Exploiting RSSI Difference among Multiple Neighbors to Improve Face-to-Machine Proximity Estimation in Industrial Human Machine Interaction

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***Abstract*—The massive machines connected to the industrial cyber-physical systems bring challenges to the machine management in the industrial human machine interaction (HMI). The engineer has to identify the target machine from a long list which is a non-trivial problem. Observing the fact that the industrial HMI is generally executed in a face-to-machine manner, the face-to-machine proximity estimation (FaceME) algorithm has been proposed to solve this problem. Nevertheless, due to the randomness of wireless signal, the estimation accuracy of FaceME is not sufficient in the scenarios with densely deployed machines. In this paper, we exploit the RSSI difference among multiple neighbors in the industrial HMI. Based on the analysis, we propose a face-to-machine proximity estimation algorithm called *FaceME+* which takes advantages of the RSSI difference among multiple neighbors to improve the estimation accuracy. Its performance is studied on the mobile industrial HMI testbed, and the results prove the efficiency of FaceME+.**

***Index Terms*—Proximity estimation, RSSI difference, multiple neighbors, face-to-machine proximity, mobile industrial human machine interaction**

I. Introduction

With the development of industrial cyber-physical systems (ICPS) [1]–[3], the mobile device plays an important role in the industrial human machine interaction (HMI). The engineer can use a mobile to control the machine and observe if it operates well simultaneously, which greatly improves the efficiency of HMI in the industrial field. Nevertheless, the massive number of machine nodes in ICPS brings challenges to the industrial HMI. Take the electric substation for example (Fig.1), the machines are densely deployed at about 30 nodes per $100m^2$ in the plant. In this case, the engineer has to manually select the target from a list with more than 20 nodes which is a non-trivial problem.

To solve this problem and improve the efficiency of the operation, NFC [4] or QR code [5] scanning can be used to obtain the ID of the target machine before connection. However, they have to be executed in extremely short range 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, most of them have high time complexity that can hardly be tolerated by the engineers.

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

Our previous work [2] observes 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. Based on FaceME, the research work [11] uses the neighbor relation among machine nodes to improve the estimation accuracy.

However, due to the randomness of RSSI, the estimation accuracy is not optimized. In the plant with dense nodes deployment, more than 3 machine nodes are left in the estimation results. It is because FaceME only uses the maximum RSSI and RSSI difference for estimation, and the RSSI of other machine nodes is not fully utilized.

In this paper, we propose the RSSI difference among multiple neighbor machine nodes, and then use it to improve the accuracy of proximity estimation in the face-to-machine HMI. Based on this idea, this paper makes the following contributions:

1) The RSSI of multiple neighbor machine nodes are analyzed in a mobile industrial HMI testbed. Then the RSSI difference among multiple neighbors is formulated based on the analysis.

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2) We propose the face-to-machine proximity estimation with the RSSI difference among multiple neighbors (FaceME+) algorithm to improve the proximity accuracy. The RSSI difference among multiple neighbors is measured in the offline measurement, then it is used in the online estimation to refine the estimation result.

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

The rest of this paper is organized as follows. Section II introduces the mobile industrial HMI testbed and the network model used in this paper. Then we provide the definition of RSSI difference among multiple neighbors in Section III. Section IV provides the details of FaceME+ algorithm, and the experiment results are given in Section V to evaluate the performance of FaceME+ algorithm. Finally, Section VI makes a conclusion of this paper.

II. Preliminaries

A. Mobile Industrial HMI Testbed

To evaluate the performance of mobile industrial HMI, we have implemented a testbed [2] as shown in Fig.2. In this testbed, the *human node* uses the Google Nexus 9 tablet which communicates with machine nodes via Bluetooth. The *machine node* is a wireless module composed of TI-CC2541 and MAX3485 chips to support Bluetooth and RS485 protocols. It communicates with the PLC (programmable logic controller) by RS485, and the PLC is the DVP12SE industrial controller developed by Delta Electronics.

