

# On the Network Packet Loss Tolerance of SVM Based Activity Recognition

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**Abstract**—In this study, data loss tolerance of Support Vector Machines (SVM) based activity recognition model and multi activity classification performance when data are received over a lossy wireless sensor network is examined. Initially, the classification algorithm we use is evaluated in terms of resilience to random data loss with 3D acceleration sensor data for sitting, lying, walking and standing actions. The results show that the proposed classification method can recognize these activities successfully despite high data loss. Secondly, the effect of differentiated quality of service performance on activity recognition success is measured with activity data acquired from a multi hop wireless sensor network, which introduces high data loss. The effect of number of nodes on the reliability and multi activity classification success is demonstrated in simulation environment. To the best of our knowledge, the effect of data loss in a wireless sensor network on activity detection success rate of an SVM based classification algorithm has not been studied before.

**Keywords**—Activity recognition, Support Vector Machines, acceleration sensor, wireless sensor networks, packet loss.

## I. INTRODUCTION

**P**EOPLE with limited physical capabilities, such as elderly and disabled people, have difficulty in leading a life without getting help. Assistive technology tools and services emerge as a way of replacing human assistance so that individuals, experiencing physically overwhelming situations, can live more freely. As a subgroup of assistive technology tools and services, ambient care systems are responsible for detecting what people are in need of and providing them with the required help. Ambient care systems implement detecting the type of necessary assistance thanks to activity monitoring systems.

Activity monitoring systems are extensively studied in health care, particularly in detecting falls [1], chronic disease management [2] [3], rehabilitation systems [4], disease prevention [5] [6] and health status monitoring [7]. Ensuring steps are implemented, conforming to what is planned in production facilities, also raises activity monitoring as an essential utility in process control, since activity monitoring can help detect whether production steps are in the correct order or not, such as in water purification plants, increasing output quality. Postures of operators, pursuing bomb disposal missions, affect performance of cooling systems embedded in operators' suits [8], which employs activity monitoring as

a security tool as well. Young and healthy people can also benefit from activity monitoring systems as well as people with physical difficulties, since activity monitoring is studied also in sports domain, as a way of preventing injuries [9], therefore increasing performance of sportsmen.

Being composed of data collection and classification modules, activity monitoring systems collect activity data with mainly environmental and wearable sensors, then feed the acquired data to classification module for identifying types of actions. Environmental sensors, attached to the objects, are embedded within the environment. As people interact with these items, sensors generate events, which form the activity data, by this way, environmental sensors can help detect complex activities. However, they may not be sufficient when used standalone, because they have to be deployed anywhere people may exist, which complicates the design. Also, daily routines of people may contain activities which do not require interaction with these sensors. Wearable sensors do not require interaction with objects and they do not interfere with privacy, contrary to sensors such as cameras. They do not limit people's actions, either. Accelerometer and gyroscope are widely used wearable sensors.

In an activity monitoring system model, the classification task can be carried out on the data collection unit as well as on a server in a network environment. In a network model with gateway, at least one sensor unit transmits the data or the results inferred from the data to the gateway. In this system model, the classification process is realized in the gateway, if the sensors transmit the data to the gateway. In the case that results inferred from the data are transmitted instead of the data itself, the classification is carried out on the sensor units. In both models, losing packets throughout data communication affects the success of activity monitoring component. In Fig. 1, an example activity monitoring network architecture, with activity data being processed on the gateway, is illustrated. Smart phone is an intermediate transmission unit in this configuration, being responsible for sensor data fusion and relaying the fused data to the gateway. In the displayed setting, a person wears various sensors on the body and a sensor is also embedded in the environment, as illustrated with the circle marked by an arrow.

In this study, we evaluate the effect of packet loss on the activity recognition success, in the case that our classification module is executed on the gateway. The SVM based classification algorithm used in assessing the effect of packet loss, is developed in our previous studies [10], which is an SVM based algorithm. Our algorithm embeds feature extraction into classification stage, also does not

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Fig. 1 An activity monitoring network with smart phone as data fusion and relaying unit

necessitate experimenting with multiple features to find the best classifying features, contrary to other approaches utilizing SVM. To further investigate in what aspects our algorithm outperforms some related studies, the readers are referred to [10].

