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# Formation Tracking Based on Approximate Velocities 

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#### Abstract

This paper analyses the formation tracking of groups of mobile robots moving on the plane. A leader robot is chosen to follow a prescribed trajectory whilst the rest, considered as followers, are formed in an open-chain configuration. Two formation-tracking control laws using approximate velocities are proposed, in which some velocities must be communicated between robots in order to ensure the simultaneous preservation of the formation and the following of the group path. The main result is analysis of the convergence of the two proposed control laws. The restriction of inaccurate information occurs in decentralized multi-robot platforms, in which the mobile agents are only able to measure positions and the velocities' functions are estimated using online numerical methods. A numerical simulation of both controllers in the case of omnidirectional robots is shown. For the case of the unicycle-type robots, real-time experiments of both controllers were implemented and tested.


Keywords Formation Control, Marching Control, Multirobot Systems, Autonomous Robots

## 1. Introduction

Recently, the motion coordination of multiple biological entities has inspired the design and implementation of natural behaviours in mobile robots for industrial and service applications [1, 2]. Observations of ethologists have determined that the ordered motion of ants, fishes or birds is constructed from local interactions between mobile agents. Each agent acts according to the local information acquired from other members [3]. Therefore, the control schemes are decentralized and the study falls within the research areas of multi-agent systems, sensor networks and distributed control systems. The decentralized schemes also permit more autonomy for the robots, a smaller computational load in control implementations and the method's applicability to large-scale groups [4].

A special case of motion coordination is formation tracking [4, 5], also called marching control [6] or flocking behaviour [7], in which a group of mobile robots achieves geometric patterns whilst the whole group follows a prescribed marching trajectory. Formation tracking appears in some applications such as the transportation and manipulation of large objects, search and rescue tasks and perimeter detection, etc. In formation tracking, it is required that the
group follows some trajectories in the workspace, while a rigid formation pattern is preserved simultaneously. Thus, the main challenge of formation tracking is the inter-robot strategic sharing of information about the marching path or the velocities of certain robots in the group, in order to ensure the formation's preservation, maintaining the greatest possible level of decentralization.

The leader-follower schemes [8,9] are frequently studied by the academic community due to the inspiration that biological behaviour creates (for instance, in ants). In these schemes, a unique leader robot follows a marching path while the rest, termed followers, converge to some formation pattern with respect to the leader. Although some contributions have been proposed in relation to formation tracking, most of the studies consider that the robots can measure the exact information about the velocities of the other robots or the marching path. For instance, [10] studies the case of a convoy-like formation, in which the robots are initially placed at the desired positions, and they know the linear and angular velocities of the adjacent robot. The positions and orientations of virtual leaders serve as reference points for the follower robots in $[11,12]$ and the exact marching path derivative is available to all robots in $[6,5]$.

Note that in the natural leader-followers scheme, each agent is able to sense the position of only the nearby agents, and the velocities must be estimated or intuited by their local controllers. As will be discussed below, if some velocities are not approximated in the control laws, then the formation is not rigid during the path following, as shown in $[13,14]$, in which the positions of the followers vary in a ball that is centred in terms of the leader's reference frame. Some papers estimated the leader's velocity using position measurements acquired through observers [15] or local sensors [16]. The problem of formation tracking is studied via an estimator designed to track a globally desired velocity that is available to a subset of robots via a consensus-based velocity term in [17]. Predictive control is applied in [18], which added a term to the cost function of the leader in order to preserve the formation. Other works focus on the reconstruction of the marching path using adaptive algorithms in [19, 20, 21, 22], and Lyapunov techniques in [23]. The velocities of neighbours are estimated in [24,25] in order to construct the desired marching path based on local information. Recently, the approximation of velocities for the case of spacecraft formations was obtained by using a non-linear filter with finite-time convergence in [26]. Most previous works designed estimation methods for the velocity of the agents based on the measurement of the marching path's exact velocity, decreasing decentralization and simplicity of the control laws. Commonly, some numerical methods are included in order to estimate velocities in the experimental platforms of multi-robot systems. However, the effects of these approximations have not been formally analysed.

In [27], two formation-tracking control laws were designed using exact velocity measurements in order to achieve
formation-tracking convergence. This paper shows the boundedness of the formation-tracking error when only position information is used. The variation of the forma-tion-tracking error can be made arbitrarily small when the approximations of velocities are close to the real values. In addition, for a class of tracking trajectory, we show the exponential convergence of the formation-tracking error. This study is important, since this is the way that such implementation is usually done. Nevertheless, the degradation of the performance on the overall system has not been formally studied. To show the effects of the approximate velocities, the control laws were extended to unicycletype robots in real-time experiments.
The rest of the paper is organized as follows. Section 2 introduces the kinematic model and the problem statement. A short summary of our previous formation-tracking control strategy, with its exact velocities, is presented in Section 3 with numerical simulations. The main result of the paper is given in Section 4, using approximate velocities with numerical simulations. The extension of the model to unicycle-type robots and the real-time experiments are shown in Sections 5 and 6, respectively. Finally, some concluding remarks are presented in Section 7.

