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# A Patient's Health Monitoring System Using Wireless Body Area Network

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## **Abstract**

The medical parameters temperature, pressure and heart beat rate of the human body has been measured by means of using respective sensors. Besides this we can keep track the person and also monitor the exact place and environment of the patient by means of using Global positioning system i.e. GPS technology The measured parameters will be sent to the hospital or care taking unit in a regular periodical manner by means of using GSM module. All the above described actions has been taken place without any manual interruption by means of using PIC Micro controller, here PIC micro controller is the heart for controlling the whole system. Using the collected value we are classifying the data into diseased, probably diseased and normal person. By analyzing the tracked records we can able to find the unsanitary regions which is the main cause of source for the diseases.

**Keywords:** Body Area Network, GPS, GSM, MSVM.

#### 1. Introduction

Wireless body area network is an area which is reaching a new step every day. With help of modern sensor elements, different body parameters can be collected in a seamless manner. Now a day because of the user's lifestyle and surroundings the number of diseased person is increasing day by day. To control the spread of these diseases is very important. Many strategies are taken by the health care department to control these diseases. To understand the range of disease spreading can be found for getting the health condition of the entire person in the region.

A real time example in case study of large 2009 pandemic influenza A (H1N1) outbreak to characterize transmission patterns of H1N1 virus in

a school area campus that possesses the property of community structure [2]. According to the social contact information from a detailed epidemiologic investigation of the structure outbreak, we construct new structure in a hierarchical social network they students are staying the apartment building damage occurred and sensor detect damage structure to recover. A compartmental based stochastic model is proposed to simulate the spreading process of the epidemic in the network, finding community outbreaks within small social groups [3]. Existing epidemic control methods are limited due to being unable to collect real time vital signs and dynamic social interaction information at the same time. Support vector machines (SVM) were originally designed for binary classification. How to effectively extend it for multi-class classification is still an on-going research issue. Several methods have been proposed where typically we construct a multi-class classifier by combining several binary classifiers. Some authors also proposed methods

that consider all classes at once. As it is computationally more expensive to solve multiclass problems, comparisons of these methods using large-scale problems have not been seriously conducted. Especially for methods solving multiclass SVM in one step, a much larger optimization problem is required so up to now experiments are limited to small data

sets.

Further, as the social information and health information are available, it is challenging to fuse this information together when they are from different information sources. Now we handle new approach to utilize network create graph based to represent the data and fuse them together. Network graphs are widely used to represent relations between interacting actors or nodes. They can be used to describe the behaviour of epidemics. The



edges in the network graph can be used to represent the presence or strength of a relationship between two nodes. Nodes can represent people and the colour of node scan represent health status (i.e., infected or not) of people [7]. The sensors are gathered information from social care networks and form a new cluster and move to data in remote control network. In existing method using a technique Cluster-based Epidemic Control based on Smartphone-based Body Area Networks they data collection from different sensors, as the social information and health information are ready to forward, and data to be delivered in different destination is very difficult. In this paper, we propose to utilize a network graph to represent the data and fuse them together. Body area network generate graph strategy for different kind of data from different time duration and it represent the relationship between the persons and sensor data. This information is described in as epidemic control model [7]. The data is collected using sensor network the collected data is send to the remote location. The collected data is encrypted before sending. The collected data is classified. The diseased people are identified and necessary action is taken.

## 2. Related works

In order to provide accurate and timely epidemic predictions, which are crucial to effective epidemic control, complete and up-to-date data about public health conditions, robust prediction models and prediction algorithms are all needed. With respect to these, epidemic prediction systems should be highly scalable, efficient and equipped with appropriate prediction models. Our EPIC is designed exactly according to these requirements. It supports epidemic prediction for a very large population. In addition to health conditions from many involved persons (called participants, hereafter), it takes social networks (which are not considered in the previous works) into account in epidemic predications [5]. The dynamic of epidemic outbreak influenced by many factors including host immunity, virus virulence, human behavior, environmental change, social and economical situation, etc. These factors influenced the virus transmission from human society, school to household, but social relationship as a special factor maybe influenced the transmission dynamic of epidemic outbreak in high density population. A stochastic model based on social contacts networks among students is constructed to simulate this outbreak, revealing that epidemic outbreaks commonly occur in local community. Moreover, effectiveness of three quarantine-based interventions is quantitatively studied by our proposed model, finding that community structure of social networks determines the effects these measures. We are to integrate mobile phone (i.e., for social interaction detection) with WBANs (i.e., for vital sign collection) for epidemic source tracing and control. There are some similarities between tracing epidemic sources and computer viruses. However, the techniques of virus source tracing algorithms [8] cannot be used to trace the epidemic data sources because due to different propagation characteristics between the person contagious diseases and computer viruses [4]. The research is main large population approximation results can be summarized as follows. We assuming a large population, sensor control collect and store data with different of the early stages of the epidemic can be approximated by a branching process, where "giving birth" corresponds to "infecting someone" and "dying" corresponds to "recovering from the disease". If the epidemic branching process/epidemic is supercritical it is possible that a large population area should be monitoring epidemic outbreak occurs. If this happens, a balance equation determines the final number of infected added with some Gaussian fluctuation of smaller order [8]. There are some of the new technologies using the remote healthcare systems especially for the elderly people to use person results from BAN. But new methods are gathered data from various machine learning or social health system but use a minimum level of storage so it is very complex to automatic decision support the large data repository. There is an urgent need for new data mining and machine learning techniques to be developed to this end. However, in this paper we propose new techniques for human activity recognition using a smart phone sensor data, and assisted live information of human activities.

