Robust Velocity Estimation of an Omnidirectional Mobile Robot Using a Polygonal Array of Optical Mice

Sungbok Kim and Sanghyup Lee

Abstract: This paper presents the robust velocity estimation of an omnidirectional mobile robot using a polygonal array of optical mice that are installed at the bottom of the mobile robot. First, the velocity kinematics from a mobile robot to an array of optical mice is derived as an overdetermined linear system. The least squares velocity estimate of a mobile robot is then obtained, which becomes the same as the simple average for a regular polygonal arrangement of optical mice. Next, several practical issues that need be addressed for the use of the least squares mobile robot velocity estimation using optical mice are investigated, which include measurement noises, partial malfunctions, and imperfect installation. Finally, experimental results with different number of optical mice and under different floor surface conditions are given to demonstrate the validity and performance of the proposed least squares mobile robot velocity estimation method.

Keywords: Least squares, mobile robot, optical mouse, robustness, velocity estimation.

1. INTRODUCTION

In the near future, personal service robots are expected to come into human daily life as supporters in education, leisure, house care, health care, and so on. Most of them built on mobile platforms require the capability of autonomous navigation in unknown and/or dynamic environments. The key ingredients for autonomous navigation are viable techniques for the map building, the obstacle detection/avoidance, and the localization in terms of velocity/position [1,2]. The concern of this paper is the robust velocity estimation for an omnidirectional mobile robot as a platform of personal service robots.

Typical sensors used for the localization of mobile robots include encoders, ultrasonic sensors, and cameras [3]. However, encoders are vulnerable to wheel slip, ultrasonic sensors require the line of sight, and cameras usually mandate heavy computation. There have been several attempts to employ optical mice for the velocity estimation of a mobile robot [4-10]. In fact, an optical mouse is an inexpensive but high performance device with sophisticated image processing engine inside [11,12]. The velocity estimation of a mobile robot using a set of optical mice can overcome to some extent the aforementioned limitations of typical sensors.

An optical mouse can continue providing two orthogonal relative displacements in both lateral and longitudinal directions at a prespecified sampling rate, from which two linear velocity components of an optical mouse can be readily computed. For the velocity estimation of an omnidirectional mobile robot on the plane, two linear velocity components and one angular velocity component need to be deter-mined. Theoretically, the minimum number of optical mice required for the mobile robot velocity estimation should be one and half. Most of previous researches [5-9] use two optical mice, while only a single optical mouse is used in [4]. However, few attempts have been made to use more than two optical mice except [10].

In this paper, we present the robust velocity estimation of a mobile robot using the redundant number of optical mice arranged in a polygonal array. This paper is organized as follows. Sections 2 and 3 derive the velocity kinematics as an overdetermined system, and obtain the least squares velocity estimate, which can reduce to the simple average. Sections 4, 5, and 6 investigate several practical issues raised for the practical use of the proposed method, including measurement noises, partial malfunctions, and imperfect installation. Section 7 gives experimental results. Finally, the conclusion is made in Section 8.

2. VELOCITY KINEMATICS

Assume that N optical mice are installed at the

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vertices, P_i, $i=1,\cdots,N$, of a polygon that is centered at the center, O_b, of a mobile robot traveling on the xy plane. Fig. 1 shows an example of a triangular array of optical mice with $N=3$. Let $\mathbf{u}_x=[1\ 0]^t$ and $\mathbf{u}_y=[0\ 1]^t$ be the unit vectors along the x axis and the y axis of the world coordinate system, respectively. The position vector, $\mathbf{p}_i=[\,p_{ix}\ \ p_{iy}\,]^t$, $i=1,\cdots,N$, from O_b to P_i, can be expressed as

$$\mathbf{p}_i=\begin{bmatrix} p_{ix} \\ p_{iy} \end{bmatrix}=\begin{bmatrix} r\cos(\theta+\phi_i) \\ r\sin(\theta+\phi_i) \end{bmatrix}, \tag{1}$$

where θ represents the heading angle of a mobile robot with $\mathbf{p}_1$ being the forwarding direction, ϕ_i, $i=2,\cdots,N$, represents the angle formed between the $(i-1)^{\text{th}}$ and the i^{th} optical mice with respect to O_b, with $\phi_1=0°$, and r represents the distance from O_b to each optical mouse. For notational convenience, let $\mathbf{q}_i$, $i=1,2,3$, be the vector obtained by rotating $\mathbf{p}_i$ by 90° counterclockwise.