## 2. Problem Definition

Denote by $N=\left\{R_{1}, \ldots, R_{n}\right\}$, a set of $n$ point robots moving in the space with positions $z_{i}(t)=\left[x_{i}(t), y_{i}(t)\right]^{T}, i=1, \ldots, n$. The kinematic model of each agent or robot $R_{i}$ is described by

$$
\begin{equation*}
\dot{z}_{i}=u_{i}, i=1, \ldots, n, \tag{1}
\end{equation*}
$$

where $u_{i} \in \mathfrak{R}^{2}$ is the velocity along the $X$ and $Y$ axes of the $i$-th robot. Let $R_{1}, \ldots, R_{n-1}$ be the follower robots, and $R_{n}$ be the leader robot. Based on the leader-follower scheme, define $z_{i}^{*}$ as the desired relative position of $R_{i}$ in a particular formation, given by

$$
\begin{align*}
& z_{i}^{*}=z_{i+1}+c_{(i+1) i}, i=1, \ldots, n-1, \\
& z_{n}^{*}=m(t), \tag{2}
\end{align*}
$$

where $c_{(i+1) i} \in \mathfrak{R}^{2}, i=1, \ldots, n-1$ denotes the vector that represents the desired relative position of $R_{i}$ with respect to $R_{i+1}$ and $m(t)=\left[m_{x}(t), m_{y}(t)\right] \in \mathfrak{R}^{2}$ is the marching path (a twicedifferentiable function) of the leader.
Remark 1 Note that the variables $z_{i}, i=1, \ldots, n$ are the absolute position vectors of the robots with respect to the global reference frame. Therefore, the variables $z_{i}^{*}, i=1, \ldots, n$ given in (2) are also absolute coordinates. However, in the context of formation control, $z_{i}{ }^{*}, i=1, \ldots, n$ are called desired relative positions in the sense that they depend on the positions of other robots. Therefore,
the word relative does not indicate that $z_{i}^{*}, i=1, \ldots, n$ are measured with respect to a different reference frame.

Figure 1 shows an example of formation tracking in which the robots satisfy a specific formation pattern while simultaneously following the trajectory $m(t)$. The goal of the leader is to follow the marching path, whereas the goal of the followers is to maintain a desired pattern formation with respect to the leader, using the position of the adjacent robot as a guide. This strategy is usually considered as an open-chain or convoy configuration [10]. Note that the marching path could be constructed online by a human operator, who controls the displacement of the leader remotely while the followers achieve a formation.


Figure 1. Desired formation tracking of the robots
Problem Statement. The goal of formation tracking is to design a control law $u_{i}=f_{i}\left(z_{i}, z_{i}^{*}\right)$ for every robot $R_{i}$, such that $\lim _{t \rightarrow \infty}\left(z_{i}-z_{i}^{*}\right)=0, i=1, \ldots, n$.

## 3. Control strategy based on the exact information of velocities

Based on [27], for every follower robot, Local Potential Functions (LPFs) are defined by

$$
\begin{equation*}
\gamma_{i}=\mathrm{P} z_{i}-z_{i}^{*} \mathrm{P}^{2}, i=1, \ldots, n-1 \tag{3}
\end{equation*}
$$

Note that $\gamma_{i}$ is always positive and reaches its minimum only when $z_{i}=z_{i}{ }^{*}$. The standard approach of (attractive) LPFs consists in applying the partial derivative of an LPF with respect to $z_{i}$, as control inputs of every robot $R_{i}$. Thus, the control inputs steer every robot to achieve the minimum of this potential function, which is designed according to the specific position vectors that construct a particular formation. Using these functions, two control laws can be defined by

$$
\begin{align*}
& \Gamma_{1}:\left\{\begin{array}{l}
u_{i}=-\frac{1}{2} k \frac{\partial \gamma_{i}}{\partial z_{i}}+\dot{m}(t), i=1, \ldots, n-1 \\
u_{n}=\dot{m}(t)-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right.  \tag{4}\\
& \Gamma_{2}:\left\{\begin{array}{l}
u_{i}=-\frac{1}{2} k \frac{\partial \gamma_{i}}{\partial z_{i}}+\dot{z}_{i+1}, i=1, \ldots, n-1 \\
u_{n}=\dot{m}(t)-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right. \tag{5}
\end{align*}
$$

where $k, k_{m}>0$. Note that the control law $\Gamma_{1}$ requires the provision of feedback $\dot{m}(t)$ to all followers, and that $\Gamma_{2}$ includes the feedback of the adjacent robot $\dot{z}_{i+1}$ for all followers. Thus, the first $n-1$ robots are not required to process complete information about $m(t)$ or the positions of all robots, unlike in [4] or [28], in which all robots must know the target position or trajectory, and more than one desired distance between robots. A schematic description of the control strategies is shown in Fig. 3. Observe that the control law of the leader requires the exact derivative of $m(t)$ to function, whilst the followers require the full knowledge of $\dot{m}(t)$ or $\dot{z}_{i+1}$.

With respect to the convergence of the desired formation tracking using (4) or (5), the next proposition can be found in [27].

