International Journal of Computer Applications (0975 – 8887)
Volume 156 – No 7, December 2016

Patient Postoperative Care Data Visualization

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ABSTRACT
This paper describes the problem of hospital patient care data visualization. Although a significant amount of different kinds of tools have been created to improve health care still there is luck of tools supports patient care decision making. We briefly describe the method for visualization and analysis of multidimensional data implemented in the NovoSpark® Visualizer software (NV). An example of problem salvation based on data of patient state observation after the laparoscopic gallbladder removal is provided as well. The experiment results indicate that it is possible to visualize all the data from nurse report in single image, to identify the anomalies, trends and regularities in it using multidimensional visualization. The decision time, error rate and amount of invested mental effort were analyzed. The conducted experiments demonstrate the significant difference between decision time and mental effort amounts for paper report analysis and visualizations analysis in favor of the visualizations.

General Terms
Visual Analytics, data analysis, multidimensional visualization

Keywords
Multidimensional visualization, patient care, medical report, medical data visualizations

1. INTRODUCTION
Many experts suggest medical data and medical systems should become the new currency [1]. Understanding what is the best way to visualize these data, is a significant challenge to improving healthcare [1].

Today, visualizations help to make data analysis in different disciplines of medicine: especially in cardiology, neurology, genetics, emergency medicine, radiobiology, whenever medicals are struggling with problem solving and decision making. Most of medical data is multidimensional; datasets contain typically more than three columns of data.

Improving the quality of patient care is the highest priority for healthcare specialists. The problem of patient care in hospital, especially after surgery, is to make quick and appropriate decisions or take implementation of various kinds of intervention in the limited time. The kind of intervention depends on nurse report results. During the patient care nurse gather the information from different sources, which should be analyzed simultaneously. So it is significant to clarify the decision-making process for improvement the quality of nursing care.

A lot of scientific works have been writing about systems and visualizations supporting patient care [2, 3], healthcare coordination [4] and patient electronic health records [5, 6, 7]. Highly challenging for medicals is complex medical data analysis with uncertainty and incomplete entries [8, 9]. Experts believe personal health data visualizations, visualizations of risk of treatments and medications, medical communications interactive visualizations will be especially helpful [10]. The integration of information visualization, visual analytics, and health informatics could produce even more benefits in personal health and care monitoring, clinician treatment decisions, and public health policy [10].

The importance of providing informatics support to nursing service is specialists described in “Nursing and Informatics for the 21st Century - an International Look at Practice, Education and EHR Trends” [11]. Authors also underline that the role of IT in nurse services is still not appreciated enough. Although a significant amount of different kinds of tools have been created to improve health care still there is luck of tools supports nurse decision making.

The patient care visualizations should reflect the dynamic character of the data. The time-oriented visualizations are commonly used in medicine. However, most of them focused on creating the time-oriented plans [12, 13, 14]. Commonly used are: lifelines, timelines, body maps, networks [10, 15, 16, 17]. Some works present other visualization types [18, 19]. The Visual Analytics [20, 21] is also relevant to this purpose. This field is focusing on combining visualizations, data mining and statistics to operate multidimensional medical data.

In recent years healthcare dashboards become very popular. Most of these dashboards focus on performance improvement and document excellence [22, 23, 24]. Dashboards usually provide front-line workers with real-time emergency room metrics [24]. Regular patient dashboard presents: average length of stay, total number of patients, lab turnaround time [24]. The user interface is most commonly created using intuitive analogies and is similar to car dashboard with traffic-light color coding [24, 25]. Effective dashboards display data within a single page and use key performance indicators, can be easily understood by all levels of medical staff.

However specialists suggest that “simply automating a process, however, does not contribute to patient care quality”[26]. The IT should provide the ability to use collected information in a new and different way to improve the nurses’ and other healthcare professionals decision making processes [26].

One of the ways to support nurse decision-making process is to use traditional multidimensional visualizations. A lot of papers have been published about multidimensional data visualization. The most widespread visualization methods are: parallel coordinates, 3-D parallel coordinates, line graphs, survey plots, scatter plots, scatter plot matrix and it’s variations, star glyphs, treemaps, Sammon’s mappining, self-organizing maps, dendrogram, radar chart, Voronoi diagrams, parallel glyphs, Bertin’s permutation matrices, Chernoff’s Faces and more other techniques. Very useful are the methods of dimensionality reduction [27, 28]. However, most of traditional methods and techniques of multidimensional data visualization have some weaknesses. Many researches are still looking for the novel methods of multidimensional data visualization [29-46]. One of the them is NovoSpark method [47]. This method was successfully implemented in NovoSpark® Visualizer software. The main aspects of the method and system are described in the following part of the paper.