In this paper, we assume that a mobile robot under consideration has omnidirectional mobility on the xy plane. Let $\mathbf{v}_b=[\,\upsilon_{bx}\ \upsilon_{by}\,]^t$, and ω_b be the linear velocity and the angular velocity at the center O_b of a mobile robot, respectively. And, let $\mathbf{v}_i=[\,\upsilon_{ix}\ \upsilon_{iy}\,]^t$, $i=1,\cdots,N$, be the linear velocity experienced by the i^{th} optical mouse placed at the vertex P_i. Then, there holds the following velocity relationship:

$$\mathbf{v}_b+\omega_b\,\mathbf{q}_i=\mathbf{v}_i\,. \tag{2}$$

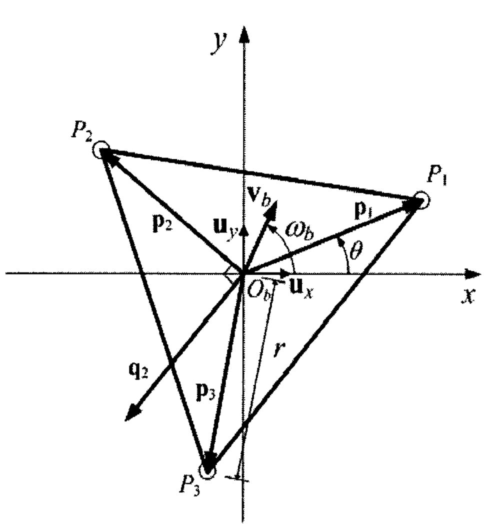


Fig. 1. A triangular array of optical mice with $N=3$.

Premultiplying (2) by $\mathbf{u}_x{}^t$ and $\mathbf{u}_y{}^t$, we have

$$\mathbf{u}_x{}^t\,\mathbf{v}_b+\omega_b\,\mathbf{u}_x{}^t\,\mathbf{q}_i=\mathbf{u}_x{}^t\,\mathbf{v}_i\,, \tag{3}$$

$$\mathbf{u}_y{}^t\,\mathbf{v}_b+\omega_b\,\mathbf{u}_y{}^t\,\mathbf{q}_i=\mathbf{u}_y{}^t\,\mathbf{v}_i\,, \tag{4}$$

respectively. Referring to Fig. 1, (3) and (4) can be rewritten as

$$\upsilon_{bx}-\omega_b\times p_{iy}=\upsilon_{ix}\,, \tag{5}$$

$$\upsilon_{by}-\omega_b\times p_{ix}=\upsilon_{iy}\,. \tag{6}$$

Using (5) and (6), the velocity mapping from a mobile robot to an array of Noptical mice can be represented as

$$\mathbf{A}\mathbf{v}_m=\mathbf{v}_s\,, \tag{7}$$

where

$$\mathbf{v}_m=\begin{bmatrix} \upsilon_{bx} \\ \upsilon_{by} \\ \omega_b \end{bmatrix}, \tag{8}$$

$$\mathbf{v}_s=\begin{bmatrix} \mathbf{v}_{s1} \\ \mathbf{v}_{s2} \\ \vdots \\ \mathbf{v}_{sN} \end{bmatrix}\in\mathbf{R}^{2N\times 1}\ \text{with}\ \mathbf{v}_{si}=\begin{bmatrix} \upsilon_{ix} \\ \upsilon_{iy} \end{bmatrix}, \tag{9}$$

and

$$\mathbf{A}=\begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_N \end{bmatrix}\in\mathbf{R}^{2N\times 3}, \tag{10}$$

with

$$\mathbf{A}_i=\begin{bmatrix} 1 & 0 & -p_{iy} \\ 0 & 1 & p_{ix} \end{bmatrix}. \tag{11}$$

Note that the expression of $\mathbf{A}$ is quite simple as a function of the position vectors of N optical mice, $\mathbf{p}_i=[\,p_{ix}\ \ p_{iy}\,]^t$, $i=1,\cdots,N$.

In the case of $N=1$, (7) represents two equations of three unknowns, including two linear velocity components, υ_{bx} and υ_{by}, and one angular velocity component, ω_b. Thus, (7) becomes an underdetermined system, which implies that the mobile robot velocity cannot be uniquely determined from the optical mouse velocity measurements. However, for $N\geq 2$, (7) becomes an overdetermined system consisting of $2N$ equations, for which the least squares solution can be sought. From now on, it is assumed that the number of optical mice in use is greater than or equal to two, that is, $N \geq 2$.

3. VELOCITY ESTIMATION

Three different types of errors may be involved in the mobile robot velocity estimation using an array of optical mice. The first type includes the deterministic errors, caused by kinematic imperfections, for example, imprecise installation of optical mice. The second type includes the stochastic errors which are random in magnitude and persistent throughout all measurements, for example, white Gaussian noise. The third type includes the stochastic errors which occur unexpectedly and last for some period of time, mainly caused by floor surface conditions. Assuming that all the deterministic errors have been corrected through proper calibration procedure, we are interested only in the two types of stochastic errors in this paper.

