Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A PATIENT'S INDOOR POSITIONING ALGORITHM USING ARTIFICIAL NEURAL NETWORK AND SVM

[1]YUSRINA TIFANI, [2]BYUNGKWAN LEE*, [3]EUNHEE JEONG

[1,2]Department of Computer Engineering, Catholic Kwandong University, Gangneung, South Korea

[3]Department of Regional Economics, Kangwon National University, Samcheok, South Korea

E-mail: [1]yusrina@gmail.com, [2]bklee@cku.ac.kr, [3]jeongeh@kangwon.ac.kr
*Corresponding author: ByungKwan Lee

ABSTRACT

This paper proposes a patient's Indoor Positioning Algorithm using Artificial Neural Network and Support Vector Machine (SVM). The proposed algorithm is ANN-SVM which combines Artificial Neural Network and Support Vector Machine to estimate the user position for IPS. The input data for the algorithm consists of Received Signal Strength Indicator and the location vector which is extracted by Access Point. The output is input weight and output weight. The input and output weight are processed by SVM with Room ID data. The last output is the estimated x and the room ID. According to the result of average class loss rate, SVM and ANN-SVM are 0.45 and 0.4, ANN-SVM has lower class loss rate by 0.05 than SVM. The accuracy rate of SVM and ANN-SVM are 65% and 70%. The ANN-SVM has more accuracy rate by 5% than SVM.

Keywords: *Indoor Positioning System, Received Signal Strength, Artificial Neural Network, Support Vector Machine, ANN-SVM*

1. INTRODUCTION

Outdoor Positioning System has become more general in use with GPS (Global Positioning System), GNSS (Global Navigation Satellite System), etc. Even though there are some new GNSS such as Galileo and COMPASS, GPS is still considered as one of the main system for outdoor positioning system. GPS with all the limitations offer a lot more potential with a lot of developments from major countries such as China, India, Japan, and Russia. So it is more common than GNSS nowadays.

However, Indoor Positioning System is still in much of talks. There are several limitations for implementing Indoor Positioning System, such as GPS is not working inside of building, the complexity architecture of the building, the thickness and material of the walls, etc.

There are several ways to overcome these limitations. Some research is using RF (Radio Frequency) sensors embedded in the building environment to detect the user location. The other way is using Wi-Fi and Received Signal Strength Indicator (RSSI), with fingerprinting method. The system estimates the location by the Received Signal Strength Indicator from Wi-Fi AP (Access Point).

In lots of positioning systems, the received signal strength (RSS) values sensed from the known reference nodes are used to calculate the coordinate of unknown objects. Thus, multiple wireless stations are required for RSS based IPSs with appropriate installation. Undoubtedly, such a condition would increase the difficulty of positioning environment deployment and the necessary equipment cost [1].

There are also several ways to process the collected data into estimated location of the user. A lot of Artificial Intelligent ways were implemented to process the data, one of that is Artificial Neural Network. Artificial Neural Network is a way to process data. The model is inspired by human biological neuron networks.

This paper proposes a patient's Indoor Positioning Algorithm using Artificial Neural Network and Support Vector Machine (ANN-SVM).

The remainder of this paper is organized as follows. Section 2 discusses the related works. Section3 proposes a patient's Indoor Positioning Algorithm using ANN-SVM. Section 4 analyzes and estimates its performance. In the Section 5, our conclusion is described.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2. REATED WORKS

There are already several researches about Indoor Positioning System (IPS). IPS are becoming increasingly important as add-ons to today's pervasive wireless technology. Location-aware services are based on some form of positioning techniques. Positioning systems enable context-aware computing with location awareness [2]. In [3] proposed a framework to analyze the indoor position utilizing Euclidean distance between signal vector and fingerprint location. The experiment produced a guideline for designing and applying IPS.

In [4] developed a hybrid algorithm for IPS by combining RF propagation loss (PL) and location fingerprinting (LF). It first formulates the RF propagation loss in a nonlinear, censored regression model and adjusts the regression function to the observed signal strength in the fingerprint dataset. In the absence of a training dataset, the hybrid method coincides with the PL method and as the spatial granularity of training dataset increases, the result of the algorithm approaches the result of the LF method. It balances flexibility and accuracy of the two traditional methods, makes intelligent use of missing values, produces error bounds, and can be made dynamic. That is, in [4] evaluated the performance of the algorithm by applying it to a real site and observed satisfactory positioning accuracy.

Artificial Neural Network (ANN) is also not a new method to be applied for IPS. In [5] developed a system using ANN based on the RSSI (Received Signal Strength Indicator) in Wi-Fi environments. It concluded that the location of the mobile user could be located in the indoor environment with different levels of accuracy and precision depending on the kind of training data set used. The backpropagation method was also compared to a probabilistic model for indoor positioning and performance comparison was made in term of accuracy. It was found that, the back propagation model using directional mean data is more accurate as compared to the probabilistic model using the directional mean data. That is, in [5] utilized backpropagation method for ANN.

Using Received Signal Strength (RSS), fingerprinting is one of the most frequently used techniques for indoor positioning. That is consists of two phases. First phase is called the offline phase in which, the RSS from all the AP is recorded at number of location in the building i.e., generating a location matrix with the "fingerprint" of all the AP at each specific location. The next phase is the online phase, where pattern matching algorithms are used to solve the location matrix and calculate the location of mobile user (MU) by comparing the RSS being observed by the MU with the one recorded in the location matrix. Till now mostly probabilistic algorithms have been used as pattern matching algorithm [6]. Also, in [7] used ANN to process the data: time of arrival (TOA), angle of arrival (AOA) which is collected from three base stations (BSs). The system will calculate the mobile station (MS) based on the collected data [5].

In [8] proposed the use of dynamic neural network to localize the data from Wi-Fi. Dynamic neural network made the connection between RSS, vector position. The time is fixed but the space location is changing continuously. While, in [9] proposed IPS based on physical motion recognition data. The collected data then will be processed with LS-SVM (Least Square-Support Vector Machines).

In [10] used Fuzzy set theory and also applied K-Nearest Neighbor algorithm to process the data localization. The data is collected with Wi-Fi fingerprinting method. While, in [11] used GSM trace mobile to collects the location data of user. It compared SVM, Multilayer Perceptron and Gaussian Process to process the data in the database for estimate the exact location of the user.

In [12] compared ANN and Bayesian Probabilistic to process the collected data. The user location data is collected using WLAN in indoor environments. This study deals with improving the common techniques of such positioning once the acquisition of the fingerprint database in offline phase is performed. The main idea is to propose a methodology that includes two layers of classification: a concurrent hierarchical partitioning of both signal and physical space in a way that signal patterns in each part of building have the highest similarity, and a precise and independent positioning in a given part. A procedure for combining the proposed classifier with either artificial neural network (ANN) or Bayesian probabilistic model is then introduced.

3. A DESIGN OF PATIENT'S INDOOR POSITIONING ALGORITHM

The proposed algorithm in this paper uses the processed data which used Wi-Fi fingerprint technology. This paper compares proposed method (NN-SVM) with ANN (Artificial Neural Network) and SVM (Support Vector Machine).

Journal of Theoretical and Applied Information Technology
31st August 2017. Vol.95. No.16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Figure 1 shows the flowchart of patient's indoor positioning.

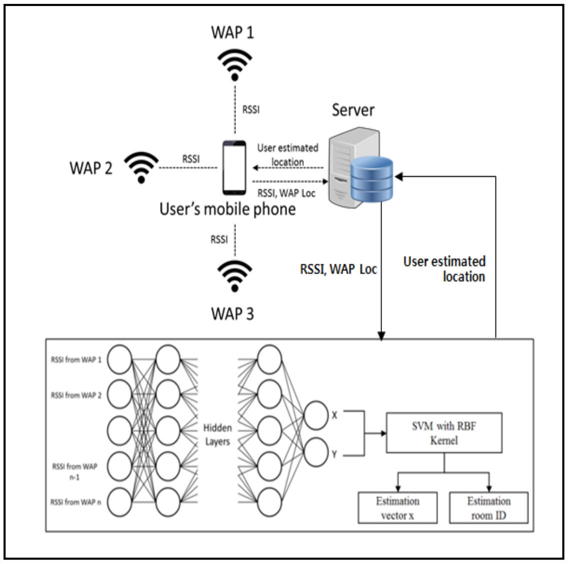


Figure 1: The flowchart of patient's indoor positioning

3.1 Artificial Neural Network (ANN)

ANN is part of Artificial Intelligence and machine learning. ANN is inspired by biological neural networks of human body. The main function of Artificial Neural Network is to estimate functions from a large number of inputs. The process work of ANN is several nodes which connected by each other and exchanging messages between each other. The nodes are divided in several layers, some layers is called hidden layers which the process of resulting function is done. The advantages of using ANN is it could work with linear and non-linear data.

The ANN is used in this paper uses two-layer-feed-forward network and Levenberg-Marquardt backpropagation algorithm. The input data is RSSI from each RP detected by Wireless Access Point. The output of ANN is predicted vector location of the RP which the RSSI information extracted. The number of hidden layer which is used in the ANN is calculated with equation (1).

Number of hidden layers =
(Number of inputs + Number of outputs) x2/3 (1)

The data Gints Jekabsons's Data Set contains of calibration data (training data) and test data. The training data consists of RSSI data, RP's vector position and the room ID number position of the extracted ID.

The input is the RSSI data from each RP with the target output is x and y vector of position.

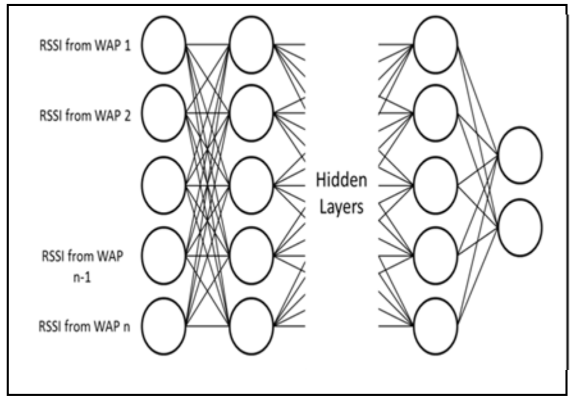


Figure 2: Architecture of Artificial Neural Network

3.2 Support Vector Machine (SVM)

Support Vector Machine is one of machine learning method. RBF kernel is a popular kernel function used in various kernel learning algorithm. In particular, it is commonly used in SVM [13, 14].

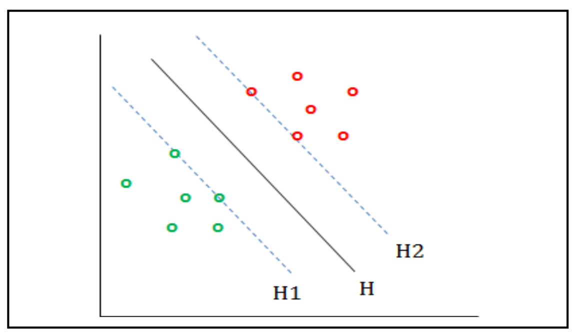


Figure 3: SVM Hyperplane Visualization

In this paper, the SVM is used to localize the position of RP and classify it. The input data which is used are RSSI and the vector location of each RP.

The output is the estimation of x to identify the room ID. The kernel function which is used in the localization is RBF (radial basis function). The RBF calculation is showed in equation (2).

$$K(x, x') = \exp\left(\frac{\|x - x'\|^2}{2\sigma^2}\right) \quad (2)$$

Here, $\|x - x'\|^2$ may be recognized as the squared Euclidean distance between the two feature vectors. σ is a free parameter[15].

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- The 1st step, the input is generated into mapping vectors.
- The 2nd step, RBF kernel is applied to the mapped vectors using equation (2).
- The 3rd step, Weights (*w*) and *b* of each vector are derived using Lagrange Multiplier which is showed in equation (3).
- The last step, x is estimated, and the location of room by Room ID data is estimated.

$$L = \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{ij}^{m}\alpha_i\alpha_j y_i y_j (x_i, x_j) \qquad (3)$$

Support Vector Machine algorithm
1. Generate Mapping Vectors of input 2. Apply RBF kernel (equation 2) 3. Calculate weight (*w*) and *b* with Lagrange Multiplier (equation 3) 4. Estimate x and Room ID

3.3 ANN-SVM

Each WAP will obtain the location of user's mobile phone and record the RSSI of each RP. The technology which is used is Wi-Fi fingerprinting. The collected data is saved in the server and processed using the proposed ANN-SVM method in this paper.

ANN is chosen because ANN can process any data and transform it into approximate function. While, SVM is chosen because SVM maximized margin between vectors so it produces more robust result. The other reason is because SVM can be modeled with kernel function, which in this proposes paper RBF kernel is chosen.

So, the proposed ANN-SVM method in this paper is combined ANN and SVM to estimate the exact location of RP. The input data for ANN-SVM are RSSI and vector position of each RP. Then the data processes in the hidden layers.

Figure 4 shows the architecture of ANN-SVM. The total number of hidden layers is calculated with equation (1). The process in the hidden layer includes calculating activates function, estimated location, estimated location error, delta output weight, output weight, delta input weight, and input weight.

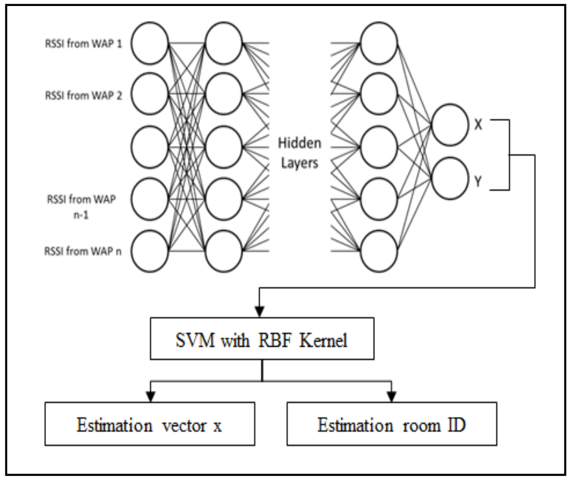


Figure 4: Architecture of ANN-SVM

Then, the input weight and output weight will be processed with Support Vector Machine. The SVM uses RBF kernel with sigma 0.1 and C value is 10. The SVM is trained, validated and tested using cross validation. The final result of the process is estimation RP's vector and estimation of Room ID based on the processed data.

ANN-SVM Algorithm

BEGIN
Generate Random Weight $(Wi_{N+1,N(L)}, Wt_{N(L)})$ in range [-1,1]
FOR j from 1 to N
Calculate output
$y[j]_{N(L)} = RSSI[j]_{N,N+1} \times Wi_{N+1,N(L)}$
Compute activates function
$y[j]_{N(L)} = sigmoid(y[j]_{N(L)})$
Calculate Estimated Location
$x_{est} = y[j]_{N(L)} \times Wt_{N(L)}$
Calculate Estimated Location Error
error[j] = $x_{est}x_{train}$
Calculate Delta Output Weight
$dow_{N(L)} = error[j] \times y_{N(L)}$
Adjust Output Weight
$Wt_{N(L)} = Wt_{N(L)} - (dow_{N(L)})^T$
Calculate Delta Input Weight
$diw_{N(L)} = error[j] \times Wt^T_{N(L)} \times (1 - (y[j]^2))$
$\times RSSI[j]_{N,N+1}$
Adjust Input Weight
$Wi_{N+1,N(L)} = Wi_{N+1,N(L)} - diw_{N(L)}^T$
ENDFOR

Apply Kernel Function (equation 2)
Calculate weight (*w*) and *b* with Lagrange Multiplier (equation 3)
Estimate *x* and Room ID
END

In ANN-SVM algorithm, the output is calculated by multiplying RSSI and the random input weight. The activated function is obtained using sigmoid of vector y[j]. Estimated location is calculated with multiplying vector y[j] and output weight. The estimated location error is multiplying estimated location and x_{train}. The delta output weight is obtained using estimated location error multiplied by vector y, and output weight is calculated by output weight minus by delta output weight. The delta input weight is calculated by multiplying estimated location error, output weight, RSSI and one minus by vector y. The obtained delta input weight is used to calculate input weight with subtract input weight with delta input weight. N is the number of hidden nodes. L is the number of the hidden layers.

ANN-SVM is aiming for less class loss rate than using ANN or SVM alone in processing the data. Automatically, with less class loss rate ANN-SVM also aims to have more accuracy rate than SVM or ANN alone.

4. SIMULATIONS

The simulation conducts in ASUS laptop with 2GB RAM and intel core i7 processor. The simulation completes using Matlab. The Gints Jekabsons's Data Set used to train, validate and test the processing system. The simulation conducts with ANN, SVM and ANN-SVM.

This paper uses open source Gints Jekabsons's Data Set [16]. The data collected using Wi-Fi fingerprinting technology. The data contains of RSSI (Received Signal Strength Indicator), position of the reference points (x, y) from GNSS. Reference point (RP) is the user location when the fingerprinting is done.

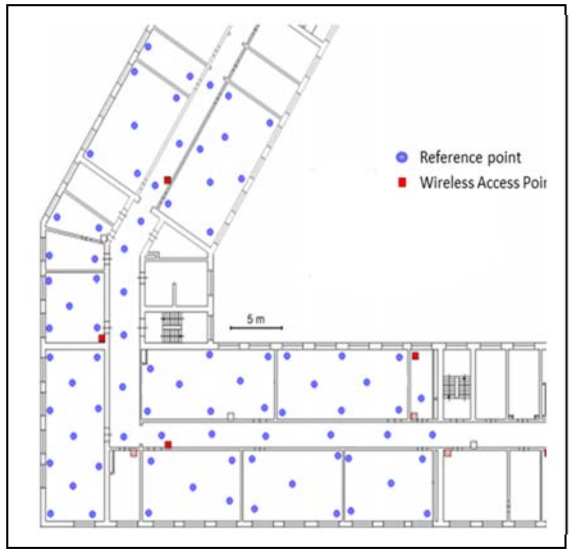


Figure 5: Layout Of The Testes Environment With Reference Points And Access Points

Figure 5 shows the layout of the tests environment with reference points and access points. The area has five WAPs installed, which have been deployed for maximum Wi-Fi internet availability, and can be sensed in at least a third part of the area. A total of 82 reference points are defined. in Figure 5. On average the distance from one reference point to the nearest other point is 3.7m within the same room and 2.6m when also the points from other rooms are considered. The number of Aps that could be sensed from a location ranges from 2 to 13 with average of 7 [17].

Table 1 shows the positon and RSSI of Reference point. The averaged RSSI values range from -99dBm to about -33dBm in close proximity to an AP. Specially, the -99dBm means that AP is not present.

Table 1: The Position And RSSI Of Reference Point

No	Position		RSSIs			
	x	y	1	2	3	4
1	4.75	31.3	-57.525	-79.75	-93.65	-78.7
2	9.27	29.66	-51.45	-64.85	-99	-83.1
3	5.59	25.08	-74.9	-59.925	-80.825	-51.025
4	1.58	25.99	-74.6	-61.175	-80.525	-53.525
5	0.85	22.77	-74.8	-57.5	-73.5	-53.325
6	16.21	24.75	-59.6	-91.55	-99	-99
7	15.25	31.69	-64.05	-95.85	-99	-99
8	16.21	28.93	-60.025	-90.425	-99	-99
9	19.21	29.21	-62.8	-96.55	-99	-99
10	28.76	9.83	-97.95	-80.775	-99	-97

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

11	23.56	14.41	-93.1	-79.2	-99	-85.525
12	23.11	9.66	-97.4	-81.075	-99	-93.5
13	26.16	12.03	-94.4	-80.375	-99	-90.525
14	10.23	9.77	-82.025	-65.675	-94.075	-68.625
15	0.85	16.72	-79.475	-44.625	-70.775	-44.125
81	18.31	5.65	-99	-75.525	-99	-93.15
82	18.08	2.26	-99	-79.175	-99	-99

Figure 6 shows the mean squared error result of ANN. The graph showed the result of training, validation and test of dataset using ANN. The overall best result is in epoch 4, when validation is done. The best result for test also in epoch 4.

The ANN regression result plot is showed in Figure 7. The regression result plot consists of training, validation, test and overall results.

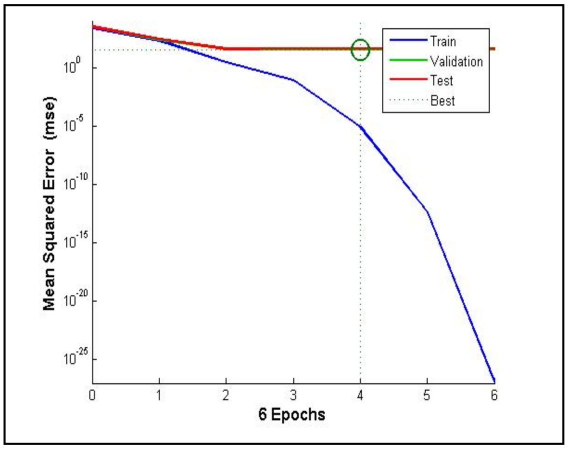
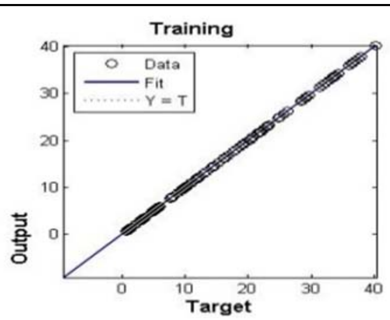
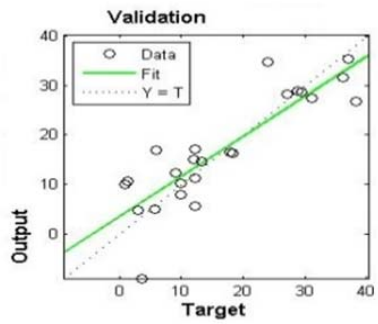


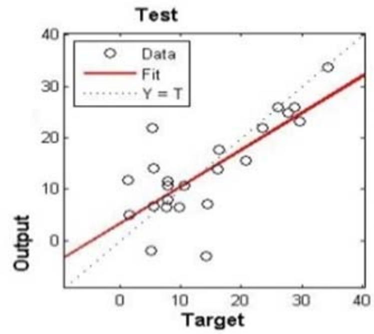
Figure 6: ANN Performance Graphic



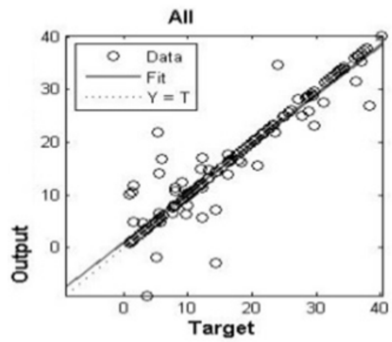
(a) Training



(b) Validation



(c) Test



(d) All

Figure 7: ANN Regression Result

SVM process is conducted using MATLAB, utilizing the Spider [18] toolbox. The Spider is an object oriented environment for machine learning in MATLAB. The SVM which is used for localization process is adjusted using the algorithm which has been explained in section 3.2. The SVM implements the kernel trick, RBF. The qualification of the RBF is in Table 2.

Table 2: SVM RBF Qualification

Sigma	C
0.1	10

The ANN-SVM is implemented as the algorithm which is explained in the section 3.3. It combines ANN and SVM. The code is made by editing the Spider SVM feature with ANN algorithm which is made before. Cross validation is used to examine the work process of SVM and ANN-SVM.

Figure 8 shows the comparison result of class loss rate of SVM and ANN-SVM based on total number of folds used to examine the process. ANN-SVM shows a higher class loss rate than SVM in 2 folds. From folds 6 until 20, ANN-SVM shows lower result of class loss rate than SVM. In folds 6 SVM shows 0.5 class loss rate while ANN-SVM has 0.4. In 10 folds, SVM obtains 0.4 while ANN-SVM get 0.3 class loss rate. SVM has 0.5 while ANN-SVM get 0.4 class loss rate in 12 folds. The 18 folds show the biggest difference between SVM and ANN-SVM, SVM obtains 0.5 class error rate while ANN-SVM obtains 0.3. In 20 folds, SVM get 0.5 and ANN-SVM has 0.4 class loss rate. However, SVM and ANN-SVM show the same result of class loss rate in 4, 14, and 16 folds.

The highest class loss rate for SVM and ANN-SVM are 0.5. However, the lowest class loss rate for SVM is 0.4 while for ANN-SVM is 0.3.

Figure 8: Compared SVM and ANN-SVM Class Loss Rate based on the total number of fold

Table 3: SVM Class Loss Rate

Folds	SVM class loss RBF
2	0.4
4	0.5
6	0.5
8	0.4
10	0.4
12	0.5
14	0.4
16	0.4
18	0.5
20	0.5

Table 4: ANN-SVM Class Loss Rate

Folds	ANN-SVM class loss RBF
2	0.5
4	0.5
6	0.4
8	0.4
10	0.3
12	0.4
14	0.4
16	0.4
18	0.3
20	0.4

Table 5 shows the average of class loss rate of SVM and ANN-SVM. The SVM average class loss rate is 0.45 while ANN-SVM average class rate loss is 0.4. ANN-SVM has lower average class rate loss by 0.05. This proves ANN-SVM provides less class loss rate than SVM, which resulting more accuracy.

Table 5: The comparison of Average Class Loss Rate

Algorithm	Average Class Loss Rate
SVM	0.45
ANN-SVM	0.4

The accuracy rate is calculated using equation (4). Table 6 shows the accuracy rate between SVM and ANN-SVM.

$$\text{Accuracy} = \frac{\sum \text{True positive} + \sum \text{True negative}}{\sum \text{Total population}} \quad (4)$$

Table 6: The comparison of Accuracy Rate

Algorithm	Accuracy Rate
SVM	65%
ANN-SVM	70%

SVM has 65% accuracy rate, while ANN-SVM has 70% accuracy rate. ANN-SVM shows

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5% increase in accuracy than SVM. This proves ANN-SVM offers a more accurate result than SVM. The overall result proves that ANN-SVM is better than SVM.

5. CONCLUSIONS

This paper proposes a data processing data from indoor positioning system using Artificial Neural Network and Support Vector Machine. The algorithm is ANN-SVM, ANN-SVM combines Artificial Neural Network and Support Vector Machine to estimate the user position for IPS. The input data for the algorithm consists of Received Signal Strength Indicator and the location vector which is extracted by AP. The data processed, the output is input weight and output weight. The input and output weight then processed by SVM with Room ID data. The last output is the estimated *x* and the room ID.

This paper simulates the data processed by ANN, SVM and ANN-SVM. In ANN the best result is when validation in epoch 4 based on MSE (Mean Squared Error). The average class loss rate of SVM and ANN-SVM are 0.45 and 0.4. ANN-SVM has lower class loss rate by 0.05 than SVM. The accuracy rate of SVM is 65% while ANN-SVM has 70% accuracy rate. The ANN-SVM has 5% more accuracy rate than SVM.

6. ACKNOWLEDGMENTS

This work was supported by research fund of Catholic Kwandong University (CKURF-201603570001).

REFRENCES:

[1] Chih-Yung Chen, Yu-Ju Chen, Ya-Chen Weng, and Rey-Chue Hwang, "A Neural-Network-based Indoor Positioning System by Usng Sectored Antenna Array," *International Journal of New Technology and Research (IJNTR*), Vol.2, No.3, March 2016, pp.26-29.

[2] J. Small, A. Smailagic, and D. P. Siewiorek, "Determining User Location For Context Aware Computing Through the Use of a Wireless LAN Infrastructure", Dec. 2000. 01/04/2016 http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.483.2448&rep=rep1&type=pdf

[3] K. Kaemarungsi and P. Krishnamurthy, "Modeling of indoor positioning systems based on location fingerprinting," *In INFOCOM 2004. Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies,* Vol. 2, April 2004, pp.1012-1022.

[4] J. Kwon, B. Dundar, and P. Varaiya, "Hybrid algorithm for indoor positioning using wireless LAN," *Vehicular technology conference, VTC2004-Fall, 2004 IEEE 60th*, Los Angeles, CA, USA, 26-29 Sept. 2004, pp. 4625-4629.

[5] H. Mehmood, N.K. Tripathi, and T. Tipdecho, "Indoor positioning system using artificial neural network," *Journal of Computer science*, Vol. 6, No. 10, 2010, pp.1026-1212.

[6] Kupper, A., "Location-Based Services Fundamentals and Operation," 1st Edition, Wiley, USA. ISBN: 13: 978-0470092316, 2005, pp: 286.

[7] C. S. Chen, "Artificial neural network for location estimation in wireless communication systems," *Sensors*, Vol.12, 2012, pp.2798-2817.

[8] D. Fahed and R. Liu, "Wi-Fi-based localization in dynamic indoor environment using a dynamic neural network," *International Journal of Machine Learning and Computing*, Vol. 3, No.1, 2013, pp. 127-131.

[9] L. Pei, J. Liu, R. Guinness, Y. Chen, H. Kuusniemi, and R. Chen, "Using LS-SVM based motion recognition for smartphone indoor wireless positioning," *Sensors*, Vol.12, 2012, pp.6155-6175.

[10] P. Torteeka and X.I.U. Chundi, "Indoor positioning based on wi-fi fingerprint technique using fuzzy k-nearest neighbor," *Applied Sciences and Technology (IBCAST), 2014 11th International Bhurban Conference on,* Islamabad, Pakistan, 14-18 Jan. 2014, pp.461-465.

[11] I. Ahriz, Y. Oussar, B. Denby, and G. Dreyfus, "Full-band GSM fingerprints for indoor localization using a machine learning approach," *International Journal of Navigation and Observation*, Vol.2010, 2010, pp.1-7.

[12] Vahidnia, M. H., Malek, M. R., Mohammadi, N., and Alesheikh, A. A. "A hierarchical signal-space partitioning technique for indoor positioning with WLAN to support location-awareness in mobile map services," *Wireless personal communications*, Vol.69, No.2, 2013, pp. 689-719.

[13] Yin-Wen Chang, Cho-Jui Hsieh, Kai-Wei Chang, Michael Ringgaard and Chih-Jen Lin "Training and testing low-degree polynomial data mappings via linear SVM," *Journal of*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Machine Learning Research **11**, 2010, pp.1471–1490.

[14] Jean-Philippe Vert, Koji Tsuda, and Bernhard Schölkopf, "A primer on kernel methods," *Kernel Methods in Computational Biology*. 2004.

[15] Radial based function kernel, 01/04/2016 https://en.wikipedia.org/wiki/Radial_basis_function_kernel

[16] Gints Jekabsons's Data Set, 01/04/2016 http://www.cs.rtu.lv/jekabsons/datasets.html

[17] Gints Jekabsons, Vadim Kairish, and Vadim Zuravlyov, "An Analysis of Wi-Fi Based Indoor Positioning Accuracy," *Scientific Journal of Riga Technical University Computer Science. Applied Computer Systems,* Vol. 47, 2011, pp.131-137.

[18] The Spider for Matlab, Version 1.71, 01/04/2016, http://people.kyb.tuebingen.mpg.de/spider/main.html