2. METHOD

The NovoSpark method of multidimensional data visualization is clearly described in [46]. The main idea is the integration and transformation of numerical and linguistic data into color curves. "The image of a multidimensional observation *A* in *N*-dimensional affine point-vector space of the originals $A=(a_0, a_1 ... a_{N-1})$ is treated as a linear combination of $\{P_i(t)\}_0^\infty$ functions, where $P_i(t)$ are Legendre orthogonal polynomials with weight = 1 defined on the segment t = [0, 1]" [47, 48, 49]:

$$f_A(t) = \sum_{i=0}^{N-1} a_i P_i(t) \tag{1}$$

The image of a point is created using the spectrum color palette in accordance with the function values. Such representation of an image $f_A(t)$ was called a *"spectrum"* of this point [47, 48, 49].

The image of a multidimensional segment AB is an image of the point *X* at a position *z*, corresponds to a surface *F* [47, 48]:

$$X = X(z) \leftrightarrow f_X(t) = \sum_{i=0}^{N-1} x_i(z) P_i(t) = f_X(t, z),$$

$$\text{where } x_i(z) = a_i + z(b_i - a_i) \tag{2}$$

The image of a multidimensional interval called a "*cloud*" is a two-dimensional area between the "minimum" and "maximum" images in the coordinate system {f, t} [47, 48, 49] (Figure 1). The process of "cloud" image creation is described in [46]. The observations, lying outside the cloud (even partially) are treated as abnormal with respect to the selected interval [47, 48, 49]. The system also provides the possibility of creating the image of a multidimensional process for dynamic data (Fig 2).

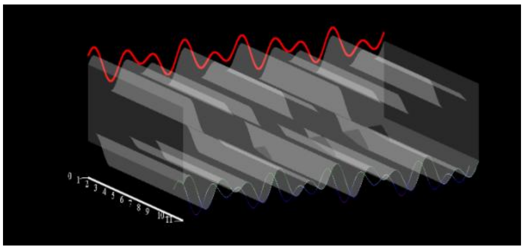


Fig 1: Image of multidimensional interval -"cloud"

The system interface is easy to use. Figure 2 illustrates the main components of the visualization window, which include: the main menu and tools, the image window, data window, and image presentation/transformation panel. The user has the possibility to modify the image settings changing the palette, view, curve type and interval options.

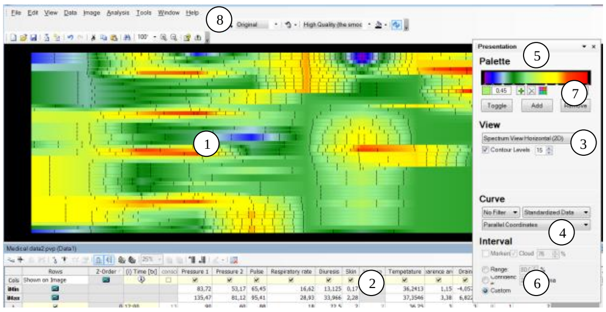


Fig 2: The NovoSpark® Visualizer main window. (1) Image window. (2) Data windows. (3) Image view settings. (4) Curve settings. (5) Image presentation/transformation options. (6) Interval settings. (7) Palette settings. (8) Main menu and tools panel.

There is a possibility to create the following visualizations: "NovoSpark Curves" [47], Andrews Curves [50] and Parallel Coordinates[51], linear plots, multiple linear plots, scatter plot matrix, polar coordinates, histograms and SOM maps.

It the following part of the paper we provide the description of the experiment of nurse report visualization. The main purpose of the experiment was to check the medic's ability to identify the anomalies, trends and regularities in patient dynamic data with NV tool.

The example presents the data of patient observation after the laparoscopic gallbladder removal. The nurses carried for the patient in the hospital recovery room observe the state of consciousness and basic life functions and introduced information into the system every hour. In case of disturbing symptoms, they should make intervention or inform the doctor who choose the treatment method. The nurses worked according to shift schedule. The patient was observed by several nurses, but they create one common nurse report.

The following parameters were tacked into consideration [52]:

1. Awareness control**.** To assess patient awareness the coma scale was used. The scale is composed of three parts: eye, verbal and motor responses. The three values separately as well as their sum are considered.
    - Generally, brain injury is classified as following:
    - Severe, < 9;
    - Moderate, 9–12;
    - Minor, ≥ 13.