Suppose that the measurement model of a array of N optical mice can be expressed as

$$\mathbf{v}_s = \mathbf{A}\mathbf{v}_m + \mathbf{n}, \tag{12}$$

where

$$\mathbf{n} = [n_1\ n_2\ n_3\ n_4\ \cdots\ n_{(2N-1)}\ n_{2N}]^t \in \mathbf{R}^{2N\times1}, \tag{13}$$

with $n_{(2i-1)}$ and n_{2i}, $i = 1, \cdots, N$, being a pair of measurement errors of the i^{th} optical mouse. From (12), the least squares velocity estimation of a mobile robot can be obtained by

$$\hat{\mathbf{v}}_m = \mathbf{J}\ \mathbf{v}_s = \begin{bmatrix} \hat{\upsilon}_{bx} \\ \hat{\upsilon}_{by} \\ \hat{\omega}_b \end{bmatrix}, \tag{14}$$

where

$$\mathbf{J} = (\mathbf{A}^t\ \mathbf{A})^{-1}\mathbf{A}^t \in \mathbf{R}^{3\times2N}, \tag{15}$$

which is the generalized inverse of $\mathbf{A}$. (14) represents the estimated velocity of a mobile robot from the noisy optical mouse velocity measurements, which minimizes the quadratic error, given by $\|\mathbf{A}\ \mathbf{v}_m - \mathbf{v}_s\|^2$ [14].

The least squares velocity estimation, given by (14), of a mobile robot makes no assumptions on the measurement errors of optical mice. If the measurement errors are independent and identically distributed zero-mean Gaussian variables, the least squares estimation becomes equivalent to the maximum likelihood estimation [13]. As will be shown later, the distribution of the optical mouse measurement errors tends to be near zero-mean Gaussian in most floor conditions except a few, for example, glass surfaces, glossy surfaces, and plastics [15]. This fact supports that the proposed least squares velocity estimation can be of physical meaning as well as mathematical meaning.

From (10) and (11), it can be shown that

$$\mathbf{A}^t\ \mathbf{A} = \begin{bmatrix} N & 0 & -\sum_{i=1}^{N} p_{iy} \\ 0 & N & \sum_{i=1}^{N} p_{ix} \\ -\sum_{i=1}^{N} p_{iy} & \sum_{i=1}^{N} p_{ix} & \sum_{i=1}^{N} \|\mathbf{p}_i\|^2 \end{bmatrix}. \tag{16}$$

Since

$$\frac{1}{N} \times \|\sum_{1}^{N} \mathbf{p}_i\|^2 < \sum_{1}^{N} \|\mathbf{p}_i\|^2, \tag{17}$$

the inverse of $\mathbf{A}^t\mathbf{A}$ always exists independently of the heading angle θ of a mobile robot, which guarantees the observability of the measurement model, given by (12).

It is interesting to consider a special arrangement of optical mice in a regular polygonal array, that is,

$$\phi_i = (i-1) \times \frac{2\pi}{N}, \tag{18}$$

for which

$$\begin{bmatrix} p_{ix} \\ p_{iy} \end{bmatrix} = \begin{bmatrix} r\cos\{\theta + (i-1)\times\frac{2\pi}{N}\} \\ r\sin\{\theta + (i-1)\times\frac{2\pi}{N}\} \end{bmatrix}. \tag{19}$$

Under the constraint of (18), we have

$$\sum_{i=1}^{N} p_{ix} = \sum_{i=1}^{N} p_{iy} = 0, \tag{20}$$

so that (16) becomes

$$\mathbf{A}^t\ \mathbf{A} = \begin{bmatrix} N & 0 & 0 \\ 0 & N & 0 \\ 0 & 0 & Nr^2 \end{bmatrix}. \tag{21}$$

Plugging (10), (11), and (21) into (15), we obtain

$$\mathbf{J} = [\ \mathbf{J}_1\ \ \mathbf{J}_2\ \ \cdots\ \ \mathbf{J}_N\ ] \in \mathbf{R}^{3\times2N}, \tag{22}$$

where

$$\mathbf{J}_i = \frac{1}{N}\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -\frac{1}{r}\sin\{\theta + \frac{(i-1)2\pi}{N}\} & \frac{1}{r}\cos\{\theta + \frac{(i-1)2\pi}{N}\} \end{bmatrix}. \tag{23}$$

Finally, for a given set of the velocity measurements from N optical mice, $\mathbf{v}_s = [\upsilon_{1x}\ \upsilon_{1y}\ \upsilon_{2x}\ \upsilon_{2y}\ \cdots\ \upsilon_{Nx}\ \upsilon_{Ny}]^t$, the estimate of the linear and the angular velocities of a mobile robot, $\hat{\mathbf{v}}_m = [\hat{\upsilon}_{bx}\ \hat{\upsilon}_{by}\ \hat{\omega}_b]^t$, can be obtained, from (9), (14), (22), and (23), as follows:

$$\hat{\upsilon}_{bx} = \frac{1}{N}\sum_{i=1}^{N}\upsilon_{ix},\quad \hat{\upsilon}_{by} = \frac{1}{N}\sum_{i=1}^{N}\upsilon_{iy},\quad \hat{\omega}_b = \frac{1}{N}\sum_{i=1}^{N}\omega_i, \tag{24}$$

where

$$\omega_i = \frac{1}{r}\left[-\sin\left\{\theta + \frac{(i-1)2\pi}{N}\right\}\times\upsilon_{ix} + \cos\left\{\theta + \frac{(i-1)2\pi}{N}\right\}\times\upsilon_{iy}\right], \tag{25}$$

which represents the angular velocity experienced by the i^{th} optical mouse. Regarding the velocity estimation based on (24), the following remarks can be made. First, the angular velocity estimate, $\hat{\omega}_b$, is dependent on the heading angle θ, while the linear velocity estimates, $\hat{\upsilon}_{bx}$ and $\hat{\upsilon}_{by}$, are not. Second, each of three velocity estimates is determined as the simple average of the corresponding velocity components experienced by all the optical mice. It should be mentioned that such computational simplicity is attributed to the arrangement of optical mice in a regular polygonal array centered at the center of a mobile robot.

4. MEASUREMENT NOISES

The redundant number of optical mice helps to reduce the effect of the measurement noises accompanying the velocity measurements from optical mice. Suppose that a mobile robot is commanded to travel at a constant linear velocity along the x axis, that is, with $\upsilon_{bx} = \mu\,\text{m/sec}$ with $\upsilon_{by} = 0.0\text{m/sec}$ and $\omega_b = 0.0\text{rad/sec}$. Then, the statistics of the optical mouse velocity measurements can be characterized by

$$E[\upsilon_{1x}] = E[\upsilon_{2x}] = \cdots = E[\upsilon_{Nx}] = \mu,\quad E[\upsilon_{1y}] = E[\upsilon_{2y}] = \cdots = E[\upsilon_{Ny}] = 0, \tag{26}$$

and

$$\text{var}[\upsilon_{1x}] = \text{var}[\upsilon_{2x}] = \cdots = \text{var}[\upsilon_{Nx}] = \sigma^2,\quad \text{var}[\upsilon_{1y}] = \text{var}[\upsilon_{2y}] = \cdots = \text{var}[\upsilon_{Ny}] = \sigma^2, \tag{27}$$

where μ and σ^2 represent, respectively, the mean and the variance of the velocity measurements from N optical mice.

For the mobile robot velocity estimation based on (24), it can be shown that

$$E[\upsilon_{bx}] = \mu,\qquad E[\upsilon_{by}] = 0, \tag{28}$$

$$\text{var}[\upsilon_{bx}] = \text{var}[\upsilon_{by}] = \frac{\sigma^2}{N}, \tag{29}$$

assuming that N optical mouse velocity measurements are independent each other. (29) tells that the greater the number of optical mice, the smaller the velocity estimation error, under the same level of measurement noises. As the number of optical mice is increased from $N(\geq 2)$ to $(N+1)$, the percent improvement in terms of standard deviation, denoted by PI, is given by

$$PI = \left(1 - \sqrt{\frac{N}{N+1}}\right)\times 100\%. \tag{30}$$

Note that the percent improvement is more significant for the smaller number of optical mice. Similar analysis to the above can be made as well for the pure angular velocity and the combined linear and angular velocity of a mobile robot.

5. PARTIAL MALFUNCTIONS

The success of the least squares mobile robot velocity estimation based on (24) is heavily dependent on whether all the optical mice function normally. It is important to detect and isolate the malfunctioning optical mice from the velocity estimation. Here, we propose a simple but effective means to cope with partial malfunctions occurring among the redundant number of optical mice. The basic rationale is that the proposed least squares mobile robot velocity estimation can be regarded as a process of building consensus among all the optical mice of equal privilege.

For a given mobile robot velocity estimate, $\hat{\mathbf{v}}_m$, the residual of the i^{th} optical mouse, denoted by $\Delta\mathbf{v}_{si}$, is [14]

$$\Delta\mathbf{v}_{si} = \hat{\mathbf{v}}_{si} - \mathbf{v}_{si} = \begin{bmatrix}\Delta\upsilon_{ix}\\ \Delta\upsilon_{iy}\end{bmatrix}, \tag{31}$$

where

$$\hat{\mathbf{v}}_{si} = \mathbf{A}_i\,\hat{\mathbf{v}}_m = \begin{bmatrix}\hat{\upsilon}_{ix}\\ \hat{\upsilon}_{iy}\end{bmatrix}. \tag{32}$$

Here, let us consider the magnitude of the residual

$\Delta\mathbf{v}_{si}$, given by

$$\rho_i = \|\Delta\mathbf{v}_{si}\| = \|\hat{\mathbf{v}}_{si} - \mathbf{v}_{si}\|. \tag{33}$$

Using (9) and (32), (33) can be expressed as

$$\rho_i^2 = (\hat{\upsilon}_{ix} - \upsilon_{ix})^2 + (\hat{\upsilon}_{iy} - \upsilon_{iy})^2, \tag{34}$$

which can be easily computed.

