Velocity Classification Model Based on Artificial Neural Network for SCTP

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ABSTRACT

The current and future trend of mobile communications is moving towards highly mobile and ubiquitous environment which consists of latest radio access technologies, such LTE and WiMAX, and previous ones such as wireless LAN which creates a heterogeneous environment. In exploiting this kind of environs, this manuscript introduced a novel **V**elocity-centric **A**CO-inspired (Ant Colony Optimization) **S**CTP **H**andover system (VASH), with specific discussion focused on a Velocity Classification Model (VCM) which enables the handover system to adapt its decision mechanism with the changes in the mobile node's velocity. The proposed VCM is designed using the artificial neural network (ANN). From the experimental evaluation, it can be concluded that the proposed model can classify the velocity of the mobile node accurately.

Keywords: *SCTP, handover, neural network, velocity classification.*

1 INTRODUCTION

In this day and age as well as the coming future, most of the communication devices which are becoming the necessity of the users consist of mobile devices such as smartphones and mobile tablets. Furthermore, with the introduction of the latest wireless broadband (WBB) technology such as the WiMAX (Worldwide Interoperability for Microwave Access) [1] and the 3GPP Long Term Evolution (LTE/LTE-Advanced) [2] which are part of the fourth generation wireless-communication technology (4G), more working equipment with more powerful specifications such as high-end laptops and tablets are equipped with the capability to access these 4G WBBs. Meanwhile, for users with devices that do not come with these capabilities, most Internet service providers (ISP) offers an alternative to connect to a WBB network by providing a mobile modem which creates a wireless LAN (WLAN) network for subscribers anywhere they like. In a nutshell, in this era, users are moving towards mobile services which can be accessed anytime and anywhere they like.

When considering a wireless network environment, it is obvious that the mobile devices will not always be connected to the same network while the users are moving. Hence, in order to maintain continuous connection to the network, a handover (HO) procedure is unavoidable. Furthermore, to widen the coverage area available for the users as well as to add more flexibility, a handover scheme that offers the ability to traverse from one radio access technology (RAT), for example, WLAN, to another different RAT, for example WiMAX or LTE, and vice-versa is most desirable. The heterogeneity of current and future RAT makes it possible to overcome the limitations of the different RATs available by initiating a vertical handover (VHO) [3].

A lot of discussion and debates on the layer best suited for mobility (handover initiation and process in particular) have been done in the field of network handover research. According to [4], the most suitable layer for handover is the Transport layer. Moreover, on the transport layer, the Stream Control Transmission Protocol (SCTP) is a new protocol which offers the best features to cater for a seamless handover [5]. This protocol has been implemented in some of the latest researches in this field [6], [7]. These works initiates the handover process by referring to the received signal strength (RSS) and the end-to-end delay (ETED) between two connected nodes based on static threshold values, thus, limiting the handover scheme to the threshold restrictions. Consequently, the specific threshold might give the optimal handover performance for certain situations, but may not be the best for other different situations.

In order to enhance the flexibility and scalability of the handover system, several factors can be considered in determining the right configuration for the right scenario. These works in particular, [8] and [9], shows that a different threshold configuration can give different performance outcomes. Hence, in this manuscript, a novel HO system which is initiated on the transport layer using the SCTP protocol and an Ant Colony Optimization (ACO) inspired selection rule. Then, in order to enhance the ability of the HO system to adapt to different types of scenarios, a practical velocity estimation algorithm will be discussed in this work. The contribution of this manuscript can be summarized as follows:

- The main contribution of this manuscript; a practical velocity classification model (VCM) using artificial neural network (ANN) is proposed, and the simulation results shows that the VCM can classify the velocity of the mobile node (MN) accurately.
- Proposing a novel handover system implemented on SCTP with a handover target selection algorithm inspired by ACO. Then the selection algorithm is expected to adapt to the velocity classification of the mobile node (MN) based on the VCM.

This paper is organized as follows: Section 2 reviews the related work. Section 3 describes the proposed handover system. A novel ANN velocity classifying model is proposed in section 4. In section 5 the effectiveness of the proposed VCM is thoroughly evaluated. Finally, section 6 concludes this work and draws out the conclusion and future research directions.

