Improving Face-to-Machine Proximity Estimation with Neighbor Relations in Mobile Industrial Human Machine Interaction

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***Abstract*—In the mobile industrial human machine interaction (HMI), the engineer has to manually select the target machine from a list to establish the data connection. It is a nontrivial problem since there are more machines connected to the industrial cyber-physical systems, and the list becomes so long that is hard to be read. Considering the characteristic that the industrial HMI is typically executed in a face-to-machine manner, the face-to-machine proximity estimation (FaceME) algorithm has been proposed to simplify the manual selection. However, due to the limited utilization of RSSI data, the estimation accuracy of FaceME is not sufficient in the application with densely deployed machines. In this paper, we propose the model to formulate the neighbor relations, and then design a new face-to-machine proximity estimation algorithm with neighbor relations (FaceMEN) to improve the estimation accuracy. The experimental results prove that FaceMEN greatly improves the estimation accuracy and time complexity.**

***Index Terms*—Proximity estimation, mobile industrial human machine interaction, HMI, neighbor relations, face-to-machine proximity**

I. Introduction

In recent years, the mobile industrial human machine interaction (HMI) becomes popular with the development of industrial cyber-physical systems (ICPS) [1]–[3]. With the help of wireless technologies such as WiFi and Bluetooth, the engineer can use mobile device to control the machine and observe if it operates well simultaneously, which greatly improves the efficiency of HMI in the industrial field.

Nevertheless, the considerable number of machine nodes in ICPS brings challenges to the mobile industrial HMI. As shown in Fig.1, the machines are densely deployed at 5-30 nodes per $100m^2$ in the plant. Thus in the data connection before interaction, the engineer has to manually select the target from a list with more than 20 nodes which is a nontrivial burden for the engineer.

Using NFC [4] or QR code [5] scanning to obtain the ID of the target machine is an intuitive solution. However, both of them have to be executed in extremely short range ($< 10cm$) which can hardly be applied in the plant with large or dangerous machines. On the other hand, the RSSI (received signal strength indicator) of wireless signal can be used to estimate the location [6]–[8] or the proximity [9], [10] of the mobile device, which is helpful to simplify the data connection. However, the time complexity of most algorithms is too high to be tolerated by the engineers.

Fig. 1. Face-to-machine interaction in the industrial plant

In our previous work [11], we observe that the industrial HMI is typically executed in a *face-to-machine* manner. As shown in Fig.1, the engineer should face to the machine during the interaction to ensure the machine works accurately. Based on this observation, the FaceME (face-to-machine proximity estimation) algorithm is proposed to use RSSI difference and two-steps estimation to estimate the machines that are close to the engineer with low time complexity.

Nevertheless, the estimation accuracy of FaceME is not optimized, and there are more than 3 machine nodes in the estimation results with dense node deployment. The major reason is that FaceME only uses the maximum RSSI and RSSI difference for estimation, and the RSSI data from other machine nodes is not fully utilized. In this paper, we argue that the neighbor information among machine nodes can be used to improve the accuracy of proximity estimation in the face-to-machine HMI. Based on this idea, this paper makes the following contributions:

1) We analyze the node deployment in a mobile industrial HMI testbed implemented in a PLC laboratory, and then propose the model to formulate the neighbor relations between the proximal node and the node with the maximum RSSI. The neighbor relations is further used in the design of proximity

estimation algorithm.

2) The face-to-machine proximity estimation algorithm with neighbor relations (FaceMEN) is proposed to improve the proximity accuracy. The neighbor relation between the proximal machine and the machine with the maximum RSSI is measured in the offline measurement, then it is used in the online estimation to refine the estimation result.

3) The performance of FaceMEN is studied by the experiments executed on the mobile industrial HMI testbed. The experiment results prove that FaceMEN has better estimation accuracy and less time complexity than FaceME.

The rest of this paper is organized as follows. Section II introduces the mobile industrial HMI testbed and provide the definition of neighbor relation base on the network model. Then we briefly introduce the FaceME algorithm and the problem that motives this work in Section III. Section IV provides the details of FaceMEN algorithm, and the experiment results are given in Section V to evaluate the performance of FaceMEN algorithm. Finally, Section VI makes a conclusion of this paper.

