The 33rd Annual Conference of the Japanese Society for Artificial Intelligence, 2019

Multimodal Neural Network-based Health Platform for Knowledge Decision-Making

Joo-Chung Kim[1], Ji-Won Baek[2], Hyun Yoo[3], Kyungyong Chung[*4]

[1,2]Data Mining Lab., Dept. of Computer Science, Kyonggi University, South Korea

[3]Dept. of Computer Information Engineering, Sangji University, South Korea

[*4]Division of Computer Science and Engineering, Kyonggi University, South Korea

There is a need for artificial intelligence-oriented information technologies (aimed at continuous monitoring and life-care of chronic diseases through health platforms) that can discover potential health-risk-factor changes and predict emerging risks. In this paper, we propose a multimodal neural network-based health platform for knowledge decision-making. The proposed method learns the relationships present between heterogeneous data and the multimodal neural network, and extracts the common information shared between the modals to estimate health-risk factors. The correlation of variables appearing in the health platform is used to construct a multimodal neural network, and shared common information is combined to estimate the health-risk factors. The correlations of the variables are shown as positive correlations and negative correlations. A positive correlation indicates a relationship in which two variables change in the same direction, and a negative correlation indicates a relationship in which they change in a different direction. The proposed multimodal neural network is used to solve the health-risk–factor problem in the health platform, improving the reliability of the data.

1. Introduction

Due to the development of information-gathering technology, a variety of data is gathered from various fields, such as society, science, and industry, and is being accumulated as big data (Rho et al., 2015). This is characterized by a continuous increase in volume, rapid change, and various properties (Chung and Roy, 2016). Especially in the health platform, the scope is expanding with the development of information processing and collection technologies such as the electronic medical record (EMR), personal health record (PHR), and life-log (Kim and Chung, 2017). In a health platform, data are mainly continuous, changing over time. Data related to human health are affected by internal and external environments. Health status changes over a short period of time or over a long period of time from variables such as weather, physical information, nutrition, and activity, etc. (Larose et al., 2014; Kim and Chung, 2018; Yoo and Chung, 2018). In these health data, the collection range changes depending on the user's surrounding environment or the device held. Missing values are likely to be generated in collected data due to differences in environments or devices among users (Sarwar et al., 2001; Chung et al., 2016). In particular, devices using low power have difficulty collecting real-time data, leading to missing values. In addition, even if the same type of device is used, the obtained data may show different properties.

Previous research (Kim and Chung, 2018) presented data mining of health-risk factors using the PHR, the EMR, and health status similarities from medical big data in a hybrid peer-to-peer (P2P) network environment. This data mining is used to provide a health service and a user-oriented healthcare promotion service for chronic diseases requiring constant care, life care, and elderly health care in health platforms. In addition, the present study predicts the potential health status of chronic diseases using a similarity-based sequence-mining algorithm.

This study is organized as follows: Section 2 describes the related researches of the health-risk factors of the health matrix, Section 3 describes the proposed multimodal neural network-based health platform for knowledge decision-making, Section 4 describes the multimodal based ontology mining for an adaptive knowledge processing, and Section 5 provides a conclusion

2. Related Works

Medical big data have a health-risk–factor problem in which the values of certain properties are missing due to human, natural, and mechanical errors in the collection process (Kim et al., 2017). Health-risk factors create a null state where there is no value for a variable or property at a particular point in time (Kim et al., 2014; Chung and Lee, 2004). Health factors are an important issue in data analysis and utilization, and various studies are under way to solve this problem. In addition, a higher percentage of missing values causes problems in the reliability of the results from a data analysis (Jung and Chung, 2016; Yoo and Chung, 2018; Phanich et al., 2010).

Health-risk–factor processing mainly uses value estimation or a substitution method, and if the influence of a property causing a large amount of health-risk factors is small, the property itself is removed. There are various methods to deal with health-risk factors: mean/median value substitution, the artificial neural network, the regression model, k-nearest neighbors, and collaborative filtering. Of the various methods, artificial neural networks have received much attention in recent years. This is an issue in various fields, such as object recognition, classification, and artificial intelligence, as well as in health-risk–factor estimation (EI-Dosuky et al., 2010; Jung and Chung, 2016; Kim

Contact: Kyungyong Chung, Kyonggi University, South Korea, 82-10-6362-4555, dragonhci@gmail.com

et al., 2014). In an artificial neural network, nodes and weights can be flexibly configured according to data characteristics.

