Face-to-Machine Proximity Estimation for Mobile Industrial Human Machine Interaction

Ting Liu*, Zhezhuang Xu*, Rongkai Wang*, Hao Jiang*, Cailian Chen†, Shih-Hau Fang‡

*School of Electrical Engineering and Automation, Fuzhou University, Fuzhou 350000, China
Email: zzxu@fzu.edu.cn
†Department of Automation, Shanghai Jiao Tong University, Shanghai 200240, China
Email: cailianchen@sjtu.edu.cn
‡Department of Electrical Engineering, Yuan Ze University, Taoyuan 320, Taiwan
Email: shfang@saturn.yzu.edu.tw

***Abstract*—In the mobile industrial human machine interaction (HMI) based on wireless sensor networks, the engineer has to manually select the target machine from a long list which may lead to wrong connection and waste of time. We observe that the engineer should face to the machine during the interaction to ensure that the machine works accurately, and this characteristic makes the proximity estimation algorithm suitable to simplify the data connection. However, due to the densely deployed machines and the frequent HMI in the industrial plant, the existing algorithms can not provide sufficient accuracy with limited latency. In this paper, we implement a mobile industrial HMI testbed to evaluate the characteristics of wireless communication in the face-to-machine HMI, and then propose the face-to-machine proximity estimation (FaceME) algorithm based on the analytical results. The experimental results prove that FaceME can provide guaranteed estimation accuracy and low time complexity that satisfies the requirements of the face-to-machine HMI.**

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

I. Introduction

Industrial human machine interaction (HMI) refers to the information interaction between the engineer and the machines located in the industrial plant. It includes reading sensor data, setting parameters, manual control and so on. With the development of industrial wireless sensor networks [1], [2], the hardware of industrial HMI evolves from fixed touchscreens to mobile devices. The engineer can execute HMI at any position around the machine which greatly improves the efficiency. However, to establish the data connection, the engineer has to remember the identification (ID) number of each machine, and then manually selects the target from a list. Since the machines are densely deployed at 5-30 nodes per $100m^2$ in the plant, the considerable number of machines may lead to wrong connection and waste of time.

As shown in Fig.1, the HMI in the industrial plant is typically executed in a *face-to-machine* manner: the engineer should face to the machine during the interaction to ensure the machine works accurately. In this case, the communication between the mobile device and the target machine is line-of-sight (LOS), and the target machine is physically proximal to the mobile device. This scenario is quite different from the existing mobile networks [3]–[5]. Therefore, how to take advantages of these characteristics to improve the efficiency of data connection becomes an interesting issue.

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

The proximity estimation [5]–[8] is a natural solution which uses RSSI (received signal strength indicator) to detect the scenario when a pair of nodes approach each other closer than a predefined proximity distance. Besides, indoor localization algorithms can estimate the location of the mobile device by WiFi triangulation [9], WiFi fingerprints [10] or a combination of multiple signals processing [11].

However, the industrial HMI network has several unique characteristics which make the existing solutions hard to be applied directly. At first, the machines are densely deployed in the industrial plant, and the distance between machines is about 0.5-5 meters. The accuracy of the existing algorithms (1-4m) is insufficient [5], [11]. Moreover, in related works, the RSSI has to be filtered before estimation due to its fluctuation. The sampling and filtering of RSSI from a large number of machines will generate considerable delay. Since the engineer has to interact with different machines 5-20 times per hour, the time complexity of the algorithm becomes a significant issue that has yet been considered.

It is important to note that face-to-machine HMI does not demand an absolute position or distance estimation as offered by the previously mentioned algorithms, but rather requires a determination of the machine that is proximal to the mobile device. With its special characteristics and requirements, we aim to propose a proximity estimation algorithm tailored for face-to-machine HMI. Specifically, our work makes the following contributions:

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1) We implement a mobile industrial HMI testbed to demonstrate the viability of using Bluetooth RSSI to realize the mobile industrial HMI and the face-to-machine proximity estimation. Based on the testbed, we provide a model to formulate the node distribution in the face-to-machine HMI.

