases. The parameters of the best maps with respect to the average quantization error are given in <Table 3>.

<Table 3> Network parameters

Year	Phase	Training Length	Learning Rate	Neighbourhood Width	Average Quantization Error
1998	1	1000	0.06	14	0.29794
	2	500000	0.02	3	
1999	1	1000	0.07	13	0.28625
	2	500000	0.02	3	
2000	1	1000	0.05	15	0.28486
	2	600000	0.02	3	

4. Results

In the construction process, hundreds of maps were initialized and trained. The best ones, in terms of average quantization error (shown in <Table 3>), were more carefully inspected, and the locations of the companies as well as the values of weights (corresponding to financial data) were visualized.

The groups, or clusters, A to D on the maps in Figure 1 to Figure 3 of <Appendix 1> were identified by analyzing the weight distributions of the maps of <Appendix 2> for the years 1998-2000 in the forms of standard 2D U-matrices and weight maps. The Figures in <Appendix 2> are the "weight maps" for the resulting map over the years 1998, 1999, and 2000. On these maps, the value of each weight in each neuron is visualized by gray-level imaging: light shades representing high values and dark shades representing low values.

4.1 Financial performance by groups

The interpretation of the defined groups based on weight maps (see <Appendix 2>) for the year 1997, 1998, and 2000 is as follows:

Firstly, individual companies are clustered from group A to group D in 1998.

Group A is divided into subgroups A1 and A2. The group A1 represents best companies in terms of ordinary income(% of sales), total liabilities(% of total equities), interest cost(% of sales), interest coverage ratio. It consists of mainly Samsung group companies such as F37(Samsung Electronics), F38(Samsung Fine Chemicals), F41(Samsung SDI). But, some companies of the group A2 such as F99(SK Telecom) and F8(Korea Green Cross) have very high value of short-term debt(% of total debt).

Group B is defined as "slightly netter than average". The rest financial ratios except for short-term debt(% of total debt), interest coverage ratio are competitive.

Group C can be considered as "average group". Individual companies in this group have average value in all financial ratios.

Group D is the worst performer in all respect of financial data. It divided into subgroups D1, D2, and D3. The group D1 is the worst performer in ordinary income to sales. The group D2 is the worst in short-term debt and total liabilities. And the group D3 is the worst in ordinary income and total liabilities. But, some companies of the group D3 have very low value of short-term debt.

Secondly, individual companies are also clustered from group A to group D in 1999.

Group A is divided into subgroups A1 and A2. The group A1 represents best companies in terms of operating income, short-term debt, and total liabilities. The group A2 represents best companies in terms of operating income, ordinary income, total liabilities, and interest cost. The main companies of group A are F41(Samsung SDI), F63(Pohang Steel), F92(LG Electronics), F94(LG Chemicals), F4(Keumkang), F10(Dau Technology), and F11(Dae Duck Electronics).

Group B is defined as "slightly netter than average". It divided into subgroup B1, B2. The group B1 represents good companies in terms of short-term debt and total liabilities, but it has weakness in profitability and indebtedness. The group B2 represents good companies in terms of operating income, but has weakness in the rest financial ratios.

Group C can be considered as "average group". Individual companies in this group have average value in all financial ratios.

Group D is the worst performer in all respect of financial data. It divided into subgroups D1, D2, and D3. The group D1 is the worst performer in profitability, short-term debt, and interest cost. The main companies of D1 are F19(Dacom), F21(Dongbu Corporation), F74(Hyundai Pipe), and F82(Hyundai Precision & Ind.). The group D2 is the worst in operating income and short-term debt. And the group D3 is the worst in operating income, ordinary income, total liabilities, and interest cost. The main companies of D3 are F31(Mirae Ind.) and F45(Saehan Industires).

Finally, individual companies are clustered from group A to group C in 2000. The analysis result of the year 2000 is characterized as follows.

First, overall financial performance of individual companies is worse than previous year. Second, the number of companies in average group has increased. Third, it is easy to find out benchmark gap between the best and the worst group.

Specifically, group A represents best companies in terms of all financial ratios. The main companies of this group are F8(Korea Green Cross), F27(Lotte Sam Kang), F80(Hyundai Motors), and F37(Samsung Electronics).

Group C is the worst performer in all respect of financial data. It has very weakness in profitability and total liabilities. Among the companies in this group, F23(Dong-Ah Construction Industrial), F48(Ssangyong Cement Industrial), and F57(Hyundai Engineering & Const) are known as company restructuring by Financial Supervisory Commission.

4.2 Financial performance over time

In this section, we focus on the financial performance of the Korean companies over the time. The result is as you see in <Appendix 3>. <Appendix 3> is the output of testing the SOM with financial data of 1998, 1999, 2000 based on the trained map using 1998 financial data. In <Appendix 3>, new notation is used, for example, 8F23 represents the state of F23 in 1998. Through the analysis of this test map, the competitive location of individual companies over the years 1998, 1999, and 2000 can be easily found.