Proposition 1 Consider the system (1) and the control laws (4) or (5) for $n$ robots. Then, in the closed-loop systems (1), (4) and (1), (5), the first $n-1$ robots converge to the desired formation, i.e., $\lim _{t \rightarrow \infty}\left(z_{i}-z_{i}^{*}\right)=0, i=1, \ldots, n-1$, whereas $R_{n}$ converges to the marching path, i.e., $\lim _{t \rightarrow \infty}\left(z_{n}(t)-m(t)\right)=0$.

A sketch of the proof is included for completeness.
Proof. The dynamics of $z_{i}$ in the closed-loop systems (1), (4) and (1), (5) are given, respectively, by

$$
\text { (1),(14): }\left\{\begin{array}{l}
\dot{z}_{i}=-k\left(z_{i}-z_{i+1}-c_{(i+1) i}\right)+\dot{m}(t),  \tag{6}\\
i=1, \ldots, n-1 \\
\dot{z}_{n}=\dot{m}(t)-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right.
$$

$$
(141),(1415):\left\{\begin{array}{l}
\dot{z}_{i}=-k\left(z_{i}-z_{i+1}-c_{(i+1) i}\right)+\dot{z}_{i+1},  \tag{7}\\
i=1, \ldots, n-1 \\
\dot{z}_{n}=\dot{m}(t)-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right.
$$

Define the error variables by

$$
\begin{equation*}
e_{i}=z_{i}-z_{i}^{*}, i=1, \ldots, n \tag{8}
\end{equation*}
$$

where $e_{1}, \ldots, e_{n-1}$ are the formation errors of the followers and $e_{n}$ is the path-following error of the leader. The dynamics of the error coordinates (8) for the two control laws are given respectively by

$$
\begin{equation*}
\dot{e}=\left(B_{1} \otimes I_{2}\right) e \tag{9}
\end{equation*}
$$

$$
\begin{equation*}
\dot{e}=\left(B_{2} \otimes I_{2}\right) e \tag{10}
\end{equation*}
$$

where $\otimes$ denotes the Kronecker product (the Kronecker product allows use of a more compact notation for the equations), $I_{2}$ is the $2 \times 2$ identity matrix and the matrices $B_{1}$ and $B_{2}$ are

$$
\begin{aligned}
& B_{1}=\left[\begin{array}{rrrrrrr}
-k & k & 0 & 0 & \cdots & 0 & 0 \\
0 & -k & k & 0 & \cdots & 0 & 0 \\
0 & 0 & -k & k & \cdots & 0 & 0 \\
0 & 0 & 0 & \ddots & \ddots & \vdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & 0 & \cdots & -k & k_{m} \\
0 & 0 & 0 & 0 & \cdots & 0 & -k_{m}
\end{array}\right], \\
& B_{2}=\left[\begin{array}{rrrrrr}
-k & 0 & 0 & \cdots & 0 & 0 \\
0 & -k & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & -k & 0 \\
0 & 0 & 0 & \cdots & 0 & -k_{m}
\end{array}\right]
\end{aligned}
$$

Clearly, the matrices $B_{1}$ and $B_{2}$ are Hurwitz ones, and the errors converge to zero. This means that the $n-1$ first agents converge to the desired formation, whereas $R_{n}$ converges to the marching path. $\square$

Remark 2 It is necessary to add $\dot{m}(t)$ in $\Gamma_{1}$ and $\dot{z}_{i+1}$ in $\Gamma_{2}$ in order to guarantee the preservation of the formation during the trajectory tracking. If they are not included, the errors' time derivatives become $\dot{e}=\left(B_{1} \otimes I_{2}\right) e+\left[S_{x^{\prime}} S_{y}\right]^{T} \quad$ or $\dot{e}=\left(B_{2} \otimes I_{2}\right) e+\left[S_{x}, S_{y}\right]^{T}$, with $S_{x}=\left[0, \ldots, 0, \dot{m}_{x}(t), 0\right]^{T} \quad$ and $S_{y}=\left[0, \ldots, 0, \dot{m}_{y}(t), 0\right]^{T}$. Even though the matrices $B_{1}$ and $B_{2}$ are clearly Hurwitz ones, the dynamics of $R_{n-1}$ is disturbed by the marching velocity and it is transmitted to the other followers.

This is an example of disturbance propagation in chain-stability in formation control using the leader-followers' scheme [9], in which the motion of the leader influences the formation stability of the followers.

The control strategies (4) and (5) are appropriated for any kind of sufficiently smooth function $m(t)$. Figure 3 shows a numerical simulation of both control laws with $n=3, k=1$ and $k_{m}=1$. The initial conditions are given by $z_{1}(0)=[-1,3]$, $z_{2}(0)=[2,2]$ and $z_{3}(0)=[2,5]$. The desired formation is a triangle defined by the vectors $c_{21}=[0,-4]$ and $c_{32}=[-3,2]$, and the marching path is a circular path given by $m(t)=[3+\cos (0.2 t), 3+\sin (0.2 t)]$. Note that the follower robots converge to the desired formation and that the leader robot, $z_{3}$ (represented by a green dashed line), converges to the marching path $m(t)$. This is shown through the convergence of the error variables. However, the two control laws present differences in the transitory regime.