2) The experimental and theoretical analysis is provided to study the Bluetooth RSSI in the face-to-machine HMI. We derive the conditions to guarantee the estimation accuracy based on the definition of *RSSI difference*. These conditions are used as the guideline to design the new algorithm.

3) The face-to-machine proximity estimation (FaceME) algorithm is proposed to estimate the machine node that is proximal to the human node. The experiment results prove that FaceME algorithm can provide guaranteed accuracy and low time complexity.

The rest of this paper is organized as follows. Section II introduces the mobile industrial HMI testbed, and then we use the testbed to evaluate the characteristics of RSSI in the face-to-machine HMI in Section III. Section IV presents 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. Mobile Industrial HMI Testbed

We implement a mobile industrial HMI testbed to evaluate the performance of wireless communication in face-to-machine HMI. As shown in Fig.2, the testbed consists of three parts: the *human node* which is defined as the mobile device carried by the engineer, the *machine node* which is defined as the wireless module integrated with Bluetooth and RS485 communication chips, and the *programmable logic controller* (PLC) which is the most popular controller in the industry. The human node can read the status and modify the parameters of PLC via Bluetooth communication with machine nodes, while the machine node converts Bluetooth packets to RS485 packets and vice versa. The details are described as follows.

A. Hardware and Software

Google Nexus 9 tablet with Android OS version 5.1 is used as the human node in the testbed. We developed an Android application called *MobileHMI* can 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.

We develop a wireless module as the machine node that consists of a Bluetooth core board and an extension board. The Bluetooth core board uses a TI-CC2541 chip, and the extension board is composed of power converter and a MAX3485 chip to support RS485 communication. The program that completes the conversion between Bluetooth packets and RS485 packets is written based on the BLE-STACK supported by TI.

The PLC is the DVP12SE series developed by Delta. Each PLC is connected to a machine node by RS485. The PLC is set as the client in the RS485 network and the data packets use Modbus protocol, such that the system software of PLC can handle the communication with the machine node.

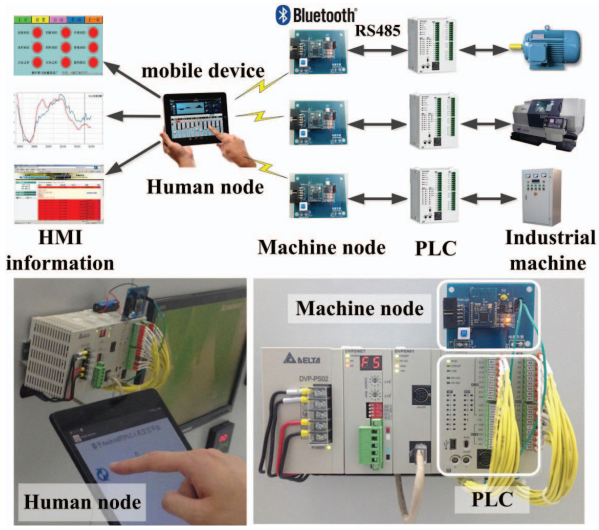

Fig. 2. The framework of the mobile industrial HMI testbed

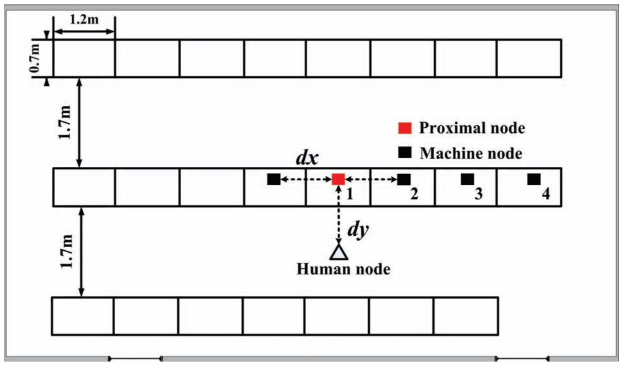

Fig. 3. The layout of the mobile industrial HMI testbed

B. Testbed Deployment

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. The size of the laboratory is 12m×7.65m, and the size of each console is 1.2m×0.7m.

The testbed represents a typical industrial plant: a large number of machines are deployed in rows with fixed spacing, while the engineer moves in the passage to interact with machines. The human-machine interaction is generally executed in a *face-to-machine* manner that the engineer should face to the machine during the interaction to ensure the machine works accurately.