Data loss resilience of our classification algorithm is firstly analyzed for random loss. After demonstrating that the method is resistant to high loss rates, as the results imply, our analysis proceeds with evaluating the method on packet loss patterns we produced in a multi hop wireless sensor network simulation environment. It is assumed that the multi hop sensor network transmits the sensor data to the sink in our network model. Classification algorithm classifies data received from each node at the sink, where each node represents data acquired from a different person. In the wireless network simulation environment, channel transmission and routing operations are performed with quality of service supported cross layer communication protocol (XLCP) [11], which we developed in our previous studies. Activity recognition analysis is shown in terms of packet transmission reliability, which depends on the number of nodes in wireless network.

In our analysis, we considered both packet level loss (in random loss case) and event level loss, where lost data contains the piece of information regarding the identified type of activity (loss patterns generated in multi hop wireless sensor network simulation environment). The study by Alemdar et. al. [12] addresses the importance of packet level and event level reliability, adding that periodic traffic requires mainly packet level reliability, whereas generating alarms for activities which signal emergency, such as falls, raises event reporting as a crucial item. They also mention that crosslayer protocols are necessary to achieve reliability for various types of traffic and for making activity monitoring service accessible in farther regions, multi-hop communication is required in terms of delivering the sensor data, which also emphasizes the importance of our study.

In the literature, there exist error correction methods and studies targeting reconstruction of the lost data [13]

[14]. However, these methods are not suitable for resource constrained network environments. For these environments, high classification success with partial data is important in terms of resource effectiveness. As a study on the effect of network loss, Radiosense [15] investigated how transmission power, packet transmission rate and correction frame parameters affect the performance in terms of classification accuracy, delay and energy cost. Nevertheless, the effect of block losses, which result from packet loss in the network level, on activity classification has not been studied for SVM classification method before. This study complements the study by Demir et. al. [11], in terms of potential collective utilization for differentiating emergency voice traffic in WSN. A more detailed description of the application scenario, which further clarifies how our work presented here can be integrated in the voice traffic differentiation subject, is given in Section III-A. Marzencki et. al. [16] proposed a wireless sensor network based activity monitoring system with reliability support. In a mesh network structure, they assign the routing tasks of a failing node to a healthy neighbour, adding that overall data communication is not affected thanks to this mechanism. Shah et. al. [17] also follows data relaying for reliability in the multihop wireless sensor network they designed for monitoring cardiac activity remotely. They experiment with at most two hop networks and two interfering nodes, yielding a reception ratio above 0.985, reception ratio being the ratio of number of packets received and the number of packets sent. Though reception ratio they obtain is high, maximum number of hops being 2 may not be sufficient for many wireless sensor network applications in activity monitoring. Hence, a classification algorithm resilient to higher data loss is necessary to compensate for the increased data loss. In addition, when deploying the activity monitoring system in real life conditions, activity data continuously stream in real time. Hence, activity data capturing should go on even for the period, starting at the instance of node failure and finishing at the instance of detecting the healthy node. Furthermore, data loss may result from instantaneous signal

deteriorations in the healthy node, instead of node failure, meaning that the node may be up and running but the transmitted signal may carry a degenerate piece of information. Hence, packet level and event level data loss should also be considered, showing the effect of these types of data loss on activity detection success, which is the focus of our study. To the best of our knowledge, the effect of data loss in a wireless sensor network on activity detection success rate of a classification algorithm has not been studied before.

The contents of the following sections are stated next: The classification algorithm, experimental methodology and network service model are elaborated in Section II, III and III-A respectively. Findings and analysis are explained in Section V and finally, conclusions derived from our study are given in Section VI.

## II. SVM BASED CLASSIFICATION ALGORITHM

Our Support Vector Machines based classification algorithm carry out both feature extraction and data classification phases at the same time. In our method, SVM training phase is used in feature extraction operation. In SVM training phase, processing training data of two classes, a hyperplane, which separates these classes, is formed. In prediction stage, whether the test data are located in the positive region of the hyperplane or not is determined. Data being located in the positive or negative region mean being classified as positive or negative respectively. If there are  $n$  classes to differentiate, the number of hyperplanes to generate is 2 times the number of binary combinations of  $n$ . According to the method we propose, for distinguishing between more than two classes (multi class categorization), the action sample is determined to belong to the class, which generates the greatest number of hyperplanes, classifying the sample as positive. Since SVM is a method discriminating between only two classes, in the feature extraction phase of our method, each action sample is compared against *reference action*. Extracted features are input to training and prediction stages of the already existing SVM algorithm.