II. Preliminaries

A. Mobile Industrial HMI Testbed

We have implemented a testbed [11] to evaluate the performance of mobile industrial HMI. As shown in Fig.2, Google Nexus 9 tablet is used as the *human node* which communicates with machine nodes via Bluetooth. We use TI-CC2541 and MAX3485 chips to develop a wireless module as the *machine node* that supports Bluetooth and RS485 simultaneously. The machine node uses RS485 to communicate with the PLC (programmable logic controller) which is the DVP12SE industrial controller developed by Delta Electronics.

The testbed is deployed in the Delta PLC laboratory located in Fuzhou University. As shown in Fig.3, there are 23 control consoles in the laboratory, and it represents a typical industrial plant: a large number of machines are deployed in rows with fixed spacing (1.2m), while the engineer moves in the passage to interact with different machines. The Android application called *MobileHMI* is developed to read the input signals and control the outputs of PLC. The proximity estimation algorithms are also implemented in MobileHMI to collect and process Bluetooth RSSI data from machine nodes.

B. Network Model

Generally, the machines are regularly deployed in the plant [12], thus the network deployment can be formulated by two variables: the spacing among machine nodes dx, and the distance between the human node and the proximal node dy. The dx is fixed in the specific industrial plant, while the dy is determined by the ideal location of the human node and its safety distance to the machine.

Moreover, we assume that the ID of machine nodes are assigned in orders (from left to right), such that the neighbor relation between node i and j can be formulated by the difference between their IDs,

$$\Delta n(i,j) = i - j \quad (1)$$

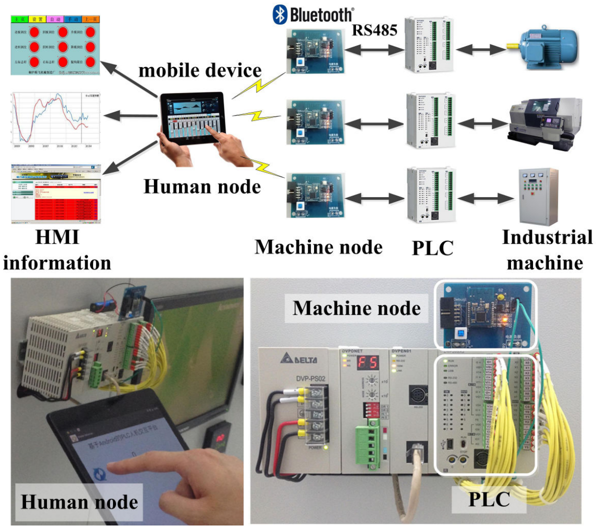

Fig. 2. The framework of the mobile industrial HMI testbed

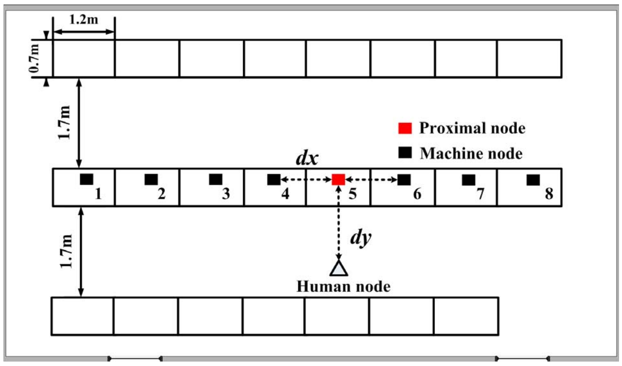

Fig. 3. The layout of the mobile industrial HMI testbed

The $\Delta n(i,j)$ will be used in the design of proximity estimation algorithm.

The *proximal node* is defined as the machine node that is closest to the human node in the physical space. Due to the powerful hardware of human node, in this paper, the human node runs the proximity estimation algorithm to sample and process the RSSI of machine nodes. The RSSI of machine node i is denoted by $R(i)$. The set of machine nodes that can be detected by the human node is denoted by M, and the proximal node is denoted by k. Then we define the set of machine nodes M^- as,

$$M^- = \{i|(i \in M) \cap (i \neq k)\} \quad (2)$$

Take the testbed shown in Fig.3 as an example, the dx is fixed at $1.2m$, and the dy varies from $0.9m$ to $1.8m$. The ID of the proximal node is $k = 5$, and its neighbor relation with nodes 4 and 6 can be described as $\Delta n(5,4) = 1$ and $\Delta n(5,6) = -1$.