III. RSSI Analysis in Face-to-Machine HMI

In this section, we analyze the characteristics of RSSI in the wireless communication of face-to-machine HMI. Motivated by the observation of RSSI fluctuation in the experiments, we provide the definition of *RSSI difference* and then use it for deriving the conditions to guarantee the estimation accuracy. These results will be used as the guideline to design the new algorithm in IV.

A. Network Model

At first, we define the *proximal node* as the machine node that is proximal to the human node in the physical space. Then 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 variable due to the mobility of the human node. Take the Delta PLC laboratory shown in Fig.3 as example, the dx is fixed at $1.2m$, and the dy varies from $0.5-1.5m$ which depends on the width of the passage and how close the engineer stands in front of the machine. This model formulates the difference of the distance from the human node to machine nodes which has great impacts on the values of RSSI.

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,

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

These definitions will be used in the next sections.

B. RSSI Fluctuation

In this paper, an essential problem is to determine whether the RSSI is sufficient to estimate the proximal machine node in the face-to-machine HMI. Therefore, we carried out an experiment to understand the RSSI fluctuation in the scenario of face-to-machine HMI. In the experiment, four machine nodes are deployed in the laboratory as 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 1. The human node locates in front of the proximal node, and its distance to the proximal node dy is 1.3 meters. The human node measures the RSSI of all machine nodes simultaneously at every 15 seconds, and the measurements are repeated over the period of 50 minutes.

Fig.4 shows the fluctuations of RSSI values with all machine nodes. Although the RSSI varies significantly for the same node, its variance is constrained in a limited interval and there is a noticeable gap exists between the proximal node and the other machine nodes. Such results further shed light on the viability of using RSSI to estimate the proximal node.

On the other hand, as shown in Fig.4, there are overlap between the RSSI fluctuation interval of machine 1 and 2. It may lead to the wrong estimation of the proximal node. This result motivates us to further evaluate the RSSI fluctuation. According to the most popular model given in [12], the RSSI can be formulated by,

$$RSSI = P_{TX} + G + 20\log(\frac{c}{4\pi f}) - 10n\log(d) \tag{2}$$

where d is the distance between the transmitter and receiver; P_{TX} is the transmitted power; G is the antenna gain; c is the speed of light ($3 \times 10^8 m/s$); f is the central frequency (2.44 GHz); n is the attenuation factor (2 in free space).

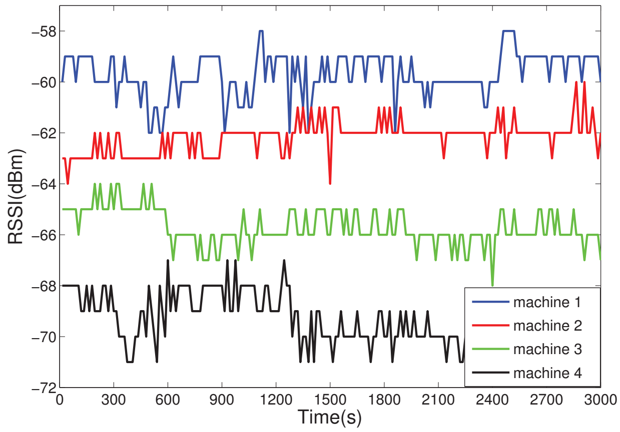

Fig. 4. RSSI of machine nodes with dx=1.2m and dy=1.3m

Based on this model, the factors that impact the RSSI can be divided into two categories: the deterministic factors and the stochastic factors. The deterministic factors include the distance between two nodes, the setting of radio parameters, and the estimated attenuation factor. The stochastic factors include the hardware heterogeneity, the power volatility, and the variation of channel state [10]. If the deterministic factors are predetermined, the RSSI of node i can be estimated as a deterministic value $E(R(i))$. According to the results shown in Fig.4, the fluctuation of $R(i)$ is formulated as,

$$R(i) \in [E(R(i)) - D_L(i), E(R(i)) + D_H(i)] \tag{3}$$

where $D_L(i)$ and $D_H(i)$ are the deviation of $R(i)$ caused by the stochastic factors. $E(R(i)) - D_L(i)$ is the lower bound of $R(i)$, and $E(R(i)) + D_H(i)$ is the upper bound of $R(i)$. Both of them can be estimated based on the statistic data of $R(i)$. Although the values of $E(R(i))$, $D_L(i)$ and $D_H(i)$ are difficult to be calculated in practice, Eqn.3 is helpful to provide an in-depth view of the face-to-machine proximity estimation. It will be discussed in the next section.