We deployed the testbed in the Delta PLC laboratory located in Fuzhou University. The layout of the laboratory is given 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. We developed an Android application called *MobileHMI* to read the input signals and control the outputs of PLC. The MobileHMI runs the proximity estimation algorithms, which will be introduced in Section IV, to collect and process Bluetooth RSSI of the machine nodes.

B. Network Model

In most industrial plants, the machines are regularly deployed [12]. Thus in this paper, we use the network model [2] that formulates the network deployment by two variables: the spacing among machine nodes dx, and the distance between the human node and the proximal node dy.

The *proximal node* is defined as the machine node that is closest to the human node in the physical space, and we assume that the ID of machine nodes are assigned in order (from left to right) [11]. Since the human node has powerful hardwares, it 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 human node can detect a set of machine nodes which is denoted by M, and the proximal node is denoted by k. Then we define the set of machine nodes M^- as,

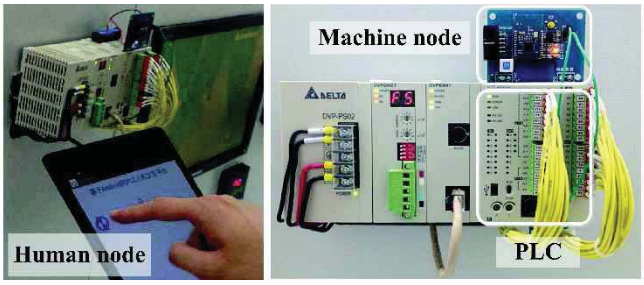

Fig. 2. The framework of the mobile industrial HMI testbed

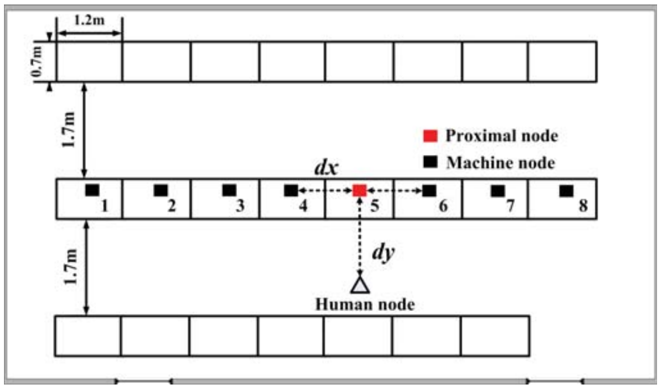

Fig. 3. The layout of the mobile industrial HMI testbed

$$M^- = \{i|(i \in M) \cap (i \neq k)\}. \quad (1)$$

For example, in the testbed shown in Fig.3, the dx is fixed at $1.2m$, and the dy varies from $0.9m$ to $1.8m$. The ID of the proximal node is $k = 5$.

C. RSSI Difference

In order to clarify the basic idea of RSSI difference [2], we firstly execute an experiment to examine the RSSI of machine nodes. There are 8 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 0.9 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 every 10 seconds, and the measurements are repeated over the period of 35 minutes.

Fig.4 shows the RSSI values with machine nodes from 4 to 6. It is clear to see that the RSSI fluctuation of machine 5 has great overlaps with that of machine 4 and 6, which may results in the wrong estimation of the proximal node. Based on this observation, the fluctuation of $R(i)$ can be formulated as