III. Motivation

To the best of our knowledge, FaceME [11] is the first algorithm that uses proximity estimation to simplify the data

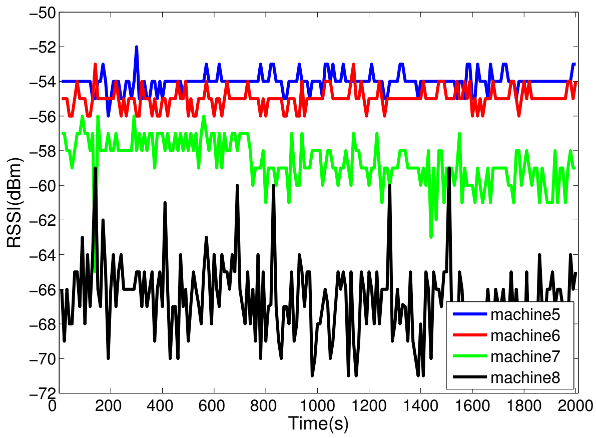

Fig. 4. RSSI of machine nodes with dx=1.2m and dy=1.2m

connection in the face-to-machine HMI. In this section, we firstly provide a brief review of FaceME based on an experimental case study, and then state the observation that motivates our works in this paper.

A. RSSI Difference and FaceME algorithm

At first, we execute an experiment to examine the RSSI of machine nodes. There are four machine nodes deployed in the testbed shown in Fig.3. Each machine node is connected to a control console separately, thus the space among them dx is 1.2 meters. The ID of the proximal node is 5. The human node locates in front of the proximal node, and its distance to the proximal node dy is 1.2 meters. The human node measures the RSSI of all machine nodes simultaneously at every 10 seconds, and the measurements are repeated over the period of 35 minutes.

Fig.4 shows the RSSI values with machine nodes from 5 to 8. There are overlaps between the RSSI fluctuation range of machine 5 and 6 which may lead to the wrong estimation of the proximal node. Nevertheless, the variance of RSSI is constrained in a limited range and there is a noticeable gap exists between the proximal node and the machine nodes 7 and 8. Based on this observation, the fluctuation of $R(i)$ can be formulated as,

$$R(i) \in [L(R(i)), U(R(i))] \tag{3}$$

where $L(R(i))$ is the lower bound of $R(i)$, and $U(R(i))$ is the upper bound of $R(i)$.

Given the set of nodes M^- (Eqn.2), the RSSI difference $\Delta R(k, M^-)$ is defined as,

$$\Delta R(k, M^-) = L(R(k)) - U(R(M^-)) \tag{4}$$

The definition of the RSSI difference $\Delta R(k, M^-)$ indicates the difference between the lower bound of $R(k)$ and the upper bound of $R(M^-)$. Then the RSSI difference can be used to formulate the relation between the RSSI of the proximal node $R(k)$ and the maximum RSSI of all machine nodes $R_{\max}$ as follows.

Theorem 1. *Given the RSSI of the proximal node $R(k)$ and the maximum RSSI of all machine nodes $R_{\max}$, if $\Delta R(k, M^-) < 0$, then,*

$$R(k) \in [R_{\max} + \Delta R(k, M^-), R_{\max}] \tag{5}$$

Otherwise, if $\Delta R(k, M^-) \geq 0$, then $R(k) = R_{\max}$.

The FaceME algorithm is developed based on Theorem 1. It includes two parts: the offline measurement to obtain the RSSI difference $\Delta R(k, M^-)$, and the online estimation that uses $\Delta R(k, M^-)$ and sampling results to estimate the proximal machine node. However, the RSSI data from other machine nodes is not fully utilized in FaceME, such that the estimation accuracy of FaceME is not optimized. We will further evaluate this problem in the next section.

B. Problem Statement

In this section, we use the experimental results given in Fig. 4 to evaluate the problem of FaceME. As shown in Fig. 4, the RSSI range of the proximal node (node 5) has overlaps with the RSSI range of node 6 and 7. According to the algorithm, both node 6 and 7 will be included in the estimation result of FaceME. However, it is clear to see that the RSSI of node 7 has never become the maximum one, which means that the estimation result of FaceME is not optimal. This problem becomes severer in the network with smaller dx or larger dy where there are more overlaps of RSSI ranges.

To solve this problem, a reasonable solution is to measure the nodes with maximum RSSI in the offline measurement, and record their neighbor relations with the proximal node Δn. Then the neighbor relation Δn can be used in the online estimation to refine the estimation results. Based on this idea, we propose a new algorithm in the next section.