2 RELATED WORK

Many researches on handover initiation and handover strategy have been done and are still continuing. A summary of the basis of handover design have been discussed in [9]. One of the most used parameters in HO initiation is the RSS. Then in order to prevent the *ping-pong* effect, the RSS value is used with either threshold or hysteresis, or even both of them at once. From this study, it can be understood that the threshold selection is a crucial point which will affect the performance of a handover design. From [9], the idea of using RSSI is established as the most basic and maybe the most effective parameter to be considered for a HO initiation.

Next, in [10], the authors studied the drawback of the handover initiation method implemented in the traditional SCTP, which is, in nature, failure-centric. The SCTP originally initiates a HO when the current primary path or network connection fails four times consecutively (meaning after four retransmission time out (RTO)). The work in [10] proposes a delay-centric HO initiation approach, where the end-to-end delay is used as the initiating parameter. The ETED signifies the congestion level of the corresponding network, where a long ETED signifies that the network is congested, whilst a short ETED shows that the network is free. Hence, this parameter is also of importance in commencing a HO.

A synergistic approach where parameters used in both previous works, [9] and [10], have been proposed in [6] and [7]. The authors of [6] have proposed an endpoint-centric handover, which considers both MOS (Mean Opinion Score) and RSS in the HO decision and initiates the HO on SCTP. This scheme constantly checks the MOS and RSS, and when one of the parameters hits a threshold, a HO decision will be made. Similar to this work, [7], uses the ETED and RSS as the decision criteria, proposes a more simplistic HO decision by implementing the ACO probabilistic equation as the path or target network selector. Both methods could overcome the previous works which only consider one HO decision parameter. However, due to the fact that both depend on a certain threshold, both methods will only provide optimal handover outcome for a specific scenario, or specifically, a certain velocity.

In the current high mobility generation, the speed of a MN is also crucial, because service consumers nowadays are always on the go and move at various kinds of speed. Hence, intuitively, some configurations of threshold might be suitable for a certain range of velocity, but might not be suitable for a different range of velocity. This point is strengthened by the conclusions in [11]. Hence, to obtain the velocity of the MN, a velocity estimation model or algorithm is needed.

The authors in [12] discussed about a velocity estimation algorithm based on the Okumura-Hata path loss model. They manipulated the formula and derived a velocity estimation equation in order to trigger the handover. The outcome of the proposed model shows superior handover performance (less ping pong effect) than the traditional way of initiating HO using HO hysteresis margin (HOM) and time-to-trigger HO (TTT) [10]. The estimation obtained has correct estimation with minimal delay which increases as the velocity of the mobile node increases.

Meanwhile, a fuzzy-based handover system which uses three layers of fuzzy logic controllers (FLCs) to classify the MN into two category of velocity, which are, slow (velocity < 40km/h) and fast (velocity > 40km/h) was discussed in [13]. After the speed classification by the first FLCs, the second or the third FLC will then make decision whether to initiate a HO accordingly for when the MN is slow or fast. The speed of the MN is determined using the distance and the error ration. However, the target scenario was for cellular networks, where the distance of the MN from the BS is calculated by the BS itself and the HO process is network initiated. Hence, a more practical proposition on the velocity classification acquisition model is needed for a terminal initiated HO.

This work is the continuation of our previous work in [7] which has already proposed a HO initiation strategy, which is part of a complete system which will be introduced in this work. Then the discussion will be focused on the velocity classification model in section four. In the next section, the components of the HO system will be discussed in more detail.

3 VELOCITY-CENTRIC ACO-INSPIRED SCTP HANDOVER SYSTEM (VASH)

This section discusses the proposed **V**elocity-centric **A**CO-inspired **S**CTP **H**andover System (VASH). Before moving to the proposed system, let's delve into the smaller components that serve as the building blocks of the proposed system. This system consists of three main components:

1. Velocity Classification Model (VCM)
2. Probing Initiation Decider (PID)
3. Path Selection Mechanism (PSM)

In this section, the PSM will be introduced. The VCM will be discussed thoroughly in the following section whilst the PID will not be discussed in this manuscript and will be discussed in future studies.

3.1 Path Selection Mechanism

The path selection mechanism comprises of two main components which are the SCTP component and the ACO probabilistic equation (APE) component.