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## 3. Data Collection

The user's data is collected using different sensor system. Each user will be having sensor system to monitor his body parameter. The parameter such as temperature, heart rate and pulse oximetry are continuously monitored. As the uses are not stable, so the location of the user is to be monitored. **GSM** Standard for communication. SMS was developed as part of the GSM Communication. Useful when the mobile phone user is not expect to answer or respond immediately. Here the data collected is send as SMS to the remote center along with the location. The values are send very 30min to the health center based on which the data is processed. Before transmitting data using GSM, it will be encrypted for security reason.

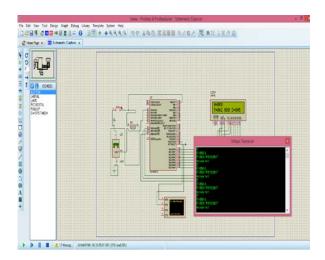
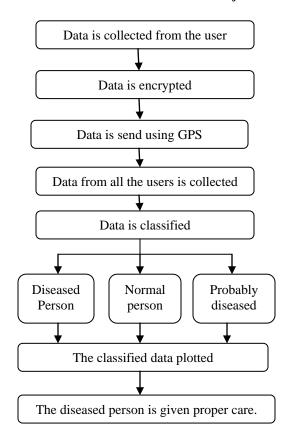


Fig. 1 data collecting system

## 3.1 Data Encryption

Security of the data collected from the patient is very important. Here before sending the data to the remote location the data is secured from any external interference. The data is encrypted using RSA algorithm. The message is encrypted using a secret key. The key is formed using section key which is generated each the time so that no one can hack the data. The key is known only by the user and the authenticated person.

# 4. Data Processing



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Fig 2: flow chart

## 4.1 MSVM data classification

Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for either classification or regression challenges. SVM consists of a learning module and a classification module. The classification module can be used to apply the learned model to new examples. Support Vector Machines only classify data into two classes. The collected values classified using multi support vector machine (MSVM) to categorize based on probably diseased, diseased person, recovered person and normal person.



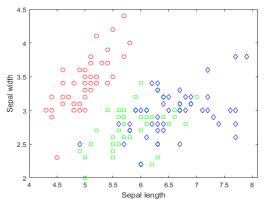


Fig 3: Classified Data

The above figure 3 shows the classified data, here the users are classified into three group based on the collected values. The three groups are diseased, probably diseased and normal person. This classification is done based on some pre defined threshold value. The selection of threshold value depends on the characteristic of the disease being observed. By identifying the probably diseased users, necessary steps can be taken to prevent the disease to spread.

## 4.2 Location tracking

Here with the help of Smartphone we can find the location of the user. By combing the sensed value and the location of the user, the rate and direction of spread of disease can be found. With the help of GPRS we can track the diseased or probably diseased person by which the proper care can be taken. By getting the location details we can also know about the source of the disease.

## 5. Conclusions

Using a sensor network we measured the body parameters. This paper has proposed WBAN sensor to sense the heart rate, blood pressure, temperature of a person, and respiration of the person based on location using GPRS. Patient's information's are encrypted and lively transmitted through GSM to healthcare center every hour. The MSVM (Multi Support Vector Machine) classification algorithms are used to predict the normal person. The diseased nodes are removed from the network. As the time pass the number of diseased person in the network is decreased.

#### References

[1] C. Fraser, C. A. Donnelly, S. Cauchemez, W. P. Hanage, M. D. Van Kerkhove, T. D. Hollingsworth, J. Griffin, R. F. Baggaley, H. E. Jenkins, E. J. Lyons, T. Jombart, W. R. Hinsley, N.C.Grassly, F. Balloux, A. C. Ghani, N. M. Ferguson, A. Rambaut, O. G. Pybus, H. Lopez-Gatell, C. M. Alpuche-Aranda, I.Bojorquez Chapela, E. Palacios Zavala, D. M. Espejo Guevara, F. Checchi, E. Garcia, S. Hugonnet, and C. Roth, "Pandemic potential of a strain of influenza a (H1N1)," Sci., vol. 324, no. 5934, pp. 1557–1561, 2009.