IV. Face-to-Machine Proximity Estimation with Neighbor Relations

In this paper, we propose a new algorithm named face-to-machine proximity estimation with neighbor relations (FaceMEN). The basic idea of FaceMEN is measuring the neighbor relations between the proximal node (k) and the node with the maximum RSSI (max) in the offline measurement, and then use it in the online estimation to refine the estimation result. The pseudo code of FaceMEN is given in Algorithm 1, and the details of FaceMEN algorithm are described as follows.

A. Offline measurement

The offline measurement needs to measure two important variables that are used in the online estimation. The first one is $\Delta n(k, max)$ which denotes the neighbor relations between the proximal node and the node with the maximum RSSI. The second variable is $\Delta R(k, M^-)$ which is the RSSI difference defined in Eqn.4. Both of them are impacted by dx and dy. Therefore, in the offline measurement, the human node should locate in front of the proximal node with different dx and dy then sample the RSSI and record the corresponding ID from every machine nodes. The offline measurement can be done

Algorithm 1 FaceMEN algorithm

Offline measurement:
Obtain $\Delta\mathbf{N}(k, max)$, $\Delta R_1(k, M^-)$, $\Delta R_m(k, M^-)$

Preliminary estimation:
Scan every machine node in the communication range;
Record the node max with the maximum RSSI $R_{max}(1)$;
repeat
  $j = max + \Delta n(k, max)$
  Add node j in CA;
until Process all $\Delta n(k, max) \in \Delta\mathbf{N}(k, max)$;
repeat
  if $R(i) \geqslant R_{\max}(1)+\Delta R_1(k, M^-)$ **then**
    Keep the node in CA;
  else
    Remove the node from CA;
  end if
until Process all $i \in CA$;

Advanced estimation:
Sample the RSSI of each machine node in CA for m times;
Smooth RSSI by Kalman filter;
Record the maximum RSSI $R_{max}(m)$;
repeat
  if $R(i) \geqslant R_{\max}(m)+\Delta R_m(k, M^-)$ **then**
    Keep the node in the final estimation result;
  else
    Remove the node from the final estimation result;
  end if
until Process all $i \in CA$.

by the manufacturer *before* implementation, thus the offline measurement is not the burden for the users.

Obtaining the ID of the proximal node and the nodes with maximum RSSI, the $\Delta n(k, max)$ can be calculated based on Eqn.1. It is important to note that, due to the RSSI fluctuation, the node with maximum RSSI may change during the offline measurement. Therefore, the offline measurement finally obtains a set of $\Delta n(k, max)$ which is denoted as $\Delta\mathbf{N}(k, max)$.

According to Eqn.4, the RSSI difference $\Delta R(k, M^-)$ can be calculated by obtaining the $L(R(k))$ of proximal node and the $U(R(M^-))$ of any other nodes. Moreover, the offline measurement is required to calculate the $\Delta R(k, M^-)$ after the RSSI are processed by the Kalman filter algorithm. Specifically, $\Delta R_1(k, M^-)$ is defined as the RSSI difference derived from the original RSSI data, and $\Delta R_m(k, M^-)$ is the RSSI difference derived from the RSSI data filtered with the sampling number m.

B. Preliminary estimation

In FaceMEN, the proximal node is estimated by the human node in two steps: preliminary estimation and advanced estimation. The goal of preliminary estimation is to reduce the machine nodes involved in the advanced estimation, such that the time complexity can be reduced.

In the preliminary estimation, the human node firstly scans the machine nodes located in its transmission range, and records their ID and RSSI respectively. Then it obtains the node max that has the maximum RSSI. Based on the

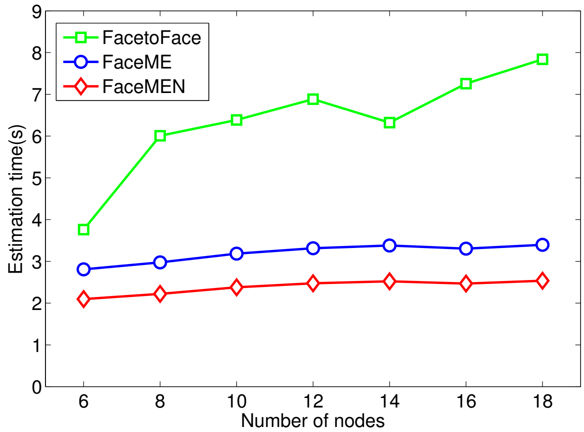

Fig. 5. The estimation time comparison

$\Delta\mathbf{N}(k, max)$ obtained in the offline measurement, the ID of proximal candidates can be obtained by adding max with all the elements in $\Delta\mathbf{N}(k, max)$. The set of proximal candidates is defined as CA.