3. Multimodal Neural Network–based Health Platform for Knowledge Decision-Making

3.1 Data Features in Health Platforms

Health data can be collected based on the same time, and they show a time-series characteristic that varies with time. An analysis of this makes it possible to distinguish whether the variables are positively or negatively correlated (Specht, 1993; Deshpande and Karypis, 2004; Chung et al., 2018). The closer the variables are to -1, the higher the negative correlation, and the closer to +1, the higher the positive correlation (Orciuoli and Parente, 2017; Adomavicius and Tuzhilin, 2015). Figure 1 shows the process of health-risk factors in health platforms.

In addition, being closer to 0 indicates that the two variables have no effect on each other. In this paper, health-risk factors are estimated through the neural network configuration using the correlations between variables.

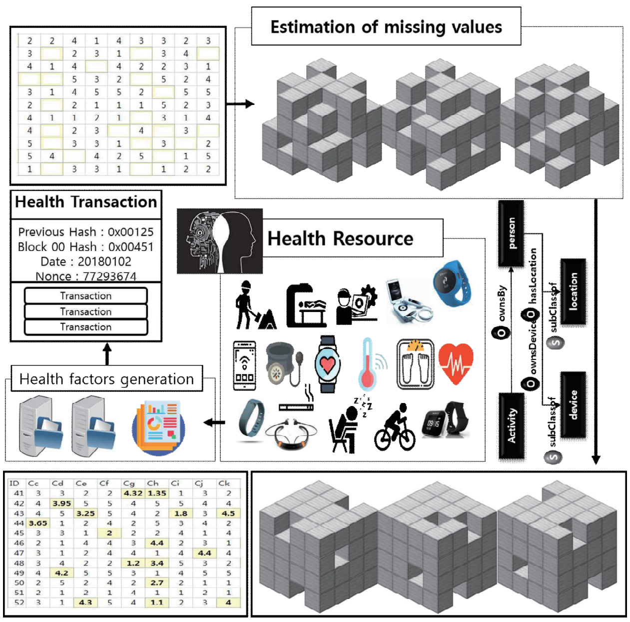

Figure 1 Process of health-risk factors in health platform

3.2 Mining Health-risk Factors using a Multimodal Neural Network

This is a correlation-based neural network for estimating health-risk factors in the platform. Figure 2 shows the estimation of health-risk factors using a multimodal neural network in a health platform.

Positive correlations and negative correlations between the variables are analyzed, and the variables representing positive correlations are grouped into neural networks. According to the results of the analysis, a fully connected network is constructed with input values by grouping the variables with a high positive correlation. This makes it possible to estimate the health-risk factors appearing in the health data. The relationship between multimodals is learned from large-capacity heterogeneous data, and common information shared between modals is extracted from multimodal input based on it.

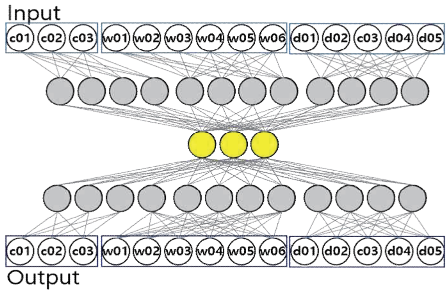

Figure 2 Process of health-risk factors in health platform

4. Multimodal based Ontology Mining for Adaptive Knowledge Processing

4.1 Adaptive Ontological Knowledge Representation

Health platforms use ontology-reasoning engines to express knowledge based on natural language. Mining is used to discover rules and to create knowledge using the discovered reasoning rules. In addition, knowledge is expanded by using inference engines according to the changing situations. Ontological knowledge representation specifies the relationship between data and attributes, and creates adaptive knowledge using language-based sequence tagging models. It consists of a top-level ontology for real-time service, and expansion in the previously developed health ontology (Chen and Tsai, 2018; Orciuoli and Parente, 2017). Figure 3 shows an adaptive ontological knowledge representation using ontology-reasoning engines.