The residual magnitude ρ_i can be interpreted as a measure of inconformity of the i^{th} optical mouse to the consensus reached by all the optical mice. If the degree of inconformity exceeds a prespecified threshold, then it would be reasonable to isolate the problematic optical mice and then to search for a new consensus among the remaining ones. Supposing that the k^{th} optical mouse is malfunctioning, the new velocity estimation can be made under

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}_1 \\ \vdots \\ \mathbf{A}_{k-1} \\ \mathbf{A}_{k+1} \\ \vdots \\ \mathbf{A}_N \end{bmatrix} \in \mathbf{R}^{2(N-1)\times 3}, \tag{35}$$

$$\mathbf{J} = [\mathbf{J}_1 \ \cdots \ \mathbf{J}_{k-1} \ \mathbf{J}_{k+1} \ \cdots \ \mathbf{J}_N] \in \mathbf{R}^{3\times 2(N-1)}, \tag{36}$$

so that

$$\begin{aligned} \hat{\upsilon}_{bx} &= \frac{1}{N-1}\sum_{i=1, i\neq k}^{N} \upsilon_{ix}, \\ \hat{\upsilon}_{by} &= \frac{1}{N-1}\sum_{i=1, i\neq k}^{N} \upsilon_{iy}, \\ \hat{\omega}_b &= \frac{1}{N-1}\sum_{i=1, i\neq k}^{N} \omega_i. \end{aligned} \tag{37}$$

Notice that both lateral and longitudinal velocity measurements from the malfunctioning optical mouse are ignored simultaneously.

Here, we assume that the malfunctions of optical mice occur unexpectedly and last for some period of time. The errors caused by the malfunctioning optical mice are different from other sporadic measurement errors, for example, random spike noises. Simple averaging or median filtering may help reducing stochastic and sporadic measurement errors, however, they seem not to be effective for stochastic but prolonged measurement errors.

6. IMPERFECT INSTALLATION

In practice, it may be rather difficult to install optical mice in an exact regular polygonal array whose center is coincident with the center of a mobile robot. The sensitivity of the least squares mobile robot velocity estimation based on (24) to imprecise installation of optical mice can be analyzed as follows. In the presence of installation error, the optical mouse position vector, denoted by $\tilde{\mathbf{p}}_i$, $i = 1, \cdots, N$, can be described as

$$\tilde{\mathbf{p}}_i = \overline{\mathbf{p}}_i + \delta\mathbf{p}_i = \begin{bmatrix} \tilde{p}_{ix} \\ \tilde{p}_{iy} \end{bmatrix}, \tag{38}$$

where $\overline{\mathbf{p}}_i = [\,\overline{p}_{ix} \ \overline{p}_{iy}\,]^t$ represents the nominal optical mouse position, and $\delta\mathbf{p}_i = [\,\delta p_{ix} \ \delta p_{iy}\,]^t$ represents the position deviation from the nominal value $\overline{\mathbf{p}}_i$. In what follows, we will use '‾' and '~' to denote the nominal value and the perturbed value of the quantity of interest, respectively.

In the presence of optical mouse installation error, the velocity kinematics, given by (7), can be expressed as

$$\tilde{\mathbf{A}}\tilde{\mathbf{v}}_m = \tilde{\mathbf{v}}_s, \tag{39}$$

with

$$\tilde{\mathbf{v}}_m = \overline{\mathbf{v}}_m + \delta\mathbf{v}_m, \tag{40}$$

$$\tilde{\mathbf{v}}_s = \overline{\mathbf{v}}_s + \delta\mathbf{v}_s, \tag{41}$$

and

$$\tilde{\mathbf{A}} = \overline{\mathbf{A}} + \delta\mathbf{A}. \tag{42}$$

It should be noted that

$$\overline{\mathbf{A}}\overline{\mathbf{v}}_m = \overline{\mathbf{v}}_s, \tag{43}$$

which is valid for perfect optical mouse installation.