    The lowest possible sum is 3 (deep coma or death), while the highest is 15 (fully awake person).

2. Blood pressure. The test was carried out every hour. More frequent measurement is recommended if the patient's condition is not very stable or deteriorates. The pressure up to 140/90 mmHg was treated as normal pressure.

3. Pulse. Normal heart rate is within 60-100 beats per minute. The frequency of the heart rate determined by doctor depending on the patient's condition, it is mostly a one-hour interval. Both post-operative pain and hypovolemia may cause rapid pulse.

4. Respiratory rate. Nurse should worry both slow and shortness of breath. The normal rate is between 6 and 34 breaths per minute. Anomalies may indicate

the occurrence of a patient cardio-respiratory disorders.

5. Diuresis. The nurses observe the daily amount of excreted urine. It should also be monitored hourly diuresis (0.5 ml per kg / h), an adult should be hourly diuresis about 30-60 ml.

6. Skin and mucosa. In the assessment of patient state is also important to control the color of the skin and mucous membranes.
   The following mucosa state scale was used:

   - White (abnormal) - 1
   - Pink (normal) - 2
   - Red (abnormal) - 3

   The following skin state scale was used:

   - Normal - 1
   - A little bit abnormal- 2
   - Abnormal - 3

7. Temperature. Patient's body temperature was measured as often as every hour. The increase of the temperature may be a signal of post-operative complications. Normally, when the temperature rises to 38 ° C or above, steps are taken to lower a fever. But often the doctor or nurse take the decision to give the pill if temperature rises to 37.0 - 37.3° C and other disturbing signals also are observed.

8. Postoperative wound. The nurse in the early postoperative period leads observation of the wound and the bandage: whether it is dry or saturated with content and what color. It also controls the volume and type of content coming from drains established during the operation (especially the amount of bile). Very soaked bandage and a large amount of discharge, especially bloody, it may be a signal of danger of the patient's life-threatening complications. The nurse make drain control every hour at the first day after operation.

   The following wound appearance scale was used:

   - Very bad - 1
   - Bad - 2
   - Normal - 3
   - Good - 4
   - Very good - 5

9. Postoperative pain. The symptoms reported by the patient orally. The numerical rating scale has been used in the assessment of pain intensity. On this scale, 0 represents no pain and 10 the highest intensity of pain.

10. Mental state. An important place in patient care takes mental state and positive attitude towards done surgery.

    The following mental state scale was used:

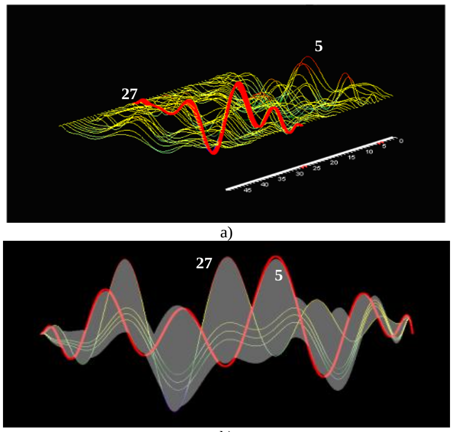
    - Inert - 1
    - Quite - 2
    - Nervous - 3
    - Panic – 4

The Table 1 (Appendix) shows the patient life parameters have been observed from 12 a.m of the first day to 12 a.m next day after surgery. System provides the possibility of introduction the parameter limits by establishing the confidence interval based on user settings. Thus, at the end of the table the maximum, minimum and optimal parameter values are presented.

We introduced the table into the data window and created the images using NovoSpark curves, Andrews's curves and Parallel coordinates. We used the standardization operation for all the data.

3. RESULTS

The Figure 3a illustrates the 3-dimentional visualization created using NovoSpark curves. Using this visualization type we concluded that the selected 5 (14:00) and 27-th (01:00) observations are abnormal (Table 1). In system image is connected with table and every selected observation show us the row with relevant data. This image is interactive; the user can rotate it in order to increase the precision of anomalies identification. It is also possible to present it in two dimensions creating the "cloud".



a)

b)

Fig 3: a) 3-D visualization with NovoSpark curves b) Abnormal observation front view 2-D visualization with "cloud"

The abnormal observations were identified using the "cloud" as shown in the Figure 4b. The curves, lying outside the cloud have been seen as abnormal with respect to the interval with confidence rate, which is equal to 3.0. According to this image the 5 and 27 observations show the most danger moments. However, this visualization gave us the possibility to identify the anomalies without taking a look at the whole situation.