C. RSSI Difference

Based on the RSSI fluctuation given in Eqn.3, for a node $i \in M^-$, the RSSI difference $\Delta R(k,i)$ is defined as,

$$\begin{aligned} \Delta R(k,i) &= [E(R(k)) - D_L(k)] - [E(R(i)) + D_H(i)] \\ &= [E(R(k)) - E(R(i))] - [(D_L(k) + D_H(i)] \end{aligned} \tag{4}$$

The definition of the RSSI difference $\Delta R(k,i)$ indicates the difference between the lower bound of $R(k)$ and the upper bound of $R(i)$. The value of $\Delta R(k,i)$ can be estimated by the statistic data of $R(k)$ and $R(i)$. In the rest of this section, we will discuss the relations between the accuracy of proximity estimation and the RSSI difference $\Delta R(k,i)$.

In practice, after RSSI sampling, the human node can obtain a list of machine nodes combining with their RSSI. It is important to note that the human node can not identify the proximal node k from the list, but rather obtain the node

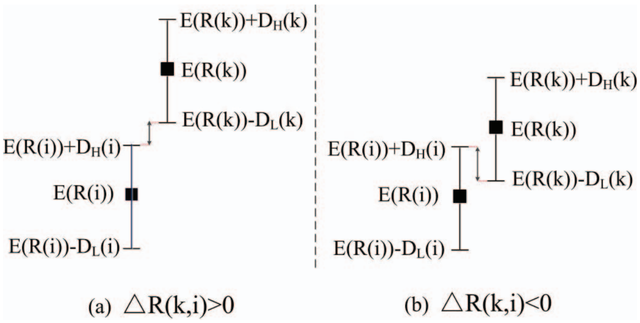

Fig. 5. Two cases of RSSI Difference

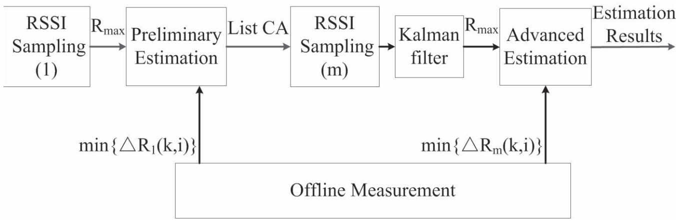

Fig. 6. The framework of FaceME algorithm

with the maximum RSSI $R_{\max}$. In this case, the accuracy of proximity estimation depends on the relations between $R(k)$ and $R_{\max}$ which can be estimated by using RSSI difference.

Fig.5 demonstrates two different cases of RSSI difference. If $\Delta R(k,i) \geq 0$ is satisfied for any $i \in M^-$, which means the minimum RSSI of proximal node is larger than the maximum RSSI of any other nodes, the node which has the maximum RSSI $R_{\max}$ will be destined to be the proximal node. Otherwise, if $\Delta R(k,i) < 0$, there will be overlap between the RSSI fluctuation interval of k and i. In this case, $R_{\max}$ may not be equal to $R(k)$ that leads to estimation error.

To clarify the analysis, we formally derive the relations between $R(k)$ and $R_{\max}$ as follows.

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

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

Otherwise, if $\min\{\Delta R(k,i)\} \geq 0$, then $R(k) = R_{\max}$.

Proof: At first, we consider the condition when $\min\{\Delta R(k,i)\} < 0$. Assume that the node j which has $R(j) = R_{\max}$, combining with Eqn.3 and 4, we have,

$$\begin{aligned} R(k) &\geq E(R(k)) - D_L(k) \\ &= E(R(j)) + D_H(j) + \Delta R(k,j) \\ &\geq R_{\max} + \min\{\Delta R(k,i)\}, i \in M^- \end{aligned} \tag{6}$$

then Eqn.5 can be easily derived based on Eqn.6.