The convergence of the errors is reached due to the strong assumption that both the velocities of the robots and the marching path are measured exactly. The requirements of the local controllers that the robots include these velocities can be translated into a greater overhead on the communication between the mobile agents. This is the reason motivating analysis of the impact of the velocities' approximation, which is addressed in the next section.

## 4. Control strategy using the approximations of velocities

Recalling the inspiration derived from nature, in which the mobile agents are capable of sensing only the position of the robots and the marching path, the two control schemes are now modified according to Fig. 4. The robots are not equipped with velocity sensors, and the control laws given


Figure 2. Formation-tracking scheme with the exact information about the velocities of robots and the trajectory


Figure 3. Formation-tracking scheme with the exact information of velocities
by the equations (4) and (5) must be modified in order to incorporate some approximation method for estimating these velocities. The impact of these inexact data on the convergence analysis needs to be studied; hence, a modelled description of the approximation of the derivatives in the system's dynamics is included.

Note that the leader robot needs to approximate the derivative of $m(t)$ and that the follower robots also need to approximate the velocity of the marching path (Figure 4 (a)) or the adjacent robot (Figure 4 (b)). In actual implementations, the velocities are calculated by the local controllers using numerical methods, performing a more
realistic and decentralized scheme. The derivative approximation function shown in Fig. 4 is defined in the frequency domain as

$$
\begin{equation*}
g(s)=\frac{s}{\tau s+1} \tag{11}
\end{equation*}
$$

where $\tau \in \mathfrak{R}$ and $\tau \geq 0$. Thus, the approximation of velocity for a robot $R_{i}$ and the trajectory $m(t)$ is established by

$$
\begin{align*}
\varphi_{i}(s) & =g(s) z_{i}(s), i=2, \ldots, n \\
\varphi_{m}(s) & =g(s) m(s) \tag{12}
\end{align*}
$$

Substituting (11) in (12), we obtain

$$
\begin{aligned}
\varphi_{i}(s) & =\left(\frac{s}{\tau s+1}\right) z_{i}(s), i=2, \ldots, n \\
& =\left(1-\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}}\right) \frac{1}{\tau} z_{i}(s), i=2, \ldots, n \\
& =\frac{1}{\tau} z_{i}(s)-\frac{1}{\tau}\left(\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}} z_{i}(s)\right), i=2, \ldots, n
\end{aligned}
$$

$$
\varphi_{m}(s)=\left(\frac{s}{\tau s+1}\right) m(s)
$$

$$
=\left(1-\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}}\right) \frac{1}{\tau} m(s)
$$

$$
=\frac{1}{\tau} m(s)-\frac{1}{\tau}\left(\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}} m(s)\right)
$$

By defining the auxiliary variables

$$
\begin{aligned}
& \eta_{i}(s)=\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}} z_{i}(s), i=2, \ldots, n \\
& \eta_{m}(s)=\frac{\frac{1}{\tau}}{s+\frac{1}{\tau}} m(s)
\end{aligned}
$$

it is possible to obtain from (14)

$$
\begin{aligned}
& s \eta_{i}(s)=-\frac{1}{\tau} \eta_{i}(s)+\frac{1}{\tau} z_{i}(s), i=2, \ldots, n \\
& s \eta_{m}(s)=-\frac{1}{\tau} \eta_{m}(s)+\frac{1}{\tau} m(s)
\end{aligned}
$$

Therefore, by substituting (14) in (13), and using the inverse Laplace transform on (13) and (15), we can obtain the following differential equations

$$
\begin{align*}
\varphi_{i} & =-\frac{1}{\tau} \eta_{i}+\frac{1}{\tau} z_{i}, i=2, \ldots, n \\
\dot{\eta}_{i} & =-\frac{1}{\tau} \eta_{i}+\frac{1}{\tau} z_{i}, i=2, \ldots, n  \tag{16}\\
\varphi_{m} & =-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t) \\
\dot{\eta}_{m} & =-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t)
\end{align*}
$$

Considering the dynamics of the approximate velocities, the control laws $\Gamma_{1}$ and $\Gamma_{2}$ are modified as

$$
\begin{align*}
& \bar{\Gamma}_{1}:\left\{\begin{array}{l}
u_{i}=-\frac{1}{2} k \frac{\partial \gamma_{i}}{\partial z_{i}}+\varphi_{m}, i=1, \ldots, n-1 \\
u_{n}=\varphi_{m}-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right.  \tag{17}\\
& \bar{\Gamma}_{2}:\left\{\begin{array}{l}
u_{i}=-\frac{1}{2} k \frac{\partial \gamma_{i}}{\partial z_{i}}+\varphi_{i+1}, i=1, \ldots, n-1 \\
u_{n}=\varphi_{m}-k_{m}\left(z_{n}-m(t)\right)
\end{array}\right. \tag{18}
\end{align*}
$$