Premultiplying (39) by $\tilde{\mathbf{A}}^t$ and plugging (42) into the resulting equation, we have

$$(\overline{\mathbf{A}}^t + \delta\mathbf{A}^t)(\overline{\mathbf{A}} + \delta\mathbf{A})\tilde{\mathbf{v}}_m = (\overline{\mathbf{A}}^t + \delta\mathbf{A}^t)\tilde{\mathbf{v}}_s. \tag{44}$$

Assuming that the optical mouse installation error is sufficiently small, we have

$$\delta\mathbf{A}^t\,\delta\mathbf{A} \cong 0_{3\times 3}, \tag{45}$$

so that (44) becomes

$$(\overline{\mathbf{P}} + \delta\mathbf{P})\,\tilde{\mathbf{v}}_m \cong (\overline{\mathbf{A}}^t + \delta\mathbf{A}^t)\,\tilde{\mathbf{v}}_s, \tag{46}$$

where

$$\overline{\mathbf{P}} = \overline{\mathbf{A}}^t\,\overline{\mathbf{A}} \in \mathbf{R}^{3\times 3}, \tag{47}$$

$$\delta\mathbf{P} = \delta\mathbf{A}^t\,\overline{\mathbf{A}} + \overline{\mathbf{A}}^t\,\delta\mathbf{A} \in \mathbf{R}^{3\times 3}. \tag{48}$$

Plugging (40) and (41) into (46), and applying (43) to the resulting equation, we obtain

$$\overline{\mathbf{P}}\,\delta\mathbf{v}_m + \delta\mathbf{P}\,\overline{\mathbf{v}}_m \cong \delta\mathbf{A}^t\,\overline{\mathbf{v}}_s + \overline{\mathbf{A}}^t\,\delta\mathbf{v}_s, \tag{49}$$

under the additional assumptions given by

$$\delta \mathbf{P}\, \delta \mathbf{v}_m \cong 0_{3\times 1}\,, \quad (50)$$

$$\delta \mathbf{A}^t\, \delta \mathbf{v}_s \cong 0_{3\times 1}\,. \quad (51)$$

Finally, from (49), the mobile robot velocity estimate error owing to imperfect optical mouse installation can be approximated by

$$\delta \mathbf{v}_m \cong \delta \mathbf{v}_{m,1} + \delta \mathbf{v}_{m,2} + \delta \mathbf{v}_{m,3}\,, \quad (52)$$

where

$$\delta \mathbf{v}_{m,1} = \overline{\mathbf{P}}^{-1}\, \delta \mathbf{A}^t\, \overline{\mathbf{v}}_s\,,$$
$$\delta \mathbf{v}_{m,2} = -\,\overline{\mathbf{P}}^{-1}\, \delta \mathbf{P}\, \overline{\mathbf{v}}_m\,, \quad (53)$$
$$\delta \mathbf{v}_{m,3} = \overline{\mathbf{P}}^{-1}\, \overline{\mathbf{A}}^t\, \delta \mathbf{v}_s\,.$$

In (52), it should be noted that the first and the second terms of the velocity estimation error are attributed to $\delta\mathbf{A}$ and $\delta\mathbf{P}$, and the third term is attributed to the additional optical mouse velocity measurements, $\delta \mathbf{v}_s (= \tilde{\mathbf{v}}_s - \overline{\mathbf{A}}\ \overline{\mathbf{v}}_m)$. It should be noticed that the source for all the three terms is the same, that is, the position deviations of optical mice, $\delta \mathbf{p}_i, i = 1,\cdots,N$.

7. EXPERIMENTAL RESULTS

To demonstrate the validity and performance of the proposed least squares mobile robot velocity estimation, we conducted several experiments using two, three and four commercial optical mice. As shown in Fig. 2, optical mice are installed in a regular polygonal array on a separate circular plate, with the lateral directions of all the optical mice aligned with the x axis of the world coordinate system. The circular plate equipped with three passive caster wheels is then rigidly attached to our laboratory built differential drive mobile robot, in place of an omnidirectional mobile robot not available. Because of the experimental setup, however, our experiments are limited to pure linear motions of a mobile robot excluding self-rotations.

7.1. Data acquisition

Commercial USB optical mice used in our experiments have the ADNS-3080 [15], a high performance optical mouse sensor from the Agilent Technologies (now the Avago Technologies). Table 1 shows the technical specifications and the parameter settings of the ADNS-3080. In stream mode, the optical mouse continues sending to the host the packet containing two relative displacements in both lateral and longitudinal directions. Note that the relative displacement is internally expressed in the unit of counts, which needs to be converted in the unit of inches or meters for use.

To reduce communication overhead from the optical mouse to the host, the downsampler is inserted as shown in Fig. 3, which is implemented using ATmega8, 8-bit AVR microcontroller with 8K bytes in-system programmable flash from Atmel Corp. [16]. Upon receiving each packet from the host, the downsampler keeps on accumulating the relative displacement counts within the packet. Once every $K(=12)$ packets from the host, the downsampler sends to the host the packet containing the accumulated values of relative displacement counts. Using these values, the host calculates, for example, the linear velocity components by

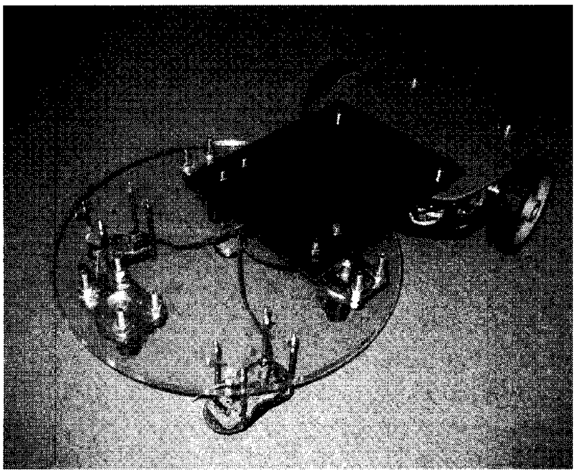


Fig. 2. Experimental setup.