When $\min\{\Delta R(k,i)\} \geq 0$, we can derive,

$$\begin{aligned} R(k) &\geq E(R(k)) - D_L(k) \\ &= E(R(i)) + D_H(i) + \Delta R(k,i) \\ &\geq R(i) + \min\{\Delta R(k,i)\} \geq R(i), i \in M^- \end{aligned} \tag{7}$$

which means that $R(k)$ is guaranteed to be larger than the RSSI of any other nodes. Therefore, $R(k) = R_{\max}$. □

According to Theorem 1, $\min\{\Delta R(k,i)\} \geq 0$ is a sufficient condition to guarantee the estimation accuracy. Combing with the definition of RSSI difference in Eqn.4, it also provides an in-depth view of the factors that impact the estimation accuracy: the growth of $E(R(k)) - E(R(i))$ and the reduction of $(D_L(k) + D_H(i)$ can improve the estimation accuracy. According to the network model given in Section III-A, $E(R(k)) - E(R(i))$ increases with the growth of dx and the reduction of dy. On the other hand, the filtering algorithm and increasing the sampling number of RSSI are helpful to reduce the $(D_L(k) + D_H(i)$. Moreover, Eqn.5 provides the guideline to filter the proximal node based on $R_{\max}$ and $\min\{\Delta R(k,i)\}$. We will use these results to design a new algorithm described in Section IV.

IV. Face-to-Machine Proximity Estimation Algorithm

In this paper, we propose a new algorithm named face-to-machine proximity estimation (FaceME) algorithm. Fig.6 demonstrates the framework of FaceME algorithm that includes two parts: the *offline measurement* to calculate the values of $\Delta R(k,i)$, and the *online estimation* that uses $\Delta R(k,i)$ and sampling results for proximity estimation. The online estimation is composed of preliminary estimation and advanced estimation. The preliminary estimation uses a rough filter to reduce the number of machine nodes that involve in the advanced estimation, while the advanced estimation combines Kalman filter algorithm and $\Delta R_m(k,i)$ to obtain the final estimation result. The details of FaceME algorithm are described as follows.

A. Offline measurement

The goal of the offline measurement is to obtain the value of $\Delta R(k,i)$ influenced by dx and dy. The dx is fixed in the specific industrial plant, while the dy is variable due to the mobility of the human node. Nevertheless, the dy is bounded by $d_{\max}$ which depends on the width of the passage in the specific plant. Therefore, in the offline measurement, the human node should locate in front of the proximal node with $dy = d_{\max}$ and sample the RSSI from every machine nodes. Then the human node can derive $\Delta R(k,i)$ based on Eqn.4.

The filtering algorithm can reduce the fluctuation of RSSI and hence impact the value of $\Delta R(k,i)$. Specifically, $\Delta R_1(k,i)$ is defined as the result without being processed by filtering algorithm, and $\Delta R_m(k,i)$ is defined as the result that is filtered with the sampling number m. The minimum value of $\Delta R_1(k,i)$ and $\Delta R_m(k,i)$, which are denoted as $\min\{\Delta R_1(k,i)\}$ and $\min\{\Delta R_m(k,i)\}$, will be used in the online estimation. Any filtering algorithm can be used in FaceME to process RSSI. In the rest of this paper, we adopt Kalman filter which has been proved to be efficient in smoothing RSSI [7].

B. Online estimation

The online estimation consists of preliminary estimation and advanced estimation. In the preliminary estimation, the human node samples the RSSI of each machine node only once. The human node can obtain $R_{\max}$ and a neighbor list from the sampling results. Then the $R_{\max}$ and the $\min\{\Delta R_1(k,i)\}$ obtained in the offline measurement is used to remove extraneous nodes based on Eqn.5: if $R(i) \geqslant R_{\max} + \min\{\Delta R_1(k,i)\}$, keep the node; otherwise, remove the node. After processing all the nodes in the neighbors list, the remaining nodes compose the proximal candidates list called CA.