SCTP: The Stream Control Transmission Protocol is a general-purpose transport protocol for IP network data communication, similar to UDP and TCP. The motivation behind the development of this protocol is to overcome the shortcomings of TCP and UDP in the transportation of telephony signaling messages over IP networks. UDP only supports unreliable data transfer service whilst TCP faces the problem of head-of-line blocking and has no built-in support for multi-homing which enables link or path-level redundancy [14]. The two main features of SCTP which is relevant to this work are the multi-homing feature and the heartbeat chunk. SCTP has a multi-homing capability built into its core, where a MN which has more than one IP addresses will be able to bind several IP addresses and network interface cards (NICs) in a single association, thus, creating multiple paths from the MN to its corresponding node (CN). One of these paths will become the primary path, and the MN will be able to switch to another available path, if the current primary path deteriorates. Meanwhile, heartbeat chunks are deployed periodically in each path in order to monitor the availability of that path.

APE: The Ant System [15] is an optimization method inspired by the foraging (the act of searching for food or provision) behavior of some ant species. As these ants move along a path, it will drop some pheromone to mark the favorable path so that other members of the colony will follow that path. An example of the foraging behavior of ants is as depicted in figure 1. Two ants set out to find food for the nest. One of them moves towards the shortest path whilst the other goes to the longer path. At t=1, the first ant has already reached the food and arrive back at the nest at t=2, leaving two layers of pheromone (higher pheromone intensity). At t=3, the pheromone intensity of the shorter path will increase, thus, other ants from the nest will choose this path, due to the higher pheromone intensity.

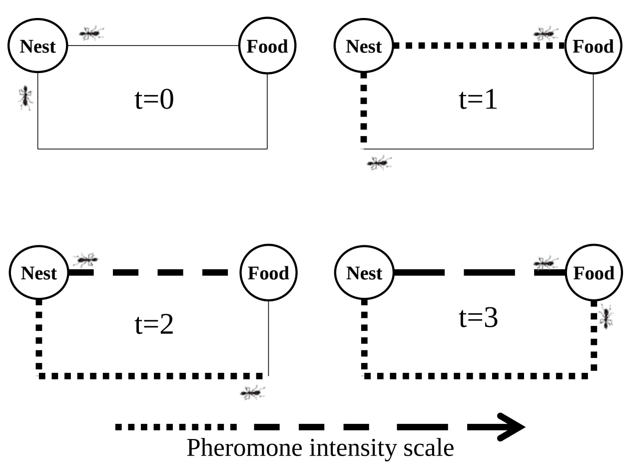

Figure 1. Foraging behavior of ants.

The path selection method used in this work is based on the probabilistic equation of the Ant System, which was developed by Dorigo [15]. The APE is as shown in equation (1), where the probability of moving from node *i* to node *j* is given as:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{u\in N_i^k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & j\in N_i^k(t)\\ 0 & j\notin N_i^k(t)\end{cases} \tag{1}$$

where τ_{ij} represents the *a posteriori* effectiveness of the move from node *i* to node *j*, as expressed in the pheromone intensity of the corresponding link, (*i*, *j*); η_{ij} represents the *a priori* effectiveness of the move from *i* to *j* (i.e. the attractiveness, or desirability of the move), computed using some heuristic.

The PSM was developed based on these two components. The implementation of the SCTP component will ensure the seamlessness of the handover process, because, theoretically, there will be no network connection disruptions during the HO due to the multi-homing capability of the SCTP. Furthermore, using the heartbeat chunks, the MN will be able to estimate the ETED of each path in its SCTP association. Combining that information with the RSS collected from the Physical layer, the MN will be able to discern the best path to switch to by calculating the probability of choosing each path using the adapted APE (as in equation (2)).

$$P_i=\frac{\tau_i^{0.5}\eta_i^{0.5}}{\sum\tau_i^{0.5}\eta_i^{0.5}} \tag{2}$$

P_i is the probability of choosing path *i*. Tau, τ_i, is the ETED of path *i*, which represents the pheromone of the path when referred to the example in figure 1. Eta, η_i, is the RSS of the NIC connected to path *i* which is obtained from the physical layer. The indices or the power of both parameters τ_i and η_i (α and β) is configured as 0.5 to give fair weightage to both parameters. As discussed earlier, this configuration will give the best results for certain scenarios only. These weightage can be configured to give the best outcome for different scenarios. That is why the VCM is needed in order for the MN to decide which configuration is the best for the current scenario (in this case the scenario directly corresponds to the diversity of velocity experienced by the MN).