The Figure 4 shows the 2-dimentional visualization created using Andrews curves. The *x*-axis presents the time intervals from left to right and the *y*–axis presents the Andrews curves. It was concluded that patient state is not stabile and there were some moments then the intervention of nurse was needed. Especially disturbing moments were observed immediately after surgery (I) and at the night from 22:00 to 02:00 (II). Next morning there were also some deviations, but not so distressing. From 7:00 to 9:00 some parameter values were increased but they are do not exceed much the normal values (III). At the end of the observed period (about 11:00) we also found some disturbing changes (IV).

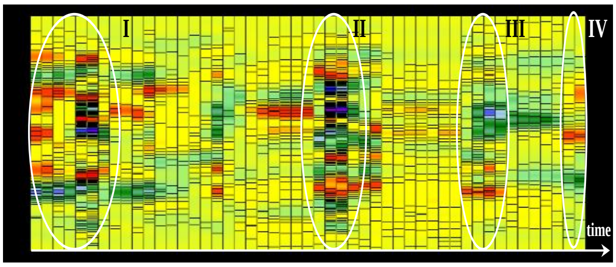


Fig 4: 2-D visualization using Andrew curves (spectrum view)

System also allows building images on the basis of parallel coordinates. The Figure 5 illustrates the *x*-axis with parameters and *y*-axis with time intervals. The violet and blue color indicates the points there the parameters values are below the minimum, the orange and red colors indicate the values which are above the maximum. Green and yellow mean that the values are in normal boundaries and not require special attention.

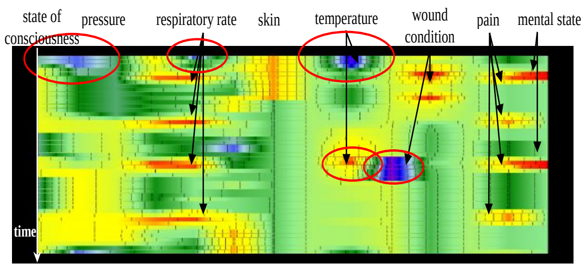


Fig 5: 2-D visualization with parallel coordinates (spectrum view)

It was observed that at the first hours after surgery 5 life functions was too low: both values of pressure, state of consciousness, temperature and respiratory rate. The respiratory rate rose four times in one day in combination with pain. From 22:00 to 02:00 the temperature increases slightly and the wound state is changes to bad. That inquired immediate intervention.

At the next step compared the results obtained on the basis of visualizations with results obtained on the basis of nurse paper report were compared. The whole experimental sample is formed by 8 nurses and 3 doctors.

The number of errors was calculated as the as the difference between the number of actual anomalies (regularities or trends) and the number of identified anomalies (regularities or trends). Error rate was calculated as the ratio of all errors number to sum of all possible anomalies (regularities or trends) identification cases.

To measure the amount of mental effort, a 9-point symmetrical category scale was used. This scale is a subjective. It asks medics to report the amount of mental effort that they invested in understanding visualizations and table report. The scale is ranging from o to 150 mm and every 10 mm is indicated. Word ratings intervals are indicated by a cross of the line from “absolutely no effort” to “extreme effort” [53].

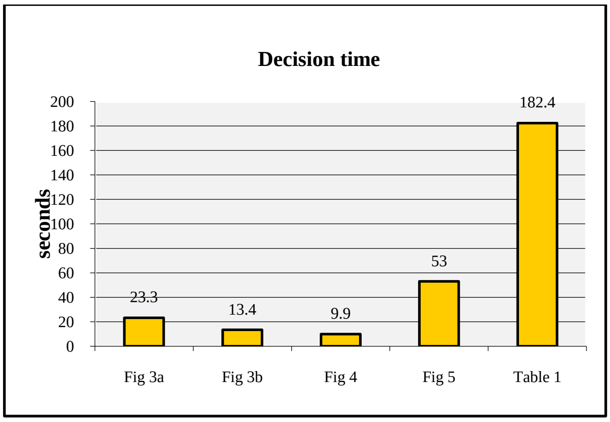


Fig 6: Representation of the average decision time

It is clear from Figure 7 that the most problematic for medics was regularities identification. Vanishingly small error rate was noticed in the case of anomalies detection in Figure 3a and Figure 5. The Figure 4 was not the appropriate choice for medics to present the anomalies. It was more useful for data trends identification. The similar error results for visualization and for paper report in the case of trends identification were obtained.