Remarkable one is transition of group D in 1998 to group C in 2000. This means improvement of financial structure of Korean companies. But, overall financial state of individual companies in 2000 becomes worse than previous years.

5. Conclusions

The objective of this study was to investigate the potential of self-organizing maps as a tool for managing the complexity in a large database by pre-processing the vast amount of financial data available. The database in this study contained financial data of 100 biggest listed companies in Korea Stock Market. Employing 6 different financial data as variables, this study constructed maps of individual company's competitive location over the years 1998, 1999, and 2000. Also, through competitive benchmarking, we could analyze individual company and group's relative weakness and strength to others in every financial data over the years.

One important issue is that SOM is intended to visualize relationships between patterns and represent high-dimensional input vectors in a low-dimensional space. We take the view that SOM is a very interesting tool for studying the information contained in individual company's accounting statements and capital markets in general.

These competitive benchmarking can be extended to provide a powerful method which is complementary to other mathematical models for predicting company bankruptcy based on Z-scores and to find out evolutionary change of individual company over times. The future research will be focused on this point.

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<부록 1> 표준 2D U-matrices

Figure 1. 1998년 2D U-matrix

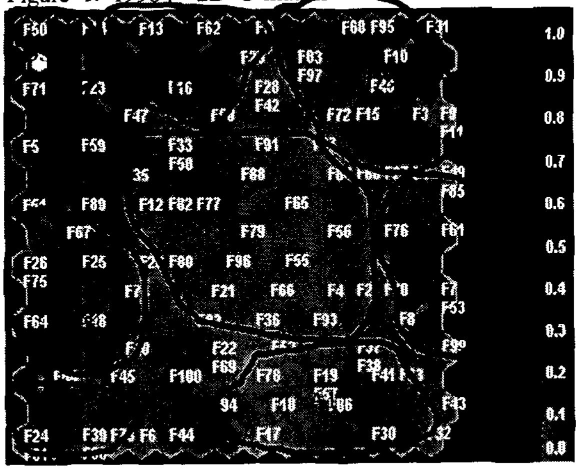


Figure 2. 1999년 2D U-matrix

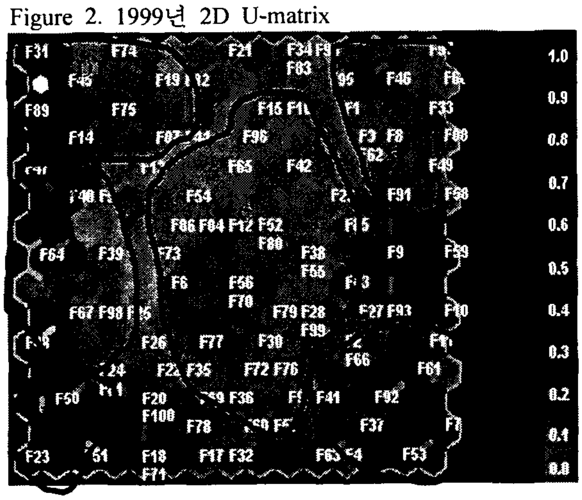
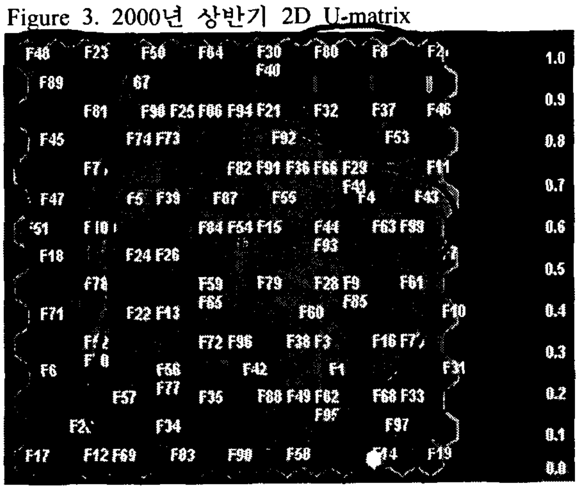