As the training module, for each binary permutation of the action set, a pattern  $P$  is generated as in (1),  $M$  initially representing a matrix with no elements, where  $N$  stands for number of training samples for an action. Depicting feature extraction scheme, the operation  $fe$  is explained in (6) and (7) in detail. In (1), using  $Q$  operator, features of each training sample in the action set, designated by  $TS_i$ , are generated and merged, to form the matrix  $M$ , which eventually represents the whole feature set for an action.  $\langle M, CT(M, C(V)).X \rangle$  tuple gives the pattern  $P$ .  $CT$ , being the core training operation, generates the separating hyperplane for an action, after solving systems of linear equations. In  $CT$ , number of support vectors, designated as  $C(V)$ , is equal to number of training samples. The solution  $X$  is generated by  $X \leftarrow F' * B$  operation, where  $F'$  is the pseudo inverse of coefficient matrix  $F$ , and  $B$  is the vector of binary labels.

$$M \leftarrow Q(M, fe(TS_i)), \forall 1 \leq i \leq N \quad (1)$$

Formation of  $F$  and  $B$  are designated in (2) and (3) respectively.  $(.)$  is used to indicate dot product operator. In (2),  $F_{ij}$ , mean the element with row  $i$  and column  $j$  in matrix  $F$  whereas  $M_j$ , show row  $j$  of matrix  $M$ , also  $K$  is the Kernel function used in order to map its input data to a higher dimensional space.

$$F_{ij} = K(M_j).K(M_i), \forall 1 \leq i, j \leq C(V) \quad (2)$$

Vector  $B$  stores binary class labels and  $b_i$  designates elements of  $B$ .

$$b_i = \begin{cases} 1, \forall 1 \leq i \leq C(V) \\ -1, \forall \frac{C(V)}{2} + 1 \leq i \leq C(V) \end{cases} \quad (3)$$

Let  $V$  be a 4-tuple vector, then  $Z=K(V)$  is a 5-tuple vector, whose elements are shown in (4).

$$z_i = \begin{cases} v_i, \forall 1 \leq i \leq 4 \\ \sum_{n=1}^4 \frac{1}{1 + e^{v_n}}, i = 5 \end{cases} \quad (4)$$

$X$  and  $w$  form the separating hyperplane parameters, which introduce the result of  $CT$  module.  $w$ , being initially zero, is calculated as in (5).

$$w \leftarrow w + x_i * K(M_i), \forall 1 \leq i \leq C(V) \quad (5)$$

Feature extraction scheme, designated as  $fe$ , gets an action sample  $A$ , which is in the form of an acceleration matrix. Each row of  $A$  corresponds to a 4-tuple composed of  $x$ ,  $y$ ,  $z$  axis acceleration values and sequence number of the tuple in the sample.  $|A|$ , being the number of rows in  $A$ , reference action matrix  $E$  is generated as in (6).

$$E_i \leftarrow \langle 1, 1, 1, i \rangle, \forall 1 \leq i \leq |A| \quad (6)$$

Then, Kernel function is applied on acceleration matrix and reference action, as in (7). Finally,  $C(V)$  is set to number of rows in  $M$  and  $CT(M, C(V)).w$  yields the features of  $A$ .

$$M_i = \begin{cases} K(A_i), \forall 1 \leq i \leq |A| \\ K(E_{i-|A|}), \forall |A| + 1 \leq i \leq 2|A| \end{cases} \quad (7)$$

For prediction scheme, a test sample is exposed to  $fe$  operation. Let  $V$  be the feature vector generated from the test sample. The function  $d$ , taking two vectors as input, appends the input vector with smaller number of elements with zero, until the two vectors become of equal size, then returns them. The value of sum, being initially zero, is determined as in (8), where  $v_1$  and  $v_2$  are calculated with (9).

$$sum \leftarrow sum + x_i * (v_1.v_2), \forall 1 \leq i \leq C(V) \quad (8)$$

If sum is a positive number, the sample is determined to be in the positive class, similarly, it is classified to be negative if sum is a negative number.