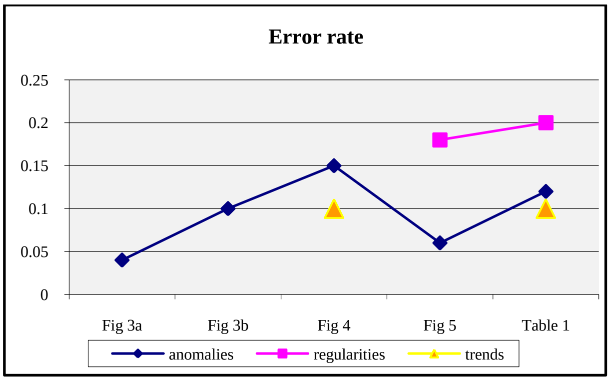


Fig 7: Average error rate

Finally, it was noticed a significant difference between mental effort amounts for paper report analysis and visualizations analysis (Figure 8).

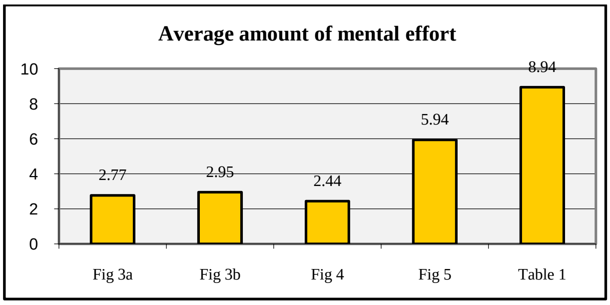


Fig 8: Representation of the average amount of mental effort

The mental effort amount for Figure 3a and 3b was between “a little effort” and “some effort” according to word scale; for Figure 5 -between “almost no effort” and “a little effort”; for Figure 6 – “rather much effort”; for Table 1 – between “great effort” and “very great effort”.

4. DISCUSSION

The conducted experiment revealed 5, 6, 27, 28 were most danger moments of the patient state. These moments were observed immediately after surgery and at the night from 00:30 to 02:30. The "cloud" images allowed us to identify the abnormal observations. The 3-D and 2-D visualization using NovoSpark curves and Andrews's curves provided us with analysis of the patient's integral state. These two types of visualization also helped us to observe regularities in data sets. In this way Figure 6 shows the connection between respiratory rate and pain.

Unfortunately, medics have had some troubles with using multidimensional visualizations at the beginning of the experiment, but after a short consultation they were able to use the system without expert's help. It should be noticed that the luck of practice with NV tool may be a reason for obtained amount of invested mental effort results. More practice likely contributes to better results.

5. CONCLUSION

It was concluded the NV visualizations enabled not only look at the situation in its entirety, identify the general trends and immediately see the source of the problem, but also make detailed analysis of selected aspects, for example to compare patient state at specific hours, to find regularities and anomalies. The system also can be used in similar situations than medics operate on different types of data and need multidimensional dynamic data presentation.

Unfortunately, some authors suggest that the comparisons with multi-colored bands to compare rows at a whole have long been known to be very perceptually difficult [54]. Regardless the number of medical systems uses color coding to visualize the data analysis results.

It is clear from experiment that the use of the NV tool by a medics requires initial training. However, every Visual Analytics tool require the portion of IT knowledge. For NV tool this portion appears to be not so significant. The future work will be based on making further experiments on medical data analysis and evaluation of visualizations efficiency.

6. ACKNOWLEDGEMENTS

The authors would like to thank the Szczecin City's "SPSK N2" Hospital staff for their expert opinions.

7. REFERENCES

[1] Zerhouni, E., A. 2008. Strategic Vision for the Future, www.nih.gov/strategicvision.htm.

[2] Inoue, M., Kuroda, M., Suekuni, C., Dannoue, H., Tsuru, S., Nakanishi, M. 2006. Structural visualization of expert nursing: Expert nursing care for a patient undergoing outpatient radiotherapy. Stud Health Technol Inform 122, 931.

[3] Matsumoto, C., Uto, Y., Muranaga, F., Kumamoto, I. 2013. DPC in acute-phase inpatient hospital care. Visualization of amount of nursing care provided and accessibility to nursing care. Methods Inf Med 52 (6), 522-535.