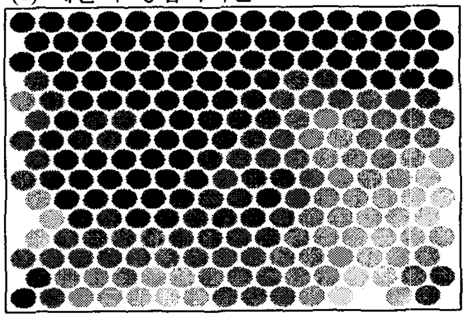
Figure 3. 2000년 상반기 2D U-matrix



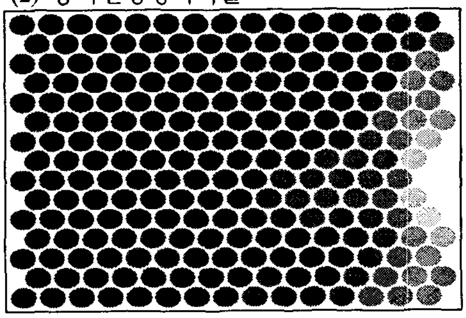
<부록 2> 1998, 1999, 2000년 연결강도 지도

1. 1998

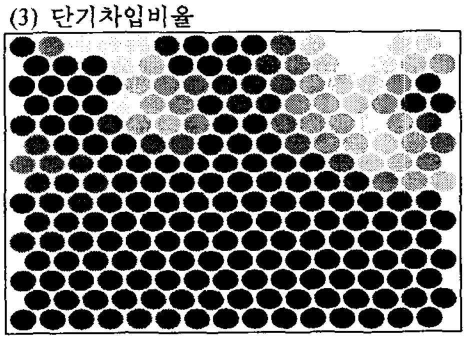
(1) 매출액 영업이익률



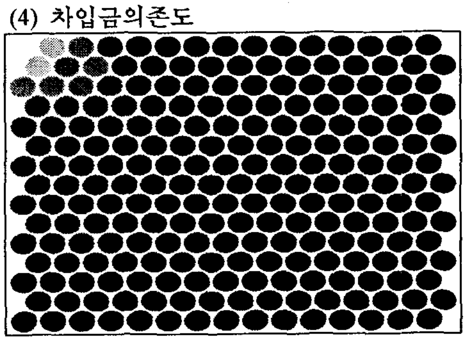
(2) 총자산경상이익률



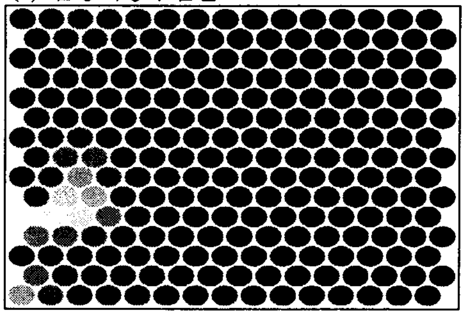
(3) 단기차입비율



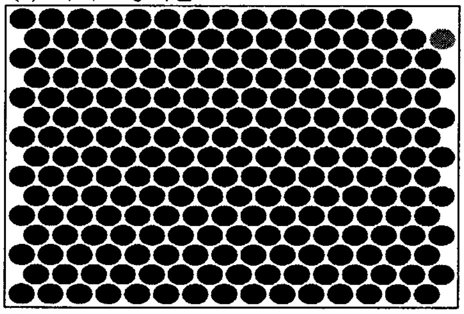
(4) 차입금의존도



(5) 금융비용부담률

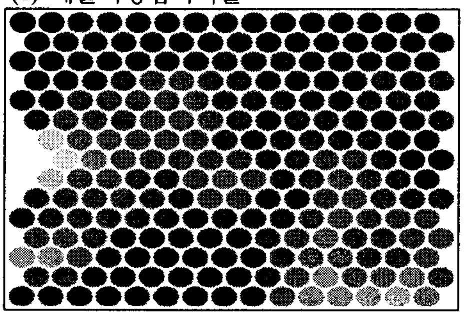


(6) 이자보상배율



2. 1999

(1) 매출액영업이익률



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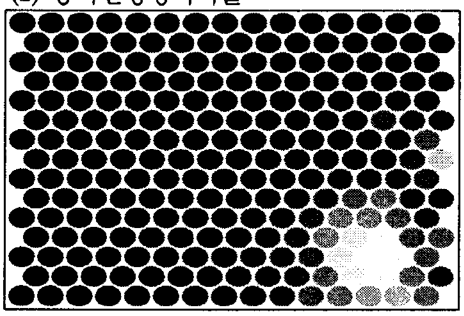

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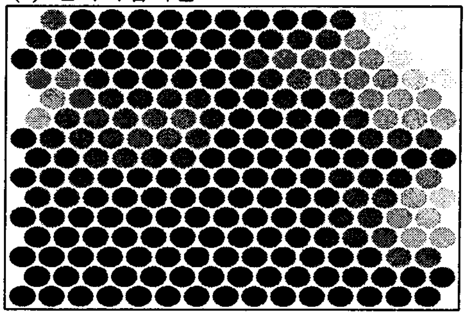
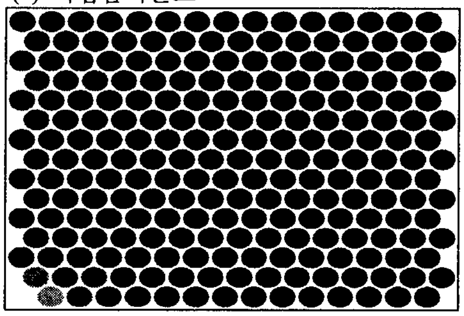