In the preliminary estimation, the R_{max} is obtained without RSSI filtering, thus we denote the maximum RSSI in the preliminary estimation as $R_{max}(1)$. Based on Eqn.5, the set CA can be refined by the $R_{max}(1)$ and the RSSI difference $\Delta R_1(k, M^-)$ as follows. For any node $i \in CA$, if $R(i) \geqslant R_{\max}(1)+\Delta R_1(k, M^-)$, keep the node in CA; otherwise, remove the node from CA. The process repeats until all the nodes in the CA are processed.

At the end of preliminary estimation, if there is only one node in the CA , this node is destined to be the proximal node. Thus the human node can connect to it directly. Otherwise, the advanced estimation will be executed based on CA.

C. Advanced estimation

In the advanced estimation, the human node should sample the RSSI of each node in CA for m times, and then process the RSSI data by Kalman filter to reduce the fluctuation. Then it can obtain the maximum value of the filtered RSSI $R_{\max}(m)$. Similar to the preliminary estimation, the set CA can be refined by the RSSI difference $\Delta R_m(k, M^-)$. For any node $i \in CA$, if $R(i) \geqslant R_{\max}(m)+\Delta R_m(k, M^-)$, keep the node; othewise, remove the node.

The final estimation result could be derived after all the nodes in CA are processed. If there is only one node left in the estimation result, the human node will directly connect to it. Otherwise, if there are more than one node in the estimation results, their ID will be displayed on the user interface of the human node for manual selection.

V. Experimental Evaluation

In this section, we execute experiments to evaluate the performance of FaceMEN, and compare it with that of FaceME [11] and Face-to-face proximity estimation [9]. The experiments are executed in the mobile industrial HMI testbed

TABLE II
THE NUMBER OF NODES IN THE FINAL ESTIMATION RESULTS

dx \ dy	1.2			1.5			1.8		
	FaceMEN	FaceME	FacetoFace	FaceMEN	FaceME	FacetoFace	FaceMEN	FaceME	FacetoFace
0.6	$1:100\%$	$1:100\%$	$1:99\%$ $2:1\%$	$2:100\%$	$2:5\%$ $3:55\%$ $4:16\%$ $5:24\%$	$2:5\%$ $3:50\%$ $4:20\%$ $5:25\%$	$1:53\%$ $2:47\%$	$1:45\%$ $2:54\%$ $3:1\%$	$1:9\%$ $2:84\%$ $3:7\%$
0.9	$1:42\%$ $2:39\%$ $3:19\%$	$1:41\%$ $2:5\%$ $3:54\%$	$2:17\%$ $3:83\%$	$1:100\%$	$1:100\%$	$1:83\%$ $2:17\%$	$1:78\%$ $2:12\%$ $3:10\%$	$1:77\%$ $2:9\%$ $3:14\%$	$1:60\%$ $2:14\%$ $3:26\%$
1.2	$1:100\%$	$1:100\%$	$1:100\%$	$1:30\%$ $2:63\%$ $3:7\%$	$1:28\%$ $2:24\%$ $3:48\%$	$1:14\%$ $2:23\%$ $3:63\%$	$1:46\%$ $2:54\%$	$1:13\%$ $2:87\%$	$1:4\%$ $2:96\%$

TABLE I
THE NUMBER OF NODES IN THE CA

dx \ dy	1.2		1.5		1.8	
	FaceMEN	FaceME	FaceMEN	FaceME	FaceMEN	FaceME
0.6	$1:100\%$	$1:99\%$ $2:1\%$	$2:100\%$	$3:31\%$ $4:25\%$ $5:44\%$	$1:17\%$ $2:71\%$ $3:12\%$	$1:8\%$ $2:52\%$ $3:39\%$ $4:1\%$
0.9	$1:33\%$ $2:39\%$ $3:28\%$	$1:33\%$ $2:1\%$ $3:66\%$	$1:76\%$ $2:24\%$	$1:75\%$ $2:25\%$	$1:41\%$ $2:24\%$ $3:35\%$	$1:41\%$ $2:19\%$ $3:40\%$
1.2	$1:100\%$	$1:100\%$	$1:21\%$ $2:72\%$ $3:7\%$	$1:19\%$ $2:23\%$ $3:58\%$	$1:9\%$ $2:67\%$ $3:24\%$	$2:31\%$ $3:66\%$ $4:3\%$

introduced in Section II-A. Each experiment runs 100 times, and the statistic results are demonstrated in the following sections.