[4] Rudin, R. S., Bates, D.W. 2014. Let the left hand know what the right is doing: a vision for care coordination and electronic health records. J Am Med Inform Assoc 21 (1), 13–16.

[5] Roque F. S., Slaughter L., Tkatchenko A. 2010. A Comparison of Several Key Information Visualization Systems for Secondary Use of Electronic Health Record Content, Proceedings of the NAACL HLT 2010 Second Louhi Workshop on Text and Data Mining of Health Documents, Los Angeles, California, USA, 76–83.

[6] Soulakis, N. D., et al. 2015. Visualizing collaborative electronic health record usage for hospitalized patients with heart failure. J Am Med Inform Assoc 22 (2), 299-311.

[7] Tai-Seale, M., Wilson, C.J., Panattoni, L., et al. 2014. Leveraging electronic health records to develop measurements for processes of care. Health Serv Res. 49 (2), 628–644.

[8] http://hcil.cs.umd.edu/localphp/hcil/vast10

[9] Faiola, A., Hillier, S. 2006. Information Visualization, Tenth International Conference on, 460 – 468.

[10] Shneiderman, B., Plaisant, C, Hesse, B. W. 2013. Improving health and healthcare with interactive visualization methods HCIL Technical Report. IEEE Computer Special Issue on Challenges in Information Visualization.

[11] Weaver, C. A., Delaney, C. W., Weber, P., Carr, R. L. 2010. Nursing and Informatics for the 21st Century An International Look at Practice, Education and EHR Trends Second Edition, Healthcare Information and Management Systems Society (HIMSS).

[12] Klimov, D., Shahar, Y., Taieb-Maimon, M. 2010. Intelligent visualization and exploration of time-oriented data of multiple patients, Artificial Intelligence in Medicine 49, 11–31.

[13] Bui, A., Aberle, D.R., Kangarloo, H. 2007. TimeLine: Visualizing Integrated Patient Records. IEEE Transactions on Information Technology in Biomedicine 11(4), 462-473.

[14] Kosara, R., Miksch, S., 2001. Metaphors of movement: a visualization and user interface for time-oriented, skeletal plans. Artif Intell Med 22, 111-131.

[15] Kielman, J., Thomas, J. 2009. Special Issue: Foundations and Frontiers of Visual Analytics, Information Visualization, Volume 8, Number 4, (Winter 2009), 239-314.

[16] Shortliffe, E. H., Cimino, J. J. 2013. Biomedical Informatics: Computer Applications in Healthcare and Biomedicine: 4th Edition, Springer, New York (2013).

[17] Hallett, C. 2008. Multi-modal presentation of medical histories, IUI '08: Proceedings of the 13th international conference on Intelligent user interfaces, ACM-89, 80-89.

[18] Wang, T.D., Plaisant, C., Shneiderman, B., Spring, N., Roseman, D., Marchand, G., Mukherjee, V., Smith, M., 2009. Temporal Summaries: Supporting Temporal Categorical Searching, Aggregation and Comparison. IEEE J VCG 15, 1049-1056.

[19] Wongsuphasawat, K., Gomez, J. A. G., Plaisant, C., Wang, T. D., Shneiderman, B., Taieb-Maimon, M. 2011. LifeFlow: Visualizing an overview of event sequences, Proc. ACM SIGCHI Conference, ACM Press, New York (May 2011), 1747-1756.

[20] Ward, M. O., Grinstein, G., Keim, D. A., 2010. Interactive Data Visualization: Foundations, Techniques, and Application, A. K. Peters, Ltd.

[21] Keim, D.A., Mansmann, F., Schneidewind, J., Thomas, J., Ziegler, H., 2008. Visual analytics: Scope and challenges. Visual Data Mining: Theory, Techniques and Tools for Visual Analytics, Springer, 76-90.

[22] Donaldson, N., Brown, D. S., Aydin, C. E., et al. 2005. Leveraging nurse-related dashboard benchmarks to expedite performance improvement and document excellence. J Nurs Adm 35, 163-172.

[23] Aydin, C.E., Burnes Bolton, L., Donaldson, N., Brown, D., Mukerji, A., 2008. Beyond Nursing Quality Measurement: The Nation's First Regional Nursing Virtual Dashboard, In Henriksen, K., Battles, J.B., Keyes, M.A., Grady, M.L., Eds. Advances in Patient Safety: New Directions and Alternative Approaches, Vol. I Assessment. AHRQ Publication No. 08-0034-1. Rockville, MD: Agency for Healthcare Research and Quality; August 2008, 217-234.