The closed-loop systems (1), (17) and (1), (18) result in the extended system's equations

$$
(1),(117):\left\{\begin{array}{c}
\dot{z}_{i}=-k\left(z_{i}-z_{i+1}-c_{(i+1) i}\right)  \tag{19}\\
\\
\quad-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t), i=1, \ldots, n-1 \\
\dot{z}_{n}=-k_{m}\left(z_{n}-m(t)\right) \\
\\
-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t) \\
\dot{\eta}_{m}=-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t)
\end{array}\right.
$$

$$
(1),(118):\left\{\begin{array}{c}
\dot{z}_{i}=-k\left(z_{i}-z_{i+1}-c_{(i+1) i}\right)  \tag{20}\\
\quad-\frac{1}{\tau} \eta_{i+1}+\frac{1}{\tau} z_{i+1}, i=1, \ldots, n-1 \\
\dot{z}_{n}=-k_{m}\left(z_{n}-m(t)\right) \\
\quad-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t) \\
\dot{\eta}_{i}=-\frac{1}{\tau} \eta_{i}+\frac{1}{\tau} z_{i}, i=2, \ldots ., n \\
\dot{\eta}_{m}=-\frac{1}{\tau} \eta_{m}+\frac{1}{\tau} m(t)
\end{array}\right.
$$

and, when written in matrix form, the closed-loop systems are given, respectively, by

$$
\begin{gather*}
{\left[\begin{array}{c}
\dot{z} \\
\dot{\eta}_{m}
\end{array}\right]=\left(\Lambda \otimes I_{2}\right)\left[\begin{array}{c}
z \\
\eta_{m}
\end{array}\right]+\left[\begin{array}{c}
C_{1} \\
\frac{1}{\tau} m(t)
\end{array}\right]}  \tag{21}\\
{\left[\begin{array}{c}
\dot{z} \\
\dot{\eta}
\end{array}\right]=\left(\Upsilon \otimes I_{2}\right)\left[\begin{array}{l}
z \\
\eta
\end{array}\right]+\left[\begin{array}{l}
C_{2} \\
M
\end{array}\right]} \tag{22}
\end{gather*}
$$

where $z=\left[z_{1}, \ldots, z_{n}\right]^{T}, \quad \eta=\left[\eta_{2}, \ldots, \eta_{n}, \eta_{m}\right]^{T}, \quad M=\left[0, \ldots, 0, \frac{1}{\tau} m(t)\right]^{T}$,
$\Lambda=\left[\begin{array}{cc}\Lambda_{11} & \Lambda_{12} \\ \Lambda_{21} & -\frac{1}{\tau}\end{array}\right]$ with the elements

$$
\Lambda_{11}=\left[\begin{array}{rrrrrrr}
-k & k & 0 & 0 & \cdots & 0 & 0 \\
0 & -k & k & 0 & \cdots & 0 & 0 \\
0 & 0 & -k & k & \cdots & 0 & 0 \\
0 & 0 & 0 & \ddots & \ddots & \vdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & 0 & \cdots & -k & k_{m} \\
0 & 0 & 0 & 0 & \cdots & 0 & -k_{m}
\end{array}\right] \in \mathfrak{R}^{n \times n},
$$

$$
\Lambda_{12}=[0, \ldots, 0]^{T} \in \mathfrak{R}^{n \times 1},
$$

$$
\Lambda_{21}=[0, \ldots, 0] \in \mathfrak{R}^{1 \times n},
$$

$=\left[\begin{array}{ll}11 & 12 \\ 21 & 22\end{array}\right]$ with elements

$$
\begin{gathered}
\Upsilon_{12}=\Upsilon_{22}=\operatorname{diag}\left[-\frac{1}{\tau}, \ldots,-\frac{1}{\tau}\right] \in \mathfrak{R}^{n \times n} \\
\left.\Upsilon_{11}=\left[\begin{array}{cccccc}
-k & \left(k+\frac{1}{\tau}\right) & 0 & \cdots & 0 & 0 \\
0 & -k & \left(k+\frac{1}{\tau}\right) & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & & 0 & \cdots & -k \\
0 & 0 & & 0 & \cdots & 0 \\
\hline
\end{array}\right] \frac{-k_{m}}{\tau}\right] \\
\Upsilon_{21}=\left[\begin{array}{cccccc}
0 & \frac{1}{\tau} & 0 & \cdots & 0 & 0 \\
0 & 0 & \frac{1}{\tau} & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & 0 & \frac{1}{\tau} \\
0 & 0 & 0 & \cdots & 0 & 0
\end{array}\right] \in \mathfrak{R}^{n \times n}
\end{gathered}
$$

and

$$
C_{1}=\left[\begin{array}{c}
k c_{21}+\frac{1}{\tau} m(t) \\
\vdots \\
k c_{n(n-1)}+\frac{1}{\tau} m(t) \\
\left(k_{m}+\frac{1}{\tau}\right) m(t)
\end{array}\right], C_{2}=\left[\begin{array}{c}
k c_{21} \\
\vdots \\
k c_{n(n-1)} \\
\left(k_{m}+\frac{1}{\tau}\right) m(t)
\end{array}\right]
$$