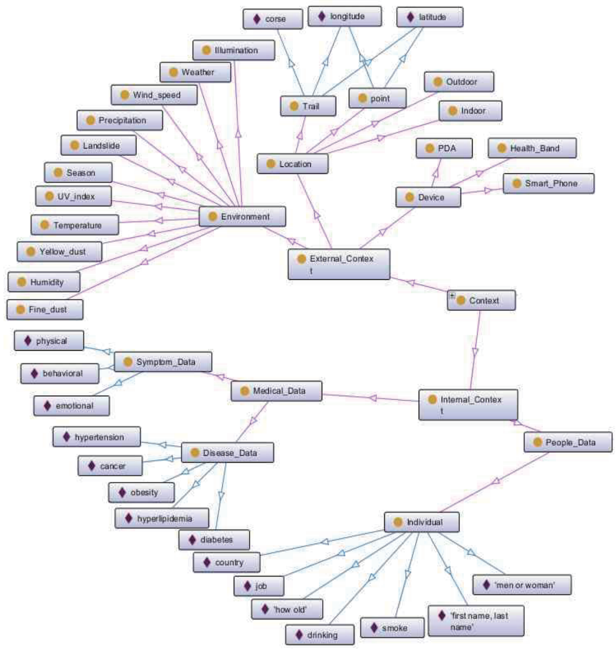

Figure 3 Adaptive ontological knowledge representation

The mining model is derived by using optimal tag prediction methods, using tag accuracy that is generated repeatedly by acquiring and refining natural language–based knowledge. An ontological knowledge model is also used to develop knowledge representation, knowledge-type conversion, and generation technologies to deal with learning data in three dimensions (Adomavicius and Tuzhilin, 2015). This can resolve the problem of a shortage in learning data by increasing the utility of learning and the use of knowledge. Knowledge is efficiently integrated and managed by configuring mining models according to predefined learning models. The model is configured to improve time, cost, and the integrity of knowledge management.

4.2 Multimodal-based Ontology Mining in Health Platforms

In the health platform, a mining model discovers association rules by constructing transactions from ontological knowledge. The life-log is collected in real-time through ambient sensors and is processed using multimodal knowledge acquisition technologies. In order to acquire knowledge based on natural language, a model is developed to extract and refine data that are considered knowledge from unstructured, semi-structured, and structured data. In the case of incomplete knowledge about the acquired information, characteristics that have not been acquired from the knowledge are inferred through mining using deep learning (Kim et al., 2014; Kim and Chung, 2017). Behavioral tips or potential risks are provided based on the inference rules related to healthcare. Users can avoid or prevent health risks by reflecting information they receive from making decisions based on behavioral predictions in their daily lives. In addition, changes in time series data are predicted through mining to provide warnings and countermeasures to users. Figure 4 shows the multimodal-based ontology mining process of health data sources, knowledge collection, knowledge processing, and knowledge analysis in health platforms.

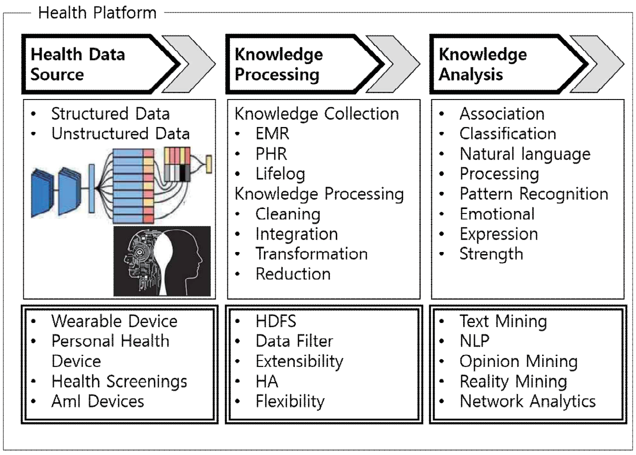

Figure 4 Multimodal-based ontology mining process

5. Conclusion

In this paper, we proposed a multimodal neural network-based health platform for knowledge decision-making. This is solved by a multimodal neural network that extracts common information about health-risk factors from multiple heterogeneous devices. In order to reflect the dynamic characteristics of the time series data, the variables showing a high correlation are grouped into multimodal neural networks for each cluster, and the health-risk factors are estimated by integrating them. The correlations between the variables were positively correlated with negative correlations. By using the proposed multimodal neural network, it is possible to construct the data with higher reliability in the health platform when estimating health-risk factors.

Acknowledgments

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. NRF-2016R1D1A1A09917313)

References

[1] M. J. Rho, K. S. Jang, K. Y. Chung, I. Y. Choi, "Comparison of Knowledge, Attitudes, and Trust for the Use of Personal Health Information in Clinical Research", Multimedia Tools and Applications, Vol. 74, No. 7, pp. 2391-2404, 2015.

[2] K. Chung, Roy C. Park, "PHR Open Platform based Smart Health Service using Distributed Object Group Framework", Cluster Computing, Vol. 19, No. 1, pp. 505-517, 2016.