If there is only one node in the CA list, this node is destined to be the proximal node. Otherwise, it means the human node is unable to accurately estimate the proximal node. Then the advanced estimation will be executed based on the CA list.

In the advanced estimation, the RSSI of the nodes in the CA list should be sampled for m times. Then the RSSI is processed by Kalman filter to reduce its fluctuation, and the maximum value of the filtered RSSI $R_{\max}$ can be obtained. Combining with the $\min\{\Delta R_m(k,i)\}$ obtained in the offline measurement, the human node can remove extraneous nodes from the CA list based on Eqn.5: if $R(i) \geqslant R_{\max} + \min\{\Delta R_m(k,i)\}$, keep the node; othewise, remove the node.

After processing all the nodes in the CA list, the human node obtains the final estimation result. If only one node is left in the estimation result, the human node will directly connect to it. On the other hand, if there are more than one nodes in the estimation results, their ID will be displayed in the user interface for manual selection.

V. Experimental Evaluation

In this section, we execute experiments to evaluate the performance of FaceME. For comparison, the Face-to-face proximity estimation [5], which has been proved to provide the best estimation accuracy in related works, is also developed in our testbed. In Face-to-face proximity estimation, the RSSI is firstly smoothed by EWMA (exponentially weighted moving average), and then the node with the processed RSSI is compared with a threshold measured in the offline phase to estimate whether the node is in proximity.

The experiment is executed in the Delta PLC laboratory shown in Fig.3. The performance is analyzed in two aspects: estimation time and accuracy. The sampling number of RSSI for filtering algorithms is $m = 20$ in both algorithms. Each experiment runs 200 times, and the statistic results are demonstrated in the following sections.

A. Offline Measurement Analysis

As an important variable in FaceME algorithm, the value of RSSI difference $min\{\Delta R(k,i)\}$ calculated in the offline measurement phase is studied at first. According to the space limitation of the laboratory, the maximum value of d_y is set as 1.5m.

The $\min\{\Delta R_1(k,i)\}$ and $\min\{\Delta R_{20}(k,i)\}$ are calculated when dx grows from 0.6m to 1.2m. The results are given in Table I. With the decrease of dx, $\min\{\Delta R_1(k,i)\}$ and $\min\{\Delta R_{20}(k,i)\}$ become smaller. Moreover, with the same dx, $\min\{\Delta R_{20}(k,i)\}$ is smaller than $\min\{\Delta R_1(k,i)\}$. It is because, $\min\{\Delta R_{20}(k,i)\}$ benefits from Kalman filtering algorithm. These results prove the analysis given in Section III-C.

TABLE I
RSSI DIFFERENCE OBTAINED IN OFFLINE MEASUREMENT

dx	0.6	0.9	1.2
$\min\{\Delta R_1(k,i)\}$	-6	-5	-5
$\min\{\Delta R_{20}(k,i)\}$	-5.14	-2.28	-1.42

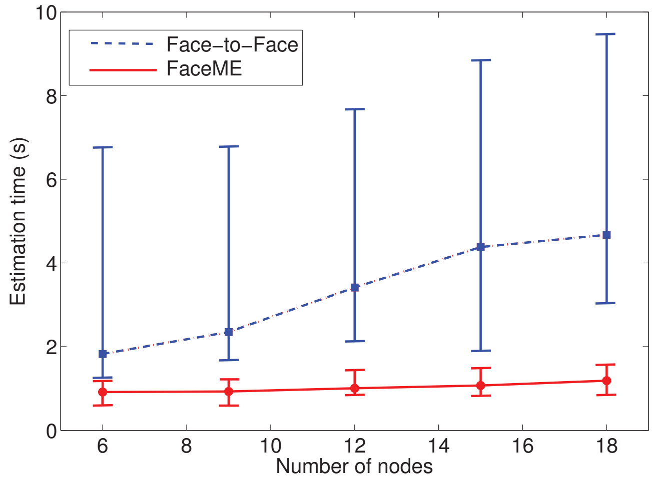

Fig. 7. The estimation time comparison

For Face-to-face proximity estimation, the threshold of the RSSI has no relation with dx. It is calculated in the scenario with $dy = 1.5$, and its value is $\theta = -60.35$. The values of $min\{\Delta R(k,i)\}$ and θ are used in the following experiments.