$$[v_1, v_2] \leftarrow d(K(M_i), K(V)), \forall 1 \leq i \leq C(V) \quad (9)$$



### III. EXPERIMENTAL METHOD

In our activity recognition model, it is assumed that classification algorithm executed on the gateway, to which sensor data are transmitted. Activity data, composed of 3D acceleration vectors, are transmitted to the server in network packets and classification algorithm assigns the action to a class after receiving the whole vector corresponding to the action. The activity set contains *sitting*, *standing*, *lying* and *walking* actions. In data collection phase, 3D accelerometer inside TI Chronos eZ430 watch is located on the left thigh for *sitting*, *standing* and *lying* activities, as shown in Fig. 2, whereas it is worn on the left wrist for *walking* action. Training data are not lossy while test data are lossy, meaning that training data are not exposed to data loss schemes we experimented. In the testbed, configuration parameters are set as follows: Acceleration data are transmitted at 33 Hz frequency. Training and test data last for 2.5 s. Number of samples per activity is 15 and 10 for training and testing respectively.



Fig. 2 Sensor placement on the body

#### A. Network Service Model

As previously stated in Section I, this work introduces the potential to be integrated to an emergency voice traffic differentiation study in WSN. The network service model, we presented here, is realized on the application scenario within a health care building context. One floor of this building is selected as the monitoring terrain and equipped with acoustic sensors on pre-defined spots, with beds of the residents, considering the size of the rooms. Placing the sink node in the middle, where a lounge and a control room are located, 20mx20m terrain contains 24 sensor nodes deployed in total. Network topology structured on the terrain is shown in Fig. 3. 3D acceleration sensors worn by the residents also participated in monitoring, by periodically transmitting the sensor data. For voice commands, acoustic sensor data are sampled with a fixed frequency and bit depth. With universal asynchronous receiver transmitter (UART) interface, this digitized data are transferred to the wireless source node, then voice data segments are injected into network packets and transmitted to the sink through the same network as an emergency class.

Each of the fixed sensor nodes, distributed in an area, transmit periodic activity data, received from a user, to the sink. Classification procedure is carried out at the sink in order to identify the activity at each node. The cross layer link and network protocol, which we developed in Matlab environment, provides quality of service support so that sensor data created at the source reach the sink in the most effective way. A node initially listens to the radio channel

for a specific amount of time to determine whether the radio channel is in use or available, when there exists a data packet to transmit. If the channel is in use, sensor node starts running a specific timer. As long as the channel is in use, timer applies exponential back-off. If the channel is available, the node gets access to the channel, in a similar way to CSMA/CA (Carrier Sense Multiple Access / Collision Avoidance) algorithm [18], and transmits the data packet. In order to find a route, cost for each channel is evaluated and the route is determined, considering the cost analysis. RTS-I (Request to Send-Indicator) packet is received by all nodes, which are close to the sink. Nodes receiving RTS-I packet, calculate a cost value, using SNR (signal-to-noise ratio) values of the packets they receive, available energy level, instantaneous data communication speed and buffer length. Calculated cost value is placed in CTS-Q (Clear to Send) packet and transmitted. Nodes, calculating a higher cost value, gain higher priority in getting access to the channel, compared to those calculating a lower cost value, and they transmit CTS-Q packet. If a node determines a higher cost value, while listening to the channel, than the cost value it calculated regarding a packet, that node transmits the CTS-Q packet with a specific probability. The node transmitting RTS-I packet, receive CTS-Q packets for a specific amount of time. When the time expires, it sends the DATA packet to the node which transmits the highest cost value in CTS-Q packet. A node receiving DATA packet, if ACK option is selected, transmits ACK to the node, which sends DATA packet. In the case that ACK is selected, an attempt is made to transmit DATA packet at as many trials as the maximum retransmit count. DATA packets, for which maximum retransmit count is filled up, are dropped from the buffer. Associated, transitive and unassociated packet receipt model, which is given in [19], is used as the radio model. In this model, it is assumed that NRZ coding and NCFSK modulation are used for SNR value ( $x(d)$ ), belonging to a point at distance  $d$ , and packet loss rate ( $p$ ), at distance  $d$  for a packet with length  $f$ , is calculated as given in (10).

$$p = 1 - \left(1 - \frac{1}{2} \exp^{-\frac{x(d)}{2} \frac{1}{0.64}}\right)^{8f} \quad (10)$$