$$R(i) \in [L(R(i)), U(R(i))], \quad (2)$$

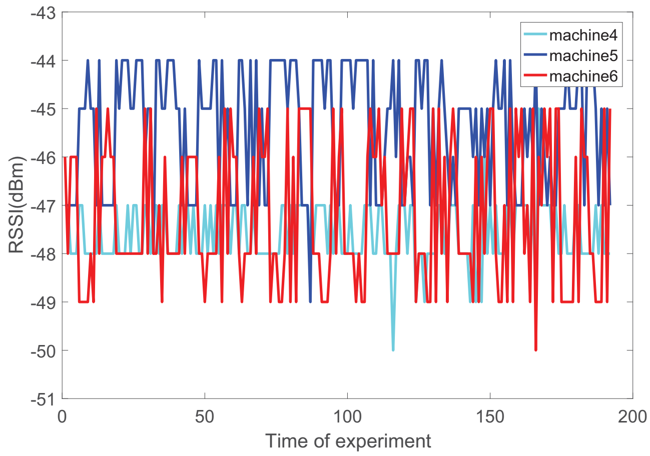

Fig. 4. RSSI of machine nodes with dx=0.9m and dy=1.2m

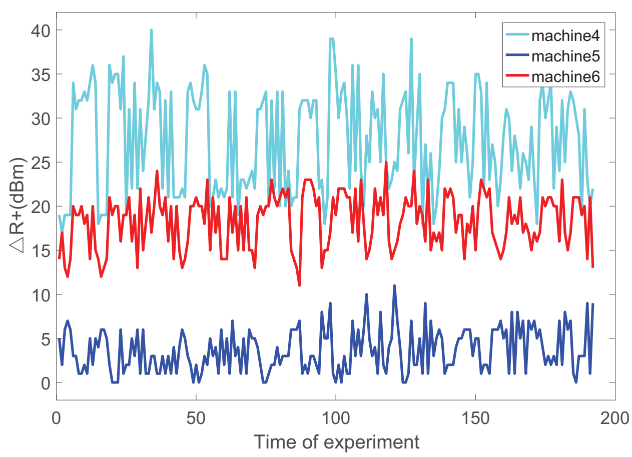

Fig. 5. RSSI difference among multiple neighbors with dx=0.9m and dy=1.2m

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.1), the RSSI difference $\Delta R(k, M^-)$ is defined as

$$\Delta R(k, M^-) = L(R(k)) - U(R(M^-)). \tag{3}$$

It formulates the relation between the RSSI of the proximal node $R(k)$ and the maximum RSSI of all the other machine nodes.

III. RSSI Difference among Multiple Neighbors

The RSSI difference is proposed to ensure that the proximal node is contained in the estimation results [2]. However, it can not distinguish the proximal node from others due to the overlap of RSSI. It motivates us to propose a new metric to improve the estimation accuracy.

The basic idea is considering the RSSI of multiple neighbor machine nodes simultaneously. Given machine node i, we define its RSSI difference among multiple neighbors as follows,

$$\Delta R^+(i, d) = \sum_{j=1}^{d} |R(i-j) - R(i+j)|, \tag{4}$$

where d determines how many neighbors are considered in the calculation.

Then we execute an experiment to examine the effectiveness of $\Delta R^+(i, d)$. In the experiment, there are 8 machine nodes deployed in the testbed shown in Fig.3, and the ID of the proximal node is 5. The dx is 0.9 meters and dy is 1.2 meters, and d is set as 2. The $\Delta R^+(i, d)$ of machine nodes 4-6 are shown in Fig.5. Compared with Fig.4, the $\Delta R^+(i, d)$ of the proximal node (machine 5) has clear difference with that of other nodes. It indicates that $\Delta R^+(i, d)$ is an effective metric for proximity estimation.

IV. Face-to-Machine Proximity Estimation with RSSI Difference among Multiple Neighbors

In this paper, the face-to-machine proximity estimation with RSSI difference among multiple neighbors (FaceME+) algorithm is proposed based on the framework of FaceME [2]. Different from FaceME, the FaceME+ algorithm measures the RSSI difference among multiple neighbors $\Delta R^+(i, d)$ in the offline measurement, and then uses it in the online estimation to refine the estimation result. The details of FaceME+ algorithm are described as follows.

A. Offline measurement

In FaceME+, the offline measurement should collect the $\Delta R^+(i, d)$ which denotes the RSSI difference among multiple neighbors defined in Eqn.4. Since the proximal node is knowable in the offline measurement, four kinds of $\Delta R^+(i, d)$ should be recorded: the maximum value of $\Delta R^+(i, d)$ of the proximal node $U(\Delta R^+(k))$, the minimum value of $\Delta R^+(i, d)$ of the proximal node $L(\Delta R^+(k))$, the maximum value of $\Delta R^+(i, d)$ of any other nodes $U(\Delta R^+(M^-))$, and the minimum value of $\Delta R^+(i, d)$ of any other nodes $L(\Delta R^+(M^-))$.