[24] Wilbanks, B. A, Langford, P. A., 2014. A review of dashboards for data analytics in nursing, Comput Inform Nurs 32 (11), 545-549.

[25] Carroll, C., Flucke, N., Barton, A. J., Thompson, T. L. 2013. Information Technology and the Clinical Nurse Specialist: The Use of Dashboards to Monitor Quality of Care, Clinical Nurse Specialist: The Journal for Advanced Nursing Practice 27 (2), 61 – 62.

[26] Barton, A. J., Thompson, T. L. 2009. Decision Support and the Clinical Nurse Specialist Clinical Nurse Specialist Clinical Nurse Specialist: The Journal for Advanced Nursing Practice, 23(1), 9-10.

[27] Kim, H., Schulze, J., Cone, A., Sosinsky, G., Martone, M. 2010. Dimensionality Reduction on Multi-Dimensional Transfer Functions for Multi-Channel Volume Data Sets, Information Visualization 9 (3), 167-180.

[28] Maaten, van der L.J.P., Postma, E.O., Herik, van der H. J. 2009. Dimensionality Reduction: A Comparative Review, Journal of Machine Learning Research 10, 66-71.

[29] Coorprider, N., Burton, R. P., 2007. Extension of star coordinates into three dimensions. In Proceedings of the SPIE, 6495.

[30] Reitsma, R., Trubin, S., 2007. Information Space Partitioning Using Adaptive Voronoi Diagrams, Information Visualization 6 (2), 123-138.

[31] Johansson, J., Forsell K., Lind M., Cooper M. Perceiving Patterns in Parallel Coordinates: Determining Thresholds for Identification of Relationships, Information Visualization 7 (2), 152-162.

[32] Slingsby, A., Dykes, J., Wood, J. Using Treemaps for Variable Selection in Spatio-Temporal Visualisation, Information Visualization 7 (3-4), 210-224.

[33] Sun, Y., Tang J., Tang, D., Xiao, W. 2008. Advanced star coordinates. In Web-Age Information Magagement, 2008. WAIM 08. The Ninth International conference, 165–170.

[34] Schreck, T., Bernard J., von Landesberger T., Kohlhammer J. Visual Cluster Analysis of Trajectory Data with Interactive Kohonen Maps, Information Visualization, 8 (1), 14-29.

[35] Shneiderman, B., Plaisant, C. 2009. Treemaps for space-constrained visualization of hierarchies. http://www.cs.umd.edu/hcil/treemap-history/

[36] Cao, H., Yichuan, S. 2010. A multi-perspective and interactive method for multidimensional data visualization. International Conference on Environmental Science and Information Application Technology (ESIAT), 3, 207 – 210.

[37] Hao, M., Dayal, U., Sharma, R., Keim, D., Janetzko H. 2010. Variable binned scatter plots, Information Visualization, 9(3), 194-203.

[38] Heilig, M., Huber, S., Demarmels, M., Reiterer, H. 2010. Scattertouch: a multi touch rubber sheet scatter plot visualization for co-located data exploration. In Proceedings ACM ITS'10, 263–264.

[39] Keim, D., Hao, M., Dayal, U., Janetzko, H., & Bak, P., 2010. Generalized scatter plots, Information Visualization; 9(4), 301-311.

[40] Lu, L. F., Zhang, J.W., Huang, M. L., Fu, L. 2010. A new concentric-circle visualization of multi-dimensional data and its application in network security. Journal of Visual Languages and Computing table of contents archive, 21(4), 194-208.

[41] Chen, Y., Cheng, X., Chen, H. 2011. A multidimensional data visualization method based on parallel coordinates and enhanced ring. International Conference on Computer Science and Network Technology (ICCSNT), 4, 2224 – 2229.

[42] Domańska, D., Wojtylak, M., & Kotarski, W. 2012. Visualization of multidimensional data in explorative forecast, Lecture Notes in Computer Science, 7594, 63-70.

[43] Buschmann, S., Nocke, T., & Tominski, C. 2013. Towards visualizing geo-referenced climate networks. Workshop GeoViz Interactive Maps that Help People Think, Hamburg, Germany, http://www.informatik.uni-rostock.de/~ct/

[44] Chung, D., Legg, P., Parry, M., Bown, R., Griffiths, I., Laramee, R., Chen, M., 2013. Glyph sorting: Interactive visualization for multi-dimensional data, arXiv preprint arXiv:1304.2889.