(4) 차입금의존도



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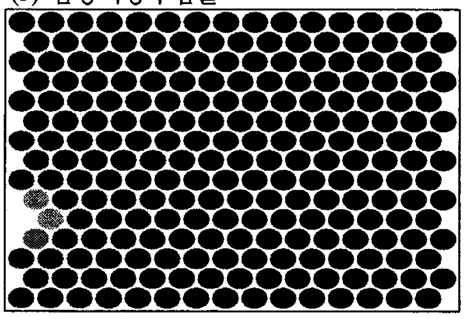

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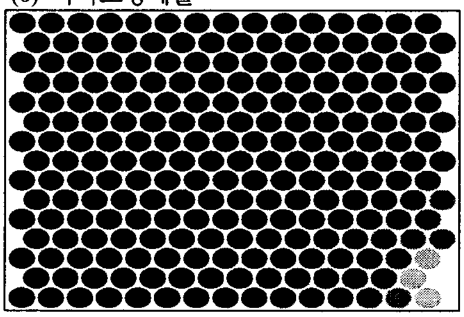
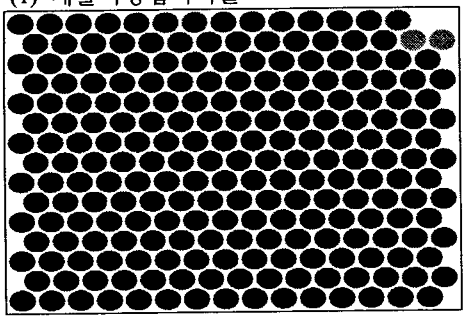
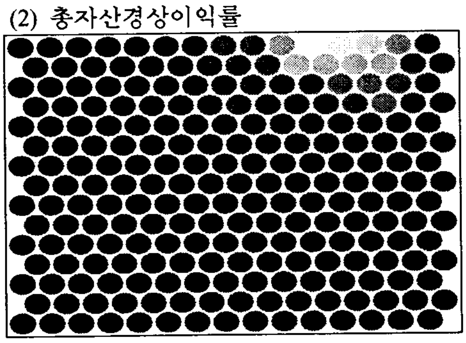


3. 2000년 상반기

(1) 매출액영업이익률



(2) 총자산경상이익률



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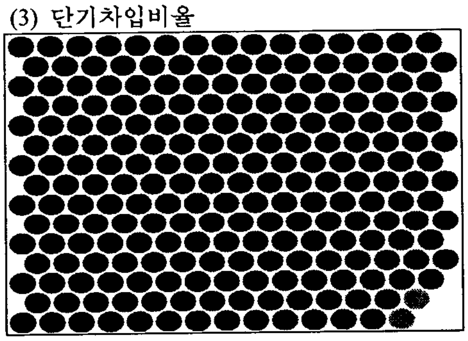
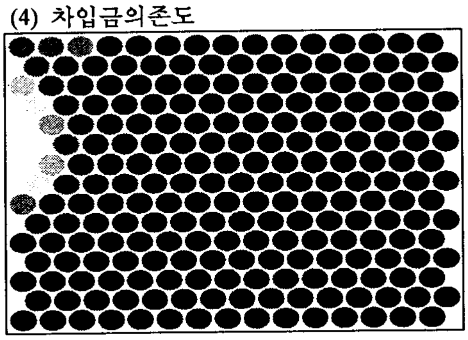
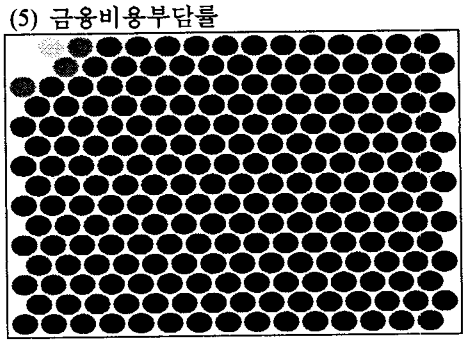


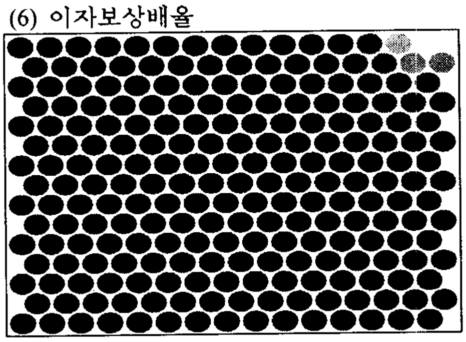
(4) 차입금의존도



(5) 금융비용부담률



(6) 이자보상배율



<부록 3> 연도별 재무구조 변화