It is clear that, due to inexact information regarding the velocities, the errors converge to a residual set around zero, which depends on the quality of the approximate velocities. Similar to the previous case, it is necessary to analyse the convergence of the robots to the formation tracking. Thus, we define the following auxiliary variables

$$
\begin{gathered}
e_{i}=z_{i}-z_{i}^{*}, i=1, \ldots, n \\
\delta_{i}=\varphi_{i}-\varphi_{i+1}, i=2, \ldots, n-1 \\
\delta_{n}=\varphi_{n}-\varphi_{m}(t) \\
\delta_{n+1}=\varphi_{m}-\dot{m}(t)
\end{gathered}
$$

where the errors $e_{i}$ are similar to (8) and the $\delta_{i}$ errors are the difference between the approximate velocities of the robots and the marching path. Note that if the errors $e_{i}$ converge to zero, the robots achieve the desired formation and the convergence of $\delta_{i}$ ensures that the robots move at the same velocity as that of the marching path, i.e., preserving the formation pattern.

The next proposition is our main result, which establishes the boundedness of the errors around zero, based on small values of $\tau$ and the behaviour of the acceleration of the marching path.

Proposition 2 Consider the system (1) and the control laws (17) or (18) for $n$ robots. Suppose that $k, k_{m}>0$. Then, in the closedloop systems (1), (17) and (1), (18), the error coordinates are bounded for any $\tau \geq 0$ and $|\ddot{m}(t)|<\infty$. Furthermore, if $\ddot{m}(t)=0$, then the errors tend exponentially towards zero, regardless of the value of $\tau$, and when $|\ddot{m}(t)|<\infty$ and $\tau \rightarrow 0$, the errors also converge to zero as $t \rightarrow \infty$.

Proof. For the closed-loop system (1), (17), the dynamics of the error coordinates is given by

$$
\begin{align*}
& \dot{e}_{i}=-k e_{i}+k e_{i+1}, i=1, \ldots, n-2 \\
& \dot{e}_{n-1}=-k e_{n-1}+k_{m} e_{n} \\
& \dot{e}_{n}=-k_{m} e_{n}+\delta_{n+1}  \tag{23}\\
& \dot{\delta}_{n+1}=-\frac{1}{\tau} \delta_{n+1}-\ddot{m}(t)
\end{align*}
$$

and written in matrix form as

$$
\left[\begin{array}{c}
\dot{e} \\
\dot{\delta}_{n+1}
\end{array}\right]=\left(\tilde{\Lambda} \otimes I_{2}\right)\left[\begin{array}{c}
e \\
\delta_{n+1}
\end{array}\right]-\left[\begin{array}{c}
0 \\
\vdots \\
0 \\
1
\end{array}\right] \ddot{m}(t)
$$

where $e=\left[e_{1}, \ldots, e_{n}\right]^{T}, \widetilde{\Lambda}=\left[\begin{array}{ll}\widetilde{\Lambda}_{11} & \widetilde{\Lambda}_{12} \\ \widetilde{\Lambda}_{21} & \widetilde{\Lambda}_{22}\end{array}\right]$ with

$$
\begin{gathered}
\tilde{\Lambda}_{11}=\left[\begin{array}{cccccc}
-k & k & 0 & 0 & \cdots & 0 \\
0 & -k & k & 0 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & -k & k_{m} \\
0 & 0 & 0 & \cdots & 0 & -k_{m}
\end{array}\right] \in \mathfrak{R}^{n \times n}, \\
\tilde{\Lambda}_{12}=[0, \ldots, 1]^{T} \in \mathfrak{R}^{n \times 1}, \\
\tilde{\Lambda}_{21}=[0, \ldots, 0] \in \mathfrak{R}^{1 \times n}, \\
\tilde{\Lambda}_{22}=0 .
\end{gathered}
$$

By using mathematical induction, it can be shown that the characteristic polynomial of matrix $\widetilde{\Lambda}$ is given by $p_{\tilde{\Lambda}}(\lambda)=(\lambda+k)^{2(n-1)}\left(\lambda+k_{m}\right)^{2}+\left(\lambda+\frac{1}{\tau}\right)^{2}$; therefore we conclude that (24) is bounded-input, bounded-state stable.
On the other hand, for the closed-loop system (1), (18), the dynamics of the errors is given by

$$
\begin{align*}
& \dot{e}_{i}=-k e_{i}+k e_{i+1}+\delta_{i+1}, i=1, \ldots, n-2 \\
& \dot{e}_{n-1}=-k e_{n-1}+k_{m} e_{n}+\delta_{n} \\
& \dot{e}_{n}=-k_{m} e_{n}+\delta_{n+1} \\
& \dot{\delta}_{i}=-\frac{1}{\tau}\left(k e_{i}-k e_{i+1}+\delta_{i}-\delta_{i+1}\right), \quad i=2, \ldots, n-2 \\
& \dot{\delta}_{n-1}=-\frac{1}{\tau}\left(k e_{n-1}-k_{m} e_{n}+\delta_{n-1}-\delta_{n}\right)  \tag{25}\\
& \dot{\delta}_{n}=-\frac{1}{\tau}\left(k_{m} e_{n}+\delta_{n}-\delta_{n+1}\right) \\
& \dot{\delta}_{n+1}=-\frac{1}{\tau} \delta_{n+1}-\ddot{m}(t)
\end{align*}
$$