Table 1. Technical specifications and parameter settings of the ADNS-3080.

	Units	Specification	Parameter Setting
Frame Rate	fps (frames-per-sec)	500 ~ 6,469	6,400
Resolution	cpi (counts-per-inch)	400/1,600	1,600
Maximum Speed	ips (inches-per-sec)	40 (@6,400fps)	40

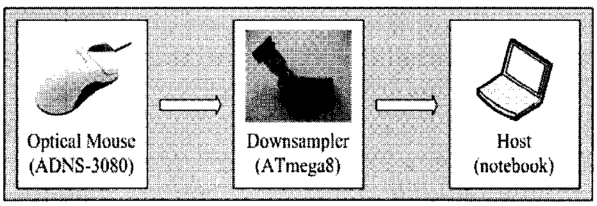
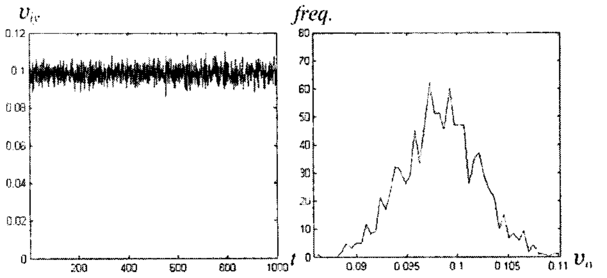


Fig. 3. Optical mouse data acquisition system.



(a) Snapshot. (b) Frequency.

Fig. 4. The velocity information, from the optical mouse.

$$\upsilon_{ix} = \frac{\Delta x}{\Delta t} = \frac{\sum_{j=1}^{K} CNT_j / \text{CPI}}{K / \text{FPS}} \quad \text{in/sec}, \tag{54}$$

where CNT_j, $j = 1, \cdots, K$, represents the relative displacement count of the j^{th}packet, and CPI represents the resolution in counts-per-inch; K represents the number of packets whose relative displacement is accumulated, and FPS represents the sampling rate in frames-per-sec.

7.2. Velocity measurements

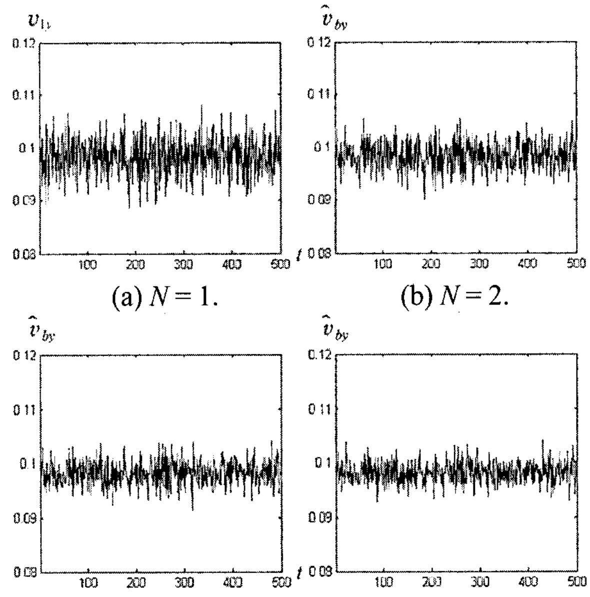
Let us examine the statistical characteristics of the optical mouse velocity measurements. With the heading angle of $\theta = 90°$, the mobile robot is commanded to travel on normal floor surfaces at a constant linear velocity along the y axis: $\upsilon_{by} = 0.1$m/sec with $\upsilon_{bx} = 0.0$m/sec and $\omega_b = 0.0$rad/sec, Note that the y axis of the world coordinate system coincides with the longitudinal directions of all the optical mice. Fig. 4(a) shows the snapshot of the velocity measurements, υ_{iy}, from the i^{th}optical mouse, for 1,000 sampling periods. Fig. 4(b) shows the plot of the number of occurrences or the frequency according to the values of the velocity measurements. Through several experiments, we found that the distribution of the optical mouse measurement noises tends to be near zero-mean Gaussian in most floor conditions except a few, for example, glass surfaces, glossy surfaces, and plastics [15].

In our experiments, the mobile robot is commanded to move rather slowly to secure stable contact between the optical mice and the floor as much as possible. However, note that the maximum speed of the ADNS-3080 itself amounts to 40 inches-per-sec at 6,400 frames-per-sec, which is about 0.1m/sec, as shown in Table 1. In fact, commercial optical mice should be restructured in a deliberate way to allow some spacing above the floor, which is necessary to avoid the damage of optical mice due to possible collisions.