[2] Y. Wang, D. Zeng, Z. Cao, Y. Wang, H. Song, and X. Zheng, "The impact of community structure of social contact network on epidemic outbreak and effectiveness of non-pharmaceutical interventions," in Proc. 6th Pac. Asia Conf. Intell. Secur. Inf., 2011, pp. 108–120.

[3] Z. Zhang, H. Wang, X. Lin, H. Fang, and D. Xuan, "Effective epidemic

control and source tracing through mobile social sensing over WBANs," in Proc. 32nd IEEE Int. Conf. Comput. Commun., 2013, pp. 300–304.

[4] Z. Zhang, K. C. K. Lee, H. Wang, D. Xuan, and H. Fang, "Epidemic control based on fused body sensed and social network information," in Proc. 32nd Int. Conf. Distrib. Comput. Syst. Workshops, Jun. 2012, pp. 285–290.

[5] C. J. Kuhlman, V. S. Anil Kumar, M. V. Marathe, S. S. Ravi, and D. J. Rosenkrantz, "Finding critical nodes for inhibiting diffusion of complex contagions in social networks," in Proc. Eur. Conf. Mach. Learn. Knowl. Discovery Databases, 2010, vol. 6322, pp. 111–127.

[6] N. Mishra, R. Schreiber, I. Stanton, and R. E. Tarjan, "Clustering social networks," in Proc. 5th Int. Workshop Algorithms Models Web-Graph, 2007, pp. 56–67.

[7] R. Nussbaum, A.-H. Esfahanian, and P.-N. Tan, "Clustering social networks using distance-preserving subgraphs," in Proc.Int. Conf. Adv. Soc. Netw. Anal. Min., Aug. 2010, pp. 380–385.

[8] M. S. Handcock, A. E. Raftery, and J. M. Tantrum, "Model-based clustering for social networks," J. Roy. Stat. Soc. Ser. A (Statist. Soc.), vol. 170, no. 2, pp. 301–354, 2007.

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- [9] P. N. Krivitsky and M. S. Handcock, "Fitting latent cluster models for networks with latentnet," J. Statist. Softw., vol. 24, no. 5, pp. 1–
- 23, May 2008. [10] W. O. Kermack and A. G. McKendrick, "A contribution to the mathematical theory of epidemics," Proc. Roy. Soc. London Ser. A, vol. 115, no. 772, pp. 700–721, 1927.
- [11] T. Britton, "Stochastic epidemic models: A survey," Math. Biosci., vol. 225, no. 1, pp. 24–35, 2010.
- [12] M. E. J. Newman, "Spread of epidemic disease on networks," Phys. Rev. E, vol. 66, no. 1, p. 16128, 2002.
- [13] J. C. Miller, "Percolation and epidemics in random clustered networks.," Phys. Rev. E, Stat., Nonlinear Soft Matter Phys., vol. 80, no. 2 Pt 1, p. 020901, 2009.
- [14] T. Zhou, Z.-Q. Fu, and B.-H. Wang, "Epidemic dynamics on complex networks," Prog. Nat. Sci., vol. 16, no. 5, pp. 452–456, 2005.
- [15] B. Hendrickson and R. Leland, "The chaco users guide version 2.0," Sandia Nat. Lab., Albuquerque, NM, USA, Tech. Rep. SAND95-2344, Oct. 1995.
- [16] B. Hendrickson and R. W. Leland, "A multilevel algorithm for partitioning graphs," in Proc. ACM/IEEE Conf. Supercomput., 1995, vol. 95, p. 28.
- [17] G. Karypis and V. Kumar, "Multilevel k-way partitioning scheme for irregular graphs," J. Parallel Distrib. Comput., vol. 48, no. 1, pp. 96–129, 1998.
- [18] R. Cohen, S. Havlin, and D. ben Avraham, "Efficient immunization strategies for computer networks and populations," Phys. Rev. Lett., vol. 91, no. 24, p. 247901, 2002.
- [19] F. Nian and X. Wang, "Efficient immunization strategies on complex networks.," J. Theor. Biol., vol. 264, no. 1, pp. 77–83, 2010.
- [20] M. Salath and J. H. Jones, "Dynamics and control of diseases in networks with community structure," PLoS Comput. Biol., vol. 6, no. 4, p. e1000736, 2010.