and written in matrix form as

$$
\left[\begin{array}{c}
\dot{e}  \tag{26}\\
\dot{\delta}
\end{array}\right]=\left(\tilde{r} \otimes I_{2}\right)\left[\begin{array}{l}
e \\
\delta
\end{array}\right]-\left[\begin{array}{c}
0 \\
\vdots \\
1
\end{array}\right] \ddot{m}(t)
$$

where $e=\left[e_{1}, \ldots, e_{n}\right]^{T}, \delta=\left[\delta_{2}, \ldots, \delta_{n}, \delta_{n+1}\right]^{T},=\left[\begin{array}{ll}11 & 12 \\ & 12 \\ 21 & 22\end{array}\right]$, with ${ }_{11}=\widetilde{\Lambda}_{11}$, ${ }_{12}$ the identity matrix of $n \times n$,

$$
\tilde{\Upsilon}_{21}=\frac{1}{\tau}\left[\begin{array}{cccccc}
0 & -k & k & \cdots & 0 & 0 \\
0 & 0 & -k & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & -k & k_{m} \\
0 & 0 & 0 & \cdots & 0 & -k_{m} \\
0 & 0 & 0 & \cdots & 0 & 0
\end{array}\right] \in \mathfrak{R}^{n \times n}
$$


(a) Formation tracking scheme with the control law $\bar{\Gamma}_{1}$.

(b) Formation tracking scheme with the control law $\bar{\Gamma}_{2}$.

[^0]\[

\tilde{\Upsilon}_{22}=\frac{1}{\tau}\left[$$
\begin{array}{cccccc}
-1 & 1 & 0 & \cdots & 0 & 0 \\
0 & -1 & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & -1 & 1 \\
0 & 0 & 0 & \cdots & 0 & -1
\end{array}
$$\right] \in \mathfrak{R}^{n \times n}
\]

Now, the characteristic polynomial of matrix is given by $p(\lambda)=(\lambda+1)^{2 n}(\lambda+k)^{2(n-1)}\left(\lambda+k_{m}\right)^{2}$; therefore we also conclude that (26) is bounded-input, bounded-state stable. In this case, observe that the eigenvalues do not depend on the value of $\tau$.

Note that if $\ddot{m}(t)=0$, then we have a homogeneous, linear system in both cases; therefore, the solution converges exponentially to zero. Finally, the solution of the coordinate $\delta_{n+1}$, as $t \rightarrow \infty$, is bounded by

$$
\begin{equation*}
\left|\delta_{n+1}\right| \leq \tau|\ddot{m}(t)| \tag{27}
\end{equation*}
$$

from which we can see that $\left|\delta_{n+1}\right| \rightarrow 0$ as $\tau \rightarrow 0$.
Figure 5 shows a numerical simulation of the closed-loop systems (1), (17) and (1), (18), with $\tau=0.5$, and the same parameters and initial conditions as in Fig. 2. The error coordinates do not converge to zero, but remain bounded around zero. The transitory regime is more evident than in the case of exact information.

Analysing the effects of the gain parameter $\tau$, define the error performance index in both cases as $\tilde{e}=\frac{1}{t_{f}} \int_{0}^{t_{f}}\left(\sqrt{\left\|e_{1}\right\|^{2}+\left\|e_{2}\right\|^{2}+\left\|e_{3}\right\|^{2}}\right) d t$ and $\delta=\frac{1}{t_{f}} \int_{0}^{t_{f}}\left(\sqrt{\left\|\delta_{4}\right\|^{2}}\right) d t$, for the control law $\bar{\Gamma}_{1}$ and $\delta=\frac{1}{t_{f}} \int_{0}^{t_{f}}\left(\sqrt{\left\|\delta_{2}\right\|^{2}+\left\|\delta_{3}\right\|^{2}+\left\|\delta_{4}\right\|^{2}}\right) d t$ for the control law $\bar{\Gamma}_{2}$. Table 1 shows the results for two values of $\tau$ in the previous simulation at the final time $t_{f}=40$. Observe the best results for the smaller values of $\tau$, and the very similar performance of the two control laws.

|  | $\bar{\Gamma}_{2}$ |  | $\tau$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\tilde{e}$ | $\delta$ | $\tilde{e}$ | $\delta$ | $\tau$ |
| 0.5 | 0.32 | 0.38 | 0.31 | 0.32 |
| 0.005 | 0.28 | 0.12 | 0.25 | 0.1 |