Moreover, the $\Delta R(k, M^-)$ which is the RSSI difference defined in Eqn.3 should also be collected in the offline measurement. 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.

Since dx and dy have impacts on the results, the human node should sample the RSSI and record the corresponding ID from every machine nodes with different dx and dy.

B. Preliminary estimation

In the preliminary estimation, the human node firstly scans the machine nodes located in its transmission range, and records their ID and RSSI respectively. The scanned machine nodes are recorded in the list called CA. The maximum RSSI obtained in the preliminary estimation is denoted as $R_{max}(1)$. Then 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;

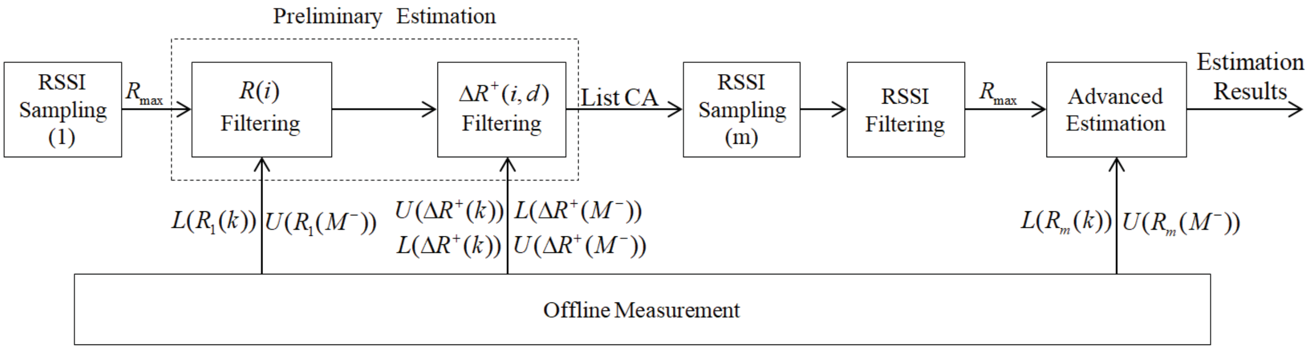

Fig. 6. The framework of FaceME+ algorithm

otherwise, remove the node from CA. The process repeats until all the nodes in the list CA are processed.

Then the list CA is further processed by $\Delta R^+(i,d)$. If $L(\Delta R^+(k)) \leqslant \Delta R^+(i,d) \leqslant U(\Delta R^+(M^-))$, keep the node in CA; otherwise, remove the node from CA. The process repeats until all the nodes in CA are processed. Next, we define the minimum value of $\Delta R^+(i,d)$ of all nodes involved in the CA as $L(\Delta R^+(i,d))$. The human node checks the $\Delta R^+(i,d)$ of all nodes in CA, if $L(\Delta R^+(i,d)) \leq \Delta R^+(i,d) \leq L(\Delta R^+(i,d)) + U(\Delta R^+(k)) - L(\Delta R^+(M^-))$, keep the node in CA; otherwise, remove the node from CA.

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 $R_{\max}(m)$. For any node $i \in CA$, if $R(i) \geqslant R_{\max}(m) + \Delta R_m(k, M^-)$, keep the node; otherwise, 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 FaceME+, and compare it with that of FaceME [13] and FaceMEN [11]. The experiments are executed in the mobile industrial HMI testbed introduced in Section II-A. Each experiment runs 100 times, and the statistic results are demonstrated in the following sections.