B. Estimation Time

In this section, we compare the estimation time of FaceME algorithm with Face-to-face proximity estimation. The dx is set as $1.2m$, and the dy is fixed at $0.9m$. The number of machine nodes grows from 6 to 18.

As shown in Fig.7, in FaceME, the average estimation time ranges in 0.923s-1.168s. Compared with Face-to-face proximity estimation, FaceME greatly reduces the estimation time from 50% to 75%. Moreover, the maximum estimation time of FaceME ranges in 1.211s-1.578s which is only a few hundred milliseconds longer than the average one. On the other hand, in Face-to-face proximity estimation, the maximum estimation time grows sharply to 6.674s-9.495s. It is because that FaceME uses $\Delta R(k,i)$ to reduce the number of nodes involved in RSSI sampling, and hence reduces the estimation time.

C. Estimation Accuracy

The estimation accuracy is measured by two metrics: 1) the probability that the proximal node is contained in the estimation result; 2) the number of nodes in the estimation result. The number of machine nodes is 18. The dx varies from 0.6m to 1.2m, and the dy grows from 0.9m to 1.5m. The experimental results are recorded in Table II-IV.

TABLE II
PROBABILITY OF THE PROXIMAL NODE CONTAINED IN THE ESTIMATION RESULTS

	Face-to-face			FaceME		
dx \ dy	0.9	1.2	1.5	0.9	1.2	1.5
0.6	100%	97%	71%	100%	100%	100%
0.9	97%	100%	79%	100%	100%	100%
1.2	100%	100%	63%	100%	100%	100%

As shown in Table II, in FaceME, the proximal node is guaranteed to be contained in the estimation results. On the other hand, in Face-to-face proximity estimation, the estimation accuracy can not be guaranteed when $dy = 1.5m$. The reason is that it uses an absolute threshold for proximity estimation, while FaceME uses both the RSSI difference measured in the offline phase and the maximum RSSI obtained in the online phase.

Then we compare the number of nodes in the estimation results. As shown in Table III, FaceME algorithm is able to estimate the proximal machine node directly when $dx \geq 0.9$m and $dy \leq 1.2$m. In other cases, the number of nodes in the estimation results is no more than 4. Table IV shows the results of Face-to-face proximity estimation. Compared with FaceME, when $dy \leq 1.2m$, the number of nodes in the estimation results is larger than that in FaceME. Although the number of nodes is reduced when $dy = 1.5m$, the proximal node is not guaranteed to be contained in the estimation results (Table II). To summarize, FaceME algorithm has better estimation accuracy than Face-to-face proximity estimation.

VI. CONCLUSION

In this paper, we propose the face-to-machine proximity estimation (FaceME) algorithm to improve the efficiency of industrial HMI. The mobile industrial HMI testbed is implemented to evaluate the performance of FaceME. The experimental results prove that the FaceME algorithm can provide guaranteed accuracy and low time complexity that satisfies the requirements of the industrial HMI.

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TABLE III
THE NUMBER OF NODES IN THE ESTIMATION RESULTS (FACEME)

dx \ dy	0.9	1.2	1.5
0.6	3 : 100%	2 : 9.5% 3 : 84.5% 4 : 6 %	2 : 0.5% 3 : 31.5% 4 : 68%
0.9	1 : 100%	1 : 100%	1 : 98% 2 : 2 %
1.2	1 : 100%	1 : 100%	1 : 99.5% 2 : 0.5%

TABLE IV
THE NUMBER OF NODES IN THE ESTIMATION RESULTS (FACE-TO-FACE PROXIMITY ESTIMATION)

dx \ dy	0.9	1.2	1.5
0.6	2 : 8.5% 3 : 91.5%	1 : 2% 2 : 80.5% 3 : 17.5%	0 : 8.5% 1 : 62.5% 2 : 24% 3 : 5%
0.9	1 : 1% 2 : 67% 3 : 32%	1 : 95% 2 : 5%	0 : 18% 1 : 72% 2 : 10%
1.2	2 : 100%	1 : 100%	0 : 37% 1 : 63%

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