A. Estimation Time

The estimation time of the FaceMEN algorithm is firstly studied in this section. The dx is set as $0.9m$, and the dy is fixed at $1.2m$. The number of machine nodes increases from 6 to 18. The RSSI sampling number m is fixed at 20, and the broadcast period of machine nodes is set at 100ms.

As shown in Fig.5, compared with Face-to-face proximity estimation, both FaceMEN and FaceME have great improvements in the estimation time. In FaceMEN, the average estimation time ranges in 2.097s-2.536s, while the average estimation time of FaceME ranges in 2.849s-3.638s. FaceMEN further reduces the estimation time over 26.4% by comparing with FaceME.

The major reason is that, in the preliminary estimation, the FaceMEN uses neighbor relations $\Delta\mathbf{N}(k, max)$ to reduce the number of nodes in CA, and thus reduces the time complexity in the advanced estimation. It will be proved by the experimental results given in the following section.

B. Results in Preliminary Estimation

To prove the effectiveness of FaceMEN, we study the number of nodes in CA after preliminary estimation. The number of machine nodes is fixed at 18. The dx varies from 0.6m to 1.2m, and the dy grows from 1.2m to 1.8m. The results are given in Table I. The numbers in the table indicate the number of nodes in CA , and the percentage that follows each number demonstrates the frequency that each number appears in the experiments. It is better to have fewer nodes in CA , since it leads to less estimation time consumed in the advanced estimation and fewer nodes in the final estimation results.

As shown in Table I, the CA of FaceMEN contains less number of nodes than the CA of FaceME. The advantage of FaceMEN grows with smaller dx. Specifically, when $dx = 0.6m$ and $dy = 1.5m$, the CA of FaceMEN has two nodes, while there are four or five nodes in the CA of FaceME. This result proves the effectiveness of using neighbor relations to reduce the number of nodes in CA.

C. Final Estimation Results

At last, we study the number of nodes in the final estimation result. The number of machine nodes is fixed at 18. The dx varies from 0.6m to 1.2m, and the dy grows from 1.2m to 1.8m. The sampling number in the advanced estimation is $m = 10$. The experimental results are recorded in Table II. The numbers in the table indicate the number of nodes in the final estimation results, and the percentage that follows each number demonstrates the frequency that each number appears in the experiments. It is better to have fewer nodes in the final estimation results, since it reduces the complexity of manual selection.

The results show that the proximal node is guaranteed to be contained in the estimation results in all three algorithms. However, they have great difference in the number of nodes in the final estimation results. As shown in Table II, compared with Face-to-face proximity estimation, both FaceMEN and FaceME have fewer nodes in the final estimation result. Furthermore, FaceMEN has less number of nodes than FaceME with all dx and dy. Particularly, when $dx = 0.6m$ and $dy = 1.5$, the estimation result of FaceMEN only has two nodes while the maximum number of nodes in FaceME is 5. Moreover, when $dx = 1.2m$ and $dy = 1.8m$, FaceMEN has a great advantage in having more probability of estimating only one node.

The reason can be derived from the results given in Section V-B. In FaceMEN, using neighbor relations $\Delta\mathbf{N}(k, max)$ is helpful to reduce the number of nodes in the CA, and thus reduces the number of nodes in the final estimation results. These results prove that FaceMEN is a reasonable solution for face-to-machine proximity estimation in most applications.

VI. Conclusion

In this paper, we analyze the node deployment in a mobile industrial HMI testbed and then propose the model to formulate the neighbor relations between the proximal node and the node with the maximum RSSI. Based on the neighbor relations, a new face-to-machine proximity estimation (FaceMEN) algorithm is proposed to improve the proximity accuracy. The performance of FaceMEN is studied on the mobile industrial HMI testbed, which proves that FaceMEN has better estimation accuracy and less time complexity than FaceME.

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