3.2 VASH Architecture

As discussed earlier in this section, the VASH has three main components which are the VCM, PID and the PSM. The features and functions of the PSM have been discussed thoroughly in the previous subsection. The VCM is needed in order to estimate the velocity of the MN and classify whether the MN is moving at a low, medium or high velocity. This feature is important in discerning the best configuration for the PSM as well as the timing for PID. In

[6] and [7], the heartbeat chunk is used to probe all existing paths between MN and CN. These trains of chunks are sent constantly through all available paths causing an increase of load traffic to all networks involved. Hence, PID is introduced in VASH in order to mitigate the load inflicted to the network due to the probing schemes used in [6] and [7]. The architecture of VASH is as shown in figure 2.

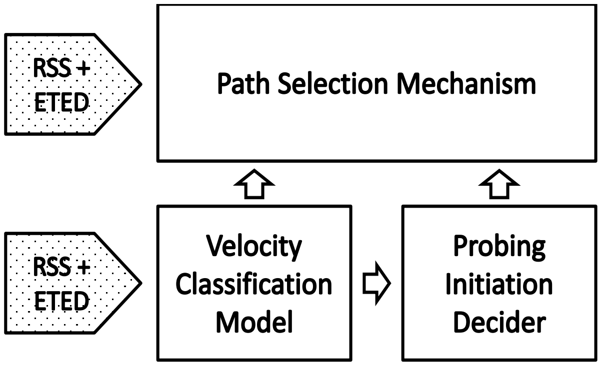

Figure 2. VASH components

From the classification made by VCM, the PID will decide when the Probing will start (start sending heartbeat chunk) whilst the PSM can reconfigure to the best weightage configuration for the current environment or situation faced by the MN.

4 ANN-BASED VELOCITY CLASSIFICATION MODEL

The velocity of the MN is one of the most important factors in the current and future mobile wireless scenario. According to [12], the RSS of a MN depends on the distance between the MN and the base station (BS) it is attached to. Therefore, the vector velocity of the mobile node will be made of 2 components which are the radial velocity, v_r, which is in meter per second (m/sec), and its counterpart, the so-called radian velocity, v_θ, which is in radian per second (rad/sec). Hence, the vector compound of the MN's velocity can be expressed as in the following equation:

$$\vec{v} = v_r + v_\theta \qquad (3)$$

However, the value of RSS is directly influenced by the v_r, whereas, the changes in v_θ does not affect the value of RSS. For example, let there be two MNs Y and Z, where Y is moving away from the BS at the speed of $\vec{v}^Y$ whilst Z is moving around the BS at the speed of $\vec{v}^Z$ and the distance between Z and the BS is always constant (x meters) as depicted in figure 3. When broken down to the velocity components of each MN, the radial component of both MNs would be; $v_r^Y = v^Y$ and $v_r^Z = 0$; whilst the radian components would be; $v_\theta^Y = 0$ and $v_\theta^Z = v^Z$. As time passes, the RSS of Y will decrease due to the increment of distance between Y and the base station. The RSS of Z, on the other hand, does not change, due to the fact that the distance between itself and the BS is constantly at x meters. Taking this idea into account, it can be deduced that the radial velocity, v_r, or in other words, the rate of change of the distance between the MN and its connected BS, is proportional to the rate of change of RSS received by MN. Hence, it can be established that it is possible to estimate the v_r from the value of RSS. Subsequently, the VCM model is developed with this concept in mind.

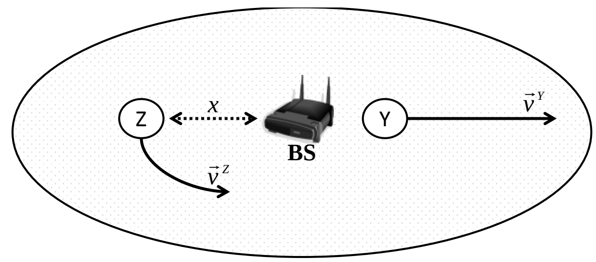

Figure 3. Difference between v_r and v_θ.

Before moving into more detail on the VCM, some understanding of the components used in this model should be established. In the following subsections, the overview of the ANN will be discussed briefly.

4.1 The Overview of the ANN

An artificial neuron (AN) is a model or a representation of the biological neuron (BN). The AN will gather signals from the environments or other ANs, and when fired, it will transmit a signal to all connected ANs. A representation of the AN is as depicted in figure 4. Each connection to the AN from the input signals are associated with positive or negative weight which will excite or inhibit the input signals respectively. The activation function controls the firing of an AN and the strength of the exiting signal. All the incoming signals collected are computed as a net input signal as a function of the respective weights by the AN. The net input is then used as the input to the activation function which will calculate the output signal of the AN [16].

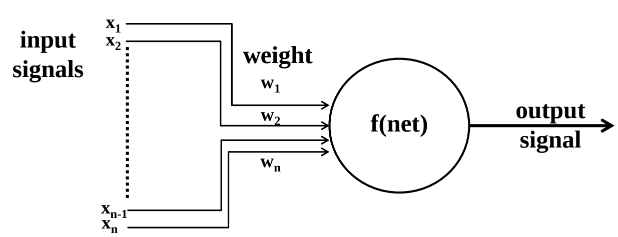

Figure 4. Artifical Neuron

An artificial neural network (ANN) is a layered network of ANs. Generally, an ANN is built of three layers which are the input layer, hidden layer and output layer. ANs in one layer are partially or fully connected to the ANs of the next layer. It is also possible for feedback connections to previous layers [16].

4.2 The proposed VCM

The Velocity Classification Model developed in order to classify the MN into three classes of velocity. The velocity classes are decided based on the work done in [17] which is as follows:

Class	Velocity Range
Pedestrian	$v < 15$km/h
Vehicle	15km/h $\leq v \leq$ 90km/h
Express bus/train	$v > 90$km/h

Table 1. Velocity Classing

The input used for the velocity classification is the RSS and the rate of change of RSS, ΔRSS. As can be seen from figure 5, the RSS received by the MN has the shape similar to a Gaussian distribution; hence, the ΔRSS will also vary with different level of RSS. It can be inferred that at certain level of RSS, the value of ΔRSS will also vary with different velocity. Thus, the value of both RSS and ΔRSS will be used to infer the velocity of the MN. Figure 5 is sample of the RSS and ΔRSS of five different velocities (1m/s to 5m/s). From this figure, the data points from 0 to 130 is the RSS and ΔRSS for 1m/s; data points from 131 to 240 is for 2m/s; data points from 241 to 350 is for 3m/s; data points from 351 to 450 is for 4m/s; data points from 451 to 550 is for 5/s. The have been simulated using inetmanet module for OMNeT++ ver. 4.1 [17].

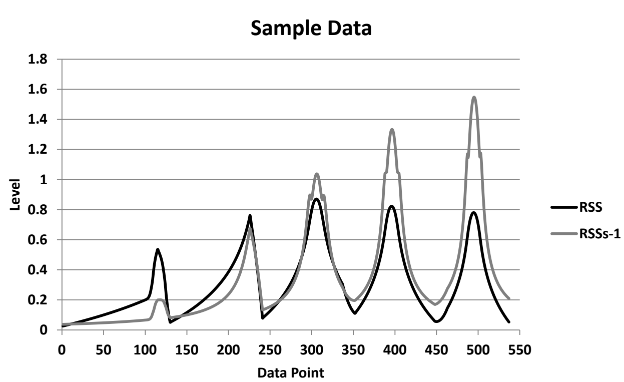

Figure 5. Sample data of the normalized RSS and the $RSSs^{-1}$ (dBm/s)

ANN model: The VCM model consists of two main blocks which are the ANN1, ANN2. The ANN1 uses the input data (RSS^i_{sensed} and ΔRSS^i_{sensed}) to estimate the velocity of the MN whilst the ANN2 will use the output of ANN1 to classify the velocity into the classes as in table 1. Figure 6 illustrates the design of the ANN component. However, due to the characteristic of the input data, even though the outcome output of the ANN model has a very high correlation with the desired output (a regression value of R = 0.99), there are some fluctuations in the output, which might inflict some error to the final velocity classification. Thence, the moving average component is added to filter out the fluctuation in the output obtained from the ANN model.

Figure 7 depicts the complete VCM model. The inputs RSS^i_{sensed} and ΔRSS^i_{sensed} are first filtered by the moving average (MA) component giving an averaged value of $MRSS^i_{sensed}$ and $M\Delta RSS^i_{sensed}$ (the label i signifies the BS that the MN is currently connected to). Then these values will be injected into the ANN1 which will produce a rough estimation of the MN's velocity, V^i_{est}. This value will be filtered again with another MA before inserted into the ANN2 which will give the estimated velocity classification, VC^i_{est}.

Figure 6. ANN1 and ANN2 design

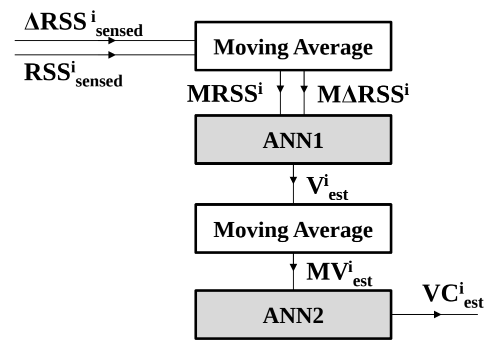

Figure 7. VCM Design

5 EVALUATION

To evaluate the proposed velocity classification model, a set of data was generated using inetmanet module for OMNeT++ ver. 4.1 as discussed in the previous section. The data collected was on the RSS value for a MN when it is moving at a constant speed. The simulation was executed for MN moving starting from a radial velocity of v_r = 1m/s up to v_r = 30m/s with a step of 1m/s. The data for ΔRSS was derived from this data. The ANN1 and ANN2 model were trained using the compilation of data from 1m/s up to 30 m/s (similar to figure 5) and the target velocity classification was given to the data according to the class range in table 1. The process is divided into two parts. The first part is the velocity estimation by ANN1. ANN1 was trained and tested using the simulation data. Figure 8 depicts the regression plot of ANN1.

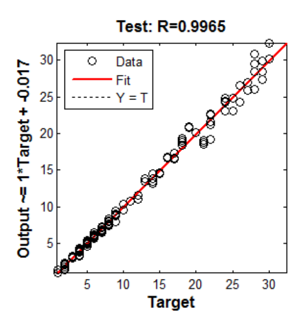

Figure 8. Regression Plot of ANN1

The x-axis is the real velocity (target), whilst the y-axis is the estimated velocity. It can be seen that the velocity estimated by ANN1 are mostly near or on the best fitting line and the R value obtained is 0.9965 which is very close to 1. These facts show that the estimated velocity has a very high correlation with the real velocity. Figure 9 shows the outcome of ANN1. As can be seen, the pattern of the estimated velocity is very similar to the target velocity. The estimation error becomes apparent after 20m/s. However, the deviated value is still acceptable. When compared to the evaluation in [12] (please refer [12]), the estimated value using ANN1 is comparable to the estimated velocity in [12].

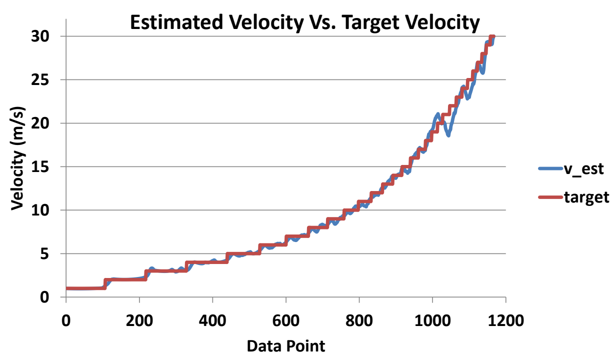

Figure 9. Comparison between estimated velocity and the desired target velocity

Then the output of ANN1 is used to train and test ANN2. The outcome is as shown in figures 10 and 11. Figure 10 shows the regression plot of ANN2.The R value of 2 clarifies that the output of ANN2 shows high correlation with the real value.

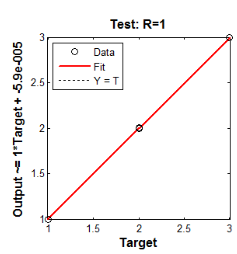

Figure 10. Regression Plot of ANN2

In figure 11, the input data points from 1 to 450 are in the range of the first class shown in table 1, also labeled as *"Pedestrian"*. Next, the data points from 451 to 1100 are in the range of the second class, *"Vehicle"*, whilst data points from 1101 to 1200 falls under the third class, *"Express bus/train"*. The outcome in figure 11 shows that the proposed VCM can accurately classify the velocity of the MN according to the classes in table 1.

To test the effectiveness of the proposed model, the proposed VCM is compared to the Velocity Estimation Method done in [12]. The outcome is as depicted in figure 12. This figure shows the classification done by each technique for each velocity (ranging from 1m/s to 30m/s). The y-axis of this graph is the velocity class, where 1, 2 and 3 signifies the *"pedestrian"*,*"vehicle"* and *"express bus/train"* classes respectively. The data from [12] was processed using thresholds according to table1. As can be seen in this figure, the VCM has better accuracy than the MEM. This is due to the increment of estimation error in the MEM as the velocity of the MN increases. However, even though in acuality, the error of MEM increases with the increment of velocity, the classification done by the MEM for velocities besides 24m/s are still accurate due to the thresholding characteristic of the classification approach. If the complete data of MEM is also trained using ANN2, an accurate classification estimation can be expected.

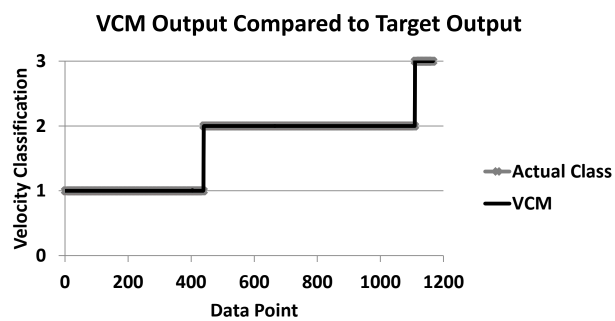

Figure 11. Comparison between the VCM output and the desired target

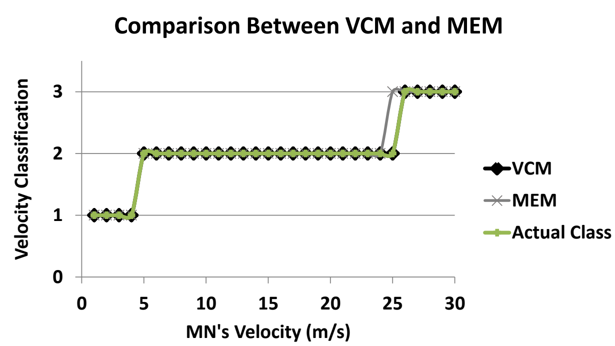

Figure 12. Comparison Between VCM and MEM

6 CONCLUSION AND FUTURE WORK

The layout of a novel handover system, specifically, the **V**elocity-centric **A**CO-inspired **S**CTP **H**andover System (VASH) which can adapt to the changes in the RSS, end to end delay and the velocity of the mobile node has been proposed. This system is built up from three main components which are; the Path Selection Mechanism (PSM) which determines the best path for the MN to handover its connection; the Velocity Classification Model

(VCM) which classifies the MN's velocity; and the Probe Initiation Decider (PID) which decides when the MN should start probing.

The main focus of this manuscript is on the design and development of the VCM. The VCM is developed using ANN and the effectiveness of the Velocity Classification was thoroughly evaluated. The evaluation results show that the proposed VCM is effective and can classify the velocity of mobile nodes or devices accurately. Furthermore, the proposed VCM shows comparable performance when compared with mobility estimation method in previous work.

The velocity classification in other radio access technology environment will be investigated in order to increase the scalability of the proposed work. Besides that, the effect of different configurations of the ACO probabilistic equation with different velocity will be thoroughly examined in order to design the PID.

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