### IV. SIMULATION ENVIRONMENT

Sensor nodes are placed over an area of 2500  $m^2$  (50m x 50m), using uniform distribution such that void regions are prevented from slipping. All of these sensor nodes transmit 55 bytes of activity data in total at 2.7 second periods. 55 byte data are composed of general protocol cost (13 bytes), data segment offset (2 bytes) and activity data (40 bytes). RTS-I, CTS-Q and ACK packets occupy 20, 20 and 15 bytes respectively. Bandwidth is 250 Kbps in the network environment where the coordinate of sink node is (25m,0m). The reason why transmission period is 2.7 seconds is the following: In a preliminary work of ours on real time activity monitoring, for performing the activities in a natural pace, a period of 2.7 seconds had to be given to the person who practices the activity. Though *sitting*, *standing* and *lying* activities can be regarded as actions, which can be completed





Fig. 3 Activity monitoring network topology

in a smaller amount of time, our activity set also contains *walking* action, duration of which highly depends on the human subject's pace in moving. As a result of calculating the size of samples coming from acceleration sensor for 2.7 seconds, we found that payload belonging to the activity data should occupy 40 bytes. In each simulation, 40, 60, 80 and 100 sensor nodes are injected in the area. 5 different topologies are simulated for each number of nodes separately and in performance evaluations, their average is calculated. For each node count, number of activity data packets transmitted is 10 times the node count. As an example, for node count 40, 10x40 activity data packets; for node count 100, 10x100 activity data packets are transmitted. The following are performance metrics used in measuring the effect of packet loss on activity recognition success:

- **Classification Success Percentage:** Correct recognition percentage of the simple actions in lossy environment. Two different loss models, which are random loss and loss obtained from network simulation, are experimented in lossy environment.
- **Reliability:** The ratio of the total number of unique packets, received at the sink, to the total number of packets sent from all nodes.

## V. ANALYSIS AND FINDINGS

40 activity test samples are obtained, repeating each of four actions 10 times. Variation in correct classification success of each action depending on data loss is analysed for different data loss percentage (R). When data loss rate is below 50%, our method recognizes the activities with 100% accuracy. This observation shows that our method introduces high loss tolerance. Then, classification success is measured for the cases where random loss rate is 50%, 60% and 70%.

In network simulation tests, the number of nodes, on which activity is identified successfully, is calculated, in the case that each node of the network sends the same activity. The convergence between packet loss reliability of the network

for different node counts and activity classification success is considered.

### A. Random Loss

Variation in correct classification success of the activities depending on random packet loss is given in Fig. 4. These values are calculated as in (11). Expressions used in the equation are explained below:

- **test no:** shows test sample being processed and corresponds to the value  $n$ .
- **p:** number of random loss sequences generated for test with no  $n$  ( $p$  is 10 in our results)
- **S(n,i):** becomes 1 if test sample  $n$  is correctly classified in random loss sequence  $i$ , becomes 0 otherwise.
- **y(n,p):** successful recognition percentage of test  $n$  (over  $p$  different random loss sequences). Corresponds to success percentage values in Fig. 4.

$$y(n, p) = \frac{\sum_{i=1}^p S(n, i)}{p} \quad (11)$$

In (12), the elements of the set  $I$  form the *random loss sequence*. Expressions in the equation are clarified below:

- $T^{lx3}$ : a matrix composed of acceleration values, containing  $l$  rows and 3 columns. ( $t(:,i)$  being  $i$ th column of  $T^{lx3}$ , are acceleration values measured along x, y and z axes respectively.)
- $t(i,:)$ :  $i$ th row of  $T^{lx3}$
- $L$ : random loss sequence function

$$I = L(T^{lx3}, R) = \{i_1, i_2, i_3, \dots, i_{l \times R/100}\} \quad (12)$$

The function  $L$  randomly selects as many acceleration vectors as  $R\%$  of the number of 3D acceleration vectors in the test sample and marks as lost packet. The function  $E$ , which removes the lost packets from the test sample, is given in (13).