7.3. Measurement noises

The mobile robot is commanded to travel on normal floor surface at the same constant velocity as before $\upsilon_{by} = 0.1$m/sec with $\upsilon_{bx} = 0.0$m/sec and $\omega_b = 0.0$rad/sec. Using two (N = 2), three (N = 3), and four (N = 4) optical mice arranged in a regular polygonal array, the mobile robot velocities are estimated from the optical mouse velocity measurements based on the least squares estimation, given by (22). For, N = 2,3 and 4, Fig. 5 shows the plots of the velocity estimates, $\hat{\upsilon}_{by}$, of the mobile robot for 500 sampling periods. The plot for N = 1 which shows the velocity measurements from the first optical mouse is added for comparison with the mobile robot velocity estimates. From Fig. 5, it can be observed that the velocity estimation error of a mobile robot tends to decrease as the number of optical mice increases.

Table 2 lists the standard deviations of the velocity estimates for the cases of N = 2,3 and 4, Seen from Table 2, it should be noticed that the increased number of optical mice strictly reduces the standard deviation of three velocity estimates, and the percent



(a) $N = 1$. (b) $N = 2$. (c) $N = 3$. (d) $N = 4$.

Fig. 5. The mobile robot velocity estimates.

Table 2. The standard deviations and the percent improvements.

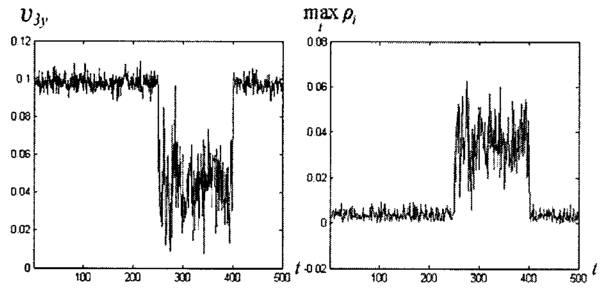
N	σ [m/sec]	PI [%]
1	0.0035	NA
2	0.0026	26.00
3	0.0022	16.94
4	0.0019	12.43

improvement is more significant for the smaller number of optical mice.

7.4 Partial malfunctions

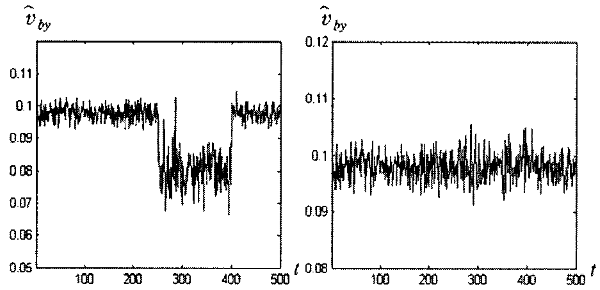
The mobile robot is commanded to travel at the same velocity as before, but now to traverse glossy surfaces. To simulate partial malfunctions, we enforce the third optical mouse to cross glossy surface zone covered with aluminum foil, unlike the first and the second optical mice passing through normal floor surfaces. Fig. 6(a) shows the snapshot of the velocity measurements, υ_{3y}, from the third optical mouse. Fig. 6(b) shows the plot of the maximum value among three residual magnitudes, that is, $\max_i \rho_i$. From Fig. 6, it can be observed that the velocity measurement errors of the malfunctioning optical mouse belong to the stochastic errors which occur unexpectedly and last for some short period of time.

Fig. 7 shows the plots of the velocity estimate $\hat{\upsilon}_{by}$, obtained without and with the remedy for partial malfunctions, respectively. From Fig. 7, it can be observed that the prolonged random measurement errors are almost completely identified and isolated from new velocity estimation based on (37). As discussed previously, simple averaging or median filtering may work well for sporadic measurement errors, but cannot be effective for prolonged measurement errors as much as our consensus based malfunction remedy.



(a) υ_{3y}. (b) $\max_i \rho_i$.

Fig. 6. The malfunctions of the third optical mouse.



(a) without the proposed remedy. (b) with the proposed remedy.

Fig. 7. The mobile robot velocity estimates.

8. CONCLUSION

In this paper, we dealt with the robust velocity estimation of an omnidirectional mobile robot using a polygonal array of optical mice. One contribution of this paper is to propose the optical mouse arrangement in a regular polygonal array, which leads to a simple but effective mobile robot velocity estimation in most floor conditions. The other contribution is to investigate several practical issues to be raised for the mobile robot velocity estimation using a set of optical mice: measurement noises, partial malfunctions, and imperfect installation. We hope that the theoretical treatment and experimental validation made in this paper can play a role of facilitating the early adoption of personal service robots in our daily life.

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