Table 1. Error-performance index with different values of $\bar{\Gamma}_{1}$

## 5. Extension of the control laws to the case of unicycletype robots

The control laws (17) and (18) can be extended to the case of nonholonomic mobile robots. Consider the kinematic model of unicycle-type robots, as shown in Figure 6, given by

$$
\left[\begin{array}{c}
\dot{x}_{i}  \tag{28}\\
\dot{y}_{i} \\
\dot{\theta}_{i}
\end{array}\right]=\left[\begin{array}{cc}
\cos \theta_{i} & 0 \\
\sin \theta_{i} & 0 \\
0 & 1
\end{array}\right]\left[\begin{array}{c}
v_{i} \\
w_{i}
\end{array}\right], i=1, \ldots, n,
$$

where $v_{i}$ and $w_{i}$ are the linear and angular velocities, respectively, of the midpoint of the wheel's axis given by $(x, y)$. It is known that the dynamical system (28) cannot be stabilized by application of a continuous time-invariant control law [29]. Because of this restriction, the selection of the coordinates $\alpha_{i}=\left(p_{i}, q_{i}\right)$, as shown in Figure 6 , as a control output instead of $(x, y)$ helps to simplify the analysis, avoiding singularities in the control law. Moreover, the position of the $\alpha_{i}$ could be the position of an actuator or the robot's center of mass. The coordinates $\alpha_{i}$ are given by

$$
\alpha_{i}=\left[\begin{array}{l}
p_{i}  \tag{29}\\
q_{i}
\end{array}\right]=\left[\begin{array}{l}
x_{i}+l \cos \theta_{i} \\
y_{i}+l \sin \theta_{i}
\end{array}\right], i=1, \ldots, n,
$$

and their dynamics can be obtained as

$$
\dot{\alpha}_{i}=\underbrace{\left[\begin{array}{cc}
\cos \theta_{i} & -l \sin \theta_{i}  \tag{30}\\
\sin \theta_{i} & l \cos \theta_{i}
\end{array}\right]}_{A_{i}\left(\theta_{i}\right)}\left[\begin{array}{c}
v_{i} \\
w_{i}
\end{array}\right], i=1, \ldots, n,
$$

where $A_{i}\left(\theta_{i}\right)$ is the so-called decoupling matrix of the robot $R_{i}$. Note that $\operatorname{det}\left(A_{i}\left(\theta_{i}\right)\right)=l \neq 0$. Therefore, it is possible to design a control strategy in order to move $\alpha_{i}$ to a desired location using the control law $\left[v_{i}, w_{i}\right]^{T}=A_{i}^{-1}\left(\theta_{i}\right) f_{i}, i=1, \ldots, n$, where functions $f_{i}$ are the desired dynamics of the coordinates $\alpha_{i}$.

Thus, extending the previous results to the case of point robots, the control laws with exact velocities given in (4)(5), or the control laws with approximate velocities expressed in (17)-(18), could be rewritten for unicycle robots by

$$
\left[\begin{array}{c}
v_{i}  \tag{31}\\
w_{i}
\end{array}\right]=\frac{1}{2} A_{i}^{-1}\left(\theta_{i}\right)\left(\bar{u}_{i}\right), i=1, \ldots n
$$

where $\bar{u}_{i}$ are identical functions of the control laws $u_{i}$ as defined in (4)-(5) and (17)-(18), depending on the coordinates $\alpha i$. Note that the dynamics of the coordinates $\alpha_{i}$ in the closed-loop system (29)-(31) are reduced to $\alpha_{i}=\bar{u}_{i}, i=1, \ldots, n$. Therefore, the analysis of the formation tracking becomes in the case of holonomic robots studied in Sections 3 and 4. Note that these input-output linearizations leave the orientation angles $\theta_{i}$ in an uncontrolled state.

(a) Control law $\bar{\Gamma}_{1}$ with $\tau=0.5$







(b) Control law $\bar{\Gamma}_{2}$ with $\tau=0.5$

Figure 5. IRobot Create


Figure 6. Simulation of formation tracking using approximate velocities


Figure 7. Kinematic model of unicycles

## 6. Experimental work

The control strategies were implemented using an experimental set-up consisting of three unicycle-type robots manufactured by IRobot, the model Create, and a vision system comprising a monochrome camera Genie HM-1024 with an Ethernet communication, developed by Teledyne Dalsa. The camera captures the position of two white circle marks placed on top of every robot, as shown in Fig. 5, indicating the coordinates $\left(x_{i}, y_{i}\right)$ and $\alpha_{i}$. The camera is installed at a height of 2.5 m and configured to work at 117 frames per second. Therefore, the sampling period is given by 8 milliseconds and the resolution of the camera is given by $1024 \times 768$ pixels which produces a position resolution of $3 \mathrm{~mm}^{2}$ per pixel. Note that both the workspace and the robots are covered in black in order to highlight the white markings.
Using the white marks, the position and orientation of every robot is calculated using a Core i5 PC with 4GB RAM. The same computer subsequently evaluates the control laws and generates the control signals $u_{i}$ and $w_{i}$ for every robot, which are transformed into the desired angular velocities for the robot wheels, by

$$
\begin{align*}
& w r_{i}=\frac{v_{i}}{r}+\frac{L}{2 r} w_{i}, i=1, \ldots n  \tag{32}\\
& w l_{i}=\frac{v_{i}}{r}-\frac{L}{2 r} w_{i}, i=1, \ldots n \tag{33}