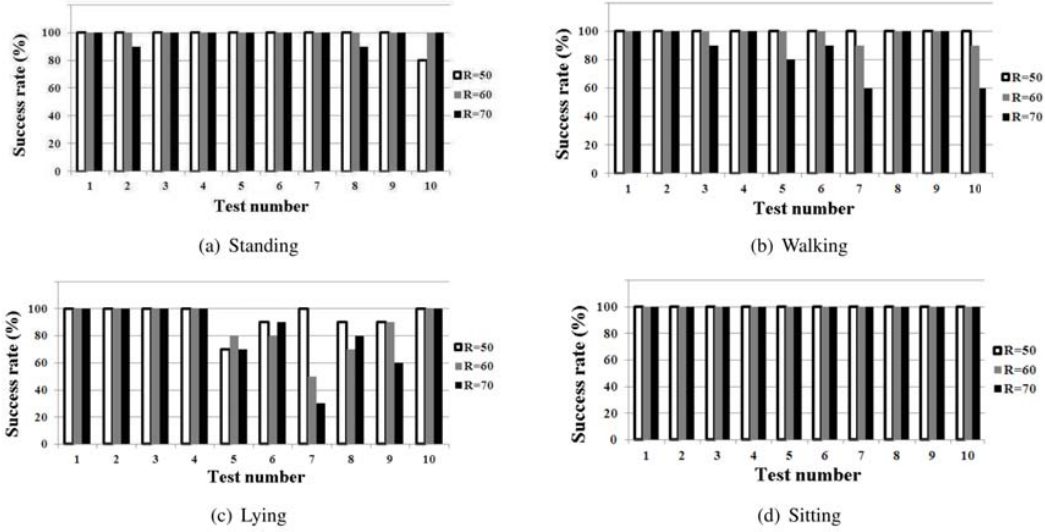


Fig. 4 Variation in correct classification success of the activities depending on random packet loss

$$E(T^{lx3}, I) = \{T^{(l-|I|)x3} | i \notin I, \forall t(i, :) \in T\} \quad (13)$$

### B. Network Environment

In this section, activity classification is analyzed in network simulation environment. In random loss case, each lost packet carries a 3D acceleration vector, whereas in the case that loss is obtained with network simulation, the number of vectors carried by the lost packet is more than one, due to the network packet size. For comparing the two loss models, multi vector packet loss is mapped to single vector packet loss, using (14). Expressions utilized in the equation are explained below:

- $l$ : number of 3D vectors in the test sample.
- $c$ : number of packets carrying the simple action in its entirety.
- $f$ : the number of packets failing to reach its destination ( $f \leq c$ )

$$R = \frac{f \times \lfloor \frac{l}{c} \rfloor}{l} \times 100 \quad (14)$$

Correct recognition percentage of each activity, for  $N$  nodes, is shown in Table I. The fact that no significant change is introduced in activity recognition success, though node count increases, shows that our classification method is scalable in the network model.

### C. Reliability Analysis

As the simulation results show, network reliability values, for 40, 60, 80 and 100 nodes, are found to be 0,48, 0,51, 0,45 and 0,39 respectively. This observation shows that packet loss rate is very high in the wireless sensor network with quality of service support. However, despite these high loss rate values, the activity classification model we propose yields very successful results, thanks to its high loss resilience.

Classification success percentages obtained in simulations, which are given in Table I, show that network reliability and activity classification success have a parallel relationship in activities except *lying*. It can be seen that a network environment, where quality of reliability service is at most 51%, is not sufficient for recognizing *lying* action, nevertheless the same service quality is adequate for *sitting*, *standing* and *walking*. A potential reason for this could be that randomness factor in network loss, introduced by simulation environment, can affect *lying* action more than the other actions we study.

## VI. CONCLUSION

In this study, data loss tolerance of accelerometer and Support Vector Machines based activity classification is shown for four different actions, with random loss analysis and wireless sensor network simulation. In addition, activity data transmission reliability of sensor nodes and activity classification success of the method in network environment is analyzed. It is shown that our SVM based classification method is suitable for network environments with high loss rates. The fact that training data are not lossy while test data are lossy, makes our method even stronger. According to the scalability test results, though highest network reliability success is obtained when the node count is 60, no significant change is observed in activity recognition success depending on node count increase, which shows that the method we propose is scalable in node count. As the results show, while *sitting*, *standing* and *walking* actions can be recognized with very high accuracy in the network environment; recognition success decreases for *lying*, which implies that the required reliability service quality should be more than 50%, for recognizing *lying* action. Inspecting this outcome signals that *lying* action is more influenced by random losses, being also supported by our results on random loss. In our future studies, reliability service quality, required for increasing



TABLE I  
ACTIVITY RECOGNITION SUCCESS PERCENTAGE IN NETWORK SIMULATION

Activity	N=40	N=60	N=80	N=100
Lying	51,2	50,9	50,9	51,3
Sitting	99,9	100	99,9	99,6
Standing	97,0	97,8	96,6	94,4
Walking	99,8	100	99,9	99,4

correct recognition success for *lying* action, will be explored. Moreover, the reason why data loss influences *lying* action more than the other actions, will be studied.

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