A. Estimation Results

In this section, we study the number of nodes in the estimation result. The number of machine nodes is fixed at 18.The

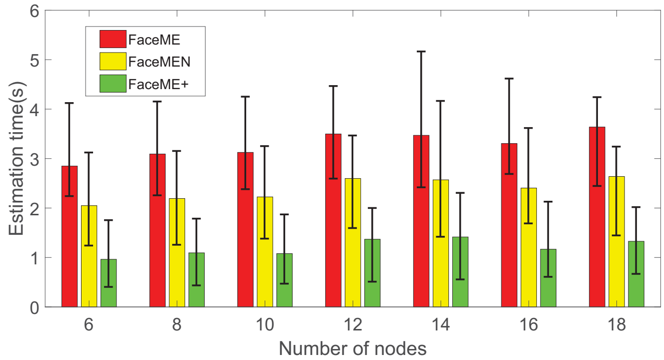

Fig. 7. The estimation time comparison

sampling number in the advanced estimation is $m = 10$. The experimental results are recorded in Table I. The numbers in the table indicate the number of nodes in 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 I, FaceME+ has less number of nodes than any other algorithms with all dx and dy.

Particularly, when $dx = 1.2m$ and $dy = 1.8m$, FaceME+ can select the proximal node directly and guarantee success rate which has an overwhelming superiority than any other algorithms. The superiority is that FaceME+ use multiple neighbor relations to further optimize the experimental results.

In FaceME+, using the sum of RSSI difference $\Delta R^+(i,d)$ is helpful to reduce the number of nodes in CA, and thus reduce the number of nodes in the estimation results. These results prove that FaceME+ is a reasonable solution for face-to-machine proximity estimation in most applications.

TABLE I
THE NUMBER OF NODES IN THE ESTIMATION RESULTS

dx \ dy	1.2			1.5			1.8		
	FaceME+	FaceMEN	FaceME	FaceME+	FaceMEN	FaceME	FaceME+	FaceMEN	FaceME
0.6	$1:100\%$	$1:100\%$	$1:100\%$	$1:\ \ 1\%$ $2:74\%$ $3:25\%$	$2:100\%$	$2:\ \ 5\%$ $3:55\%$ $4:16\%$ $5:24\%$	$1:56\%$ $2:44\%$	$1:53\%$ $2:47\%$	$1:45\%$ $2:54\%$ $3:\ \ 1\%$
0.9	$1:100\%$	$1:42\%$ $2:39\%$ $3:19\%$	$1:41\%$ $2:\ \ 5\%$ $3:54\%$	$1:100\%$	$1:100\%$	$1:100\%$	$1:79\%$ $2:21\%$	$1:78\%$ $2:12\%$ $3:10\%$	$1:77\%$ $2:\ \ 9\%$ $3:14\%$
1.2	$1:100\%$	$1:100\%$	$1:100\%$	$1:97\%$ $2:\ \ 3\%$	$1:30\%$ $2:63\%$ $3:\ \ 7\%$	$1:28\%$ $2:24\%$ $3:48\%$	$1:100\%$	$1:46\%$ $2:54\%$	$1:13\%$ $2:87\%$

B. Estimation Time

Finally, the estimation time of the FaceME+ is 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.7, compared with FaceMEN and FaceME, FaceME+ has great improvements in the estimation time. In FaceME+, the average estimation time ranges in 0.963s-1.327s. On the other hand, the average estimation time of FaceMEN ranges in 2.097s-2.536s, and the average estimation time of FaceME ranges in 2.849s-3.638s. FaceME+ reduces the estimation time over 54.1% by comparing with FaceMEN, and 66.2% by comparing with FaceME.

The major reason is that the FaceME+ greatly reduces the number of nodes in the CA list, and thus reduces the time complexity in the advanced estimation.

VI. Conclusion

In this paper, we exploit the RSSI difference among multiple neighbors in the mobile industrial HMI. Based on the analysis, we propose the FaceME+ algorithm that takes advantages of the RSSI difference among multiple neighbors to improve the estimation accuracy in the face-to-machine proximity estimation. The performance of FaceME+ is studied on the mobile industrial HMI testbed, and the experimental results prove that FaceME+ has better estimation accuracy and less time complexity than both FaceMEN and FaceME.

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