[3] J. C. Kim, K. Chung, "Depression Index Service using Knowledge based Crowdsourcing in Smart Health", Wireless Personal Communication, Vol. 93, No. 1, pp. 255-268, 2017.

[4] D. T. Larose, C. D. Larose, "Discovering Knowledge in Data: An Introduction to Data Mining", John Wiley & Sons, 2014.

[5] J. C. Kim, K. Chung, "Mining Health-Risk Factors using PHR Similarity in a Hybrid P2P Network", Peer-to-Peer Networking and Applications, Vol. 11, No. 6, pp. 1278-1287, 2018.

[6] B. Sarwar, G. Karypis, J. Konstan, J. Riedl, "Item-based collaborative filtering recommendation algorithms", In Proc. of the 10th international conference on World Wide Web, pp. 285-295, 2001.

[7] K. Chung, J. C. Kim, R. C. Park, "Knowledge-based Health Service considering User Convenience using Hybrid Wi-Fi P2P", Information Technology and Management, Vol. 17, No. 1, pp. 67-80, 2016.

[8] J. C. Kim, K. Chung, "Depression Index Service using Knowledge based Crowdsourcing in Smart Health", Wireless Personal Communication, Vol. 93, No. 1, pp. 255-268, 2017.

[9] J. H. Kim, D. Lee, K. Y. Chung, "Item Recommendation based on Context-aware Model for Personalized u-Healthcare Service", Multimedia Tools and Applications, Vol. 71, No. 2, pp. 855-872, 2014.

[10] K. Y. Chung, J. H. Lee, "User Preference Mining through Hybrid Collaborative Filtering and Content-based Filtering in Recommendation System", IEICE Transaction on Information and Systems, Vol. E87-D, No. 12, pp. 2781-2790, 2004.

[11] H. Jung, K. Chung, "Knowledge-based dietary nutrition recommendation for obese management", Information Technology and Management, Vol. 17, No. 1, pp. 29-42, 2016.

[12] H. Yoo, K. Chung, "Mining-based Lifecare Recommendation using Peer-to-Peer Dataset and Adaptive Decision Feedback", Peer-to-Peer Networking and Applications, Vol. 11, No. 6, pp. 1309-1320, 2018.

[13] M. Phanich, P. Pholkul, S. Phimoltares, "Food Recommendation System Using Clustering Analysis for

Diabetic Patients", In Proc. of the International Conference on Information Science and Applications, pp. 1-8. 2010.
[14] M. A. El-Dosuky, M. Z. Rashad, T. T. Hamza, A. H. El-Bassiouny, "Food Recommendation Using Ontology and Heuristics", In Proc. of the International Conference on Advanced Machine Learning Technologies and Applications, pp. 423-429, 2012.
[15] H. Jung, K. Chung, "Life Style Improvement Mobile Service for High Risk Chronic Disease based on PHR Platform", Cluster Computing, Vol. 19, No. 2, pp. 967-977, 2016.
[16] J. H. Kim, J. Kim, D. Lee, K. Y. Chung, "Ontology Driven Interactive Healthcare with Wearable Sensors", Multimedia Tools and Applications, Vol. 71, No. 2, pp. 827-841, 2014.
[17] D. F. Specht, "The General Regression Neural Network-rediscovered. Neural Networks", Vol. 6, No. 7, pp. 1033-1034. 1993.
[18] M. Deshpande, G. Karypis, "Item-based top-n recommendation algorithms", ACM Transactions on Information Systems (TOIS), Vol. 22, No. 1, pp. 143-177, 2004.
[19] K. Chung, H. Yoo, D. E. Choe, "Ambient Context-based Modeling for Health Risk Assessment Using Deep Neural Network", Journal of Ambient Intelligence and Humanized Computing, 2018. DOI: 10.1007/s12652-018-1033-7
[20] T. Chen, H. R. Tsai, "Application of industrial engineering concepts and techniques to ambient intelligence: a case study", Journal of Ambient Intelligence and Humanized Computing, Vol 9, No. 2, pp. 215-223, 2018.
[21] F. Orciuoli, M. Parente, "An ontology-driven context-aware recommender system for indoor shopping based on cellular automata", Journal of Ambient Intelligence and Humanized Computing, Vol 8, No. 6, pp. 937-955, 2017.
[22] G. Adomavicius, A. Tuzhilin, "Context-Aware Recommender Systems", Recommender Systems Handbook pp 191-226, 2015.