[45] Li, X., Hu, S. 2013. Poisson coordinates visualization and computer graphics, IEEE Transactions on, 19(2), 344 – 352.

[46] Liu, Z., Jiang B., Heer, J. 2013. imMens: Real-time visual querying of big data, Computer Graphics Forum (Proceedings of the EuroVis), 32(3), 421-430.

[47] Eidenzon, D., Volovodenko V, 2009. Method for visualization of multidimensional data, Patent Application 20090252436, USA.

[48] Eidenzon, D., Volovodenko, V., Shamroni, D. 2013. Method and system for multidimensional data visualization, Saarbrücken: Lambert Academic Publishing.

[49] Eidenzon, D., Pilipczuk, O. 2015. Multidimensional data visualization, Encyclopedia of Information Science and Technology, IGI-Global, Hershey, 1600-1610.

[50] Andrews, D. 1972. Plots of High Dimensional Data, Biometrics 28, 125–136.

[51] Inselberg, A. 1996. Parallel Coordinates: A guide for the Perplexed, in Hot Topics Proc. of IEEE Conference on Visualization, IEEE Computer Society, Los Alamitos, CA, 35-38.

[52] Kostrzewa-Michalik, A. 2010. Obserwacja pacjenta na sali pooperacyjnej, Magazyn Pielęgniarki i Położnej, 4.

[53] De Waard, D. 1996. The Measurement of Drivers' Mental Workload., University of Groningen, Groningen.

[54] Borland D., Taylor R. M. 2007. Rainbow color map (still) considered harmful, IEEE CG&A 27 (2), 14-17.

8. APPENDIX

Table 1. The patient daily observation data.

Time	State of consciousness	Pressure	Pulse	Respiratory rate	Diuresis	Skin	Mucosa	Tempetature	Wound condition			Pain	Mental state
									Appearence	Drain	Bile		
12:00	13	90/60	88	18	45	2	2	36.25	3	3	0	1	2
13:00	14	90/60	85	20	50	2	2	36.3	3	5	0	2	2
14:00	15	95/60	87	24	45	2	2	36.65	3	8	0	5	3
15:00	15	100/60	82	25	42	2	2	36.75	3	5	0	5	2
16:00	15	100/60	77	22	40	2	2	36.6	3	3	0	2	2
17:00	15	100/60	76	22	55	2	2	36.6	3	7	0	2	2
18:00	15	100/60	76	22	55	1	2	36.65	3	3	0	2	2
19:00	15	105/60	77	23	45	1	2	36.75	3	2.3	0	4	2
20:00	15	115/70	91	29	48	1	2	36.8	3	0.7	0	6	2
21:00	15	115/70	81	22	47	1	2	36.95	3	0.1	0	2	2
22:00	13	110/70	75	21	35	1	2	37.0	3	0	0	2	2
23:00	13	110/70	77	20	31	1	2	37.1	3	0	0	1	2
00:00	13	105/70	76	20	37	1	2	37.1	3	0.1	0	1	2
01:00	15	110/70	94	27	38	1	2	37.3	2	0.5	0	6	3
02:00	15	120/70	85	24	42	1	2	37.0	2	0.05	0	4	2
03:00	13	120/70	75	22	45	1	2	36.9	2	0	0	1	2
04:00	13	120/70	75	22	47	1	2	36.85	3	0	0	1	2
05:00	13	120/70	74	22	42	1	2	36.85	3	0	0	1	2
06:00	13	120/70	75	22	44	1	2	36.8	3	0	0	1	2
07:00	14	120/70	78	26	44	1	2	36.8	3	0	0	5	2
08:00	15	125/75	92	28	54	1	2	36.85	3	0	0	6	2
09:00	15	120/75	84	23	58	1	2	36.8	3	0	0	2	2
10:00	15	120/75	79	22	62	1	2	36.8	3	0	0	2	2
11:00	15	115/70	79	21	61	1	2	36.8	3	0	0	2	2
12:00	15	90/60	77	21	62	1	2	36.55	3	0	0	3	2
min	**3**	**90/60**	**55**	**6**	**5**	**1**	**1**	**35.5**	**1**	**0**	**0**	**0**	**1**
max	**15**	**140/90**	**105**	**34**	**60**	**3**	**3**	**38.0**	**5**	**20**	**10**	**10**	**3**
optim	**15**	**120/80**	**75**	**17**	**45**	**1,2**	**2**	**36.4-36.8**	**3**	**0**	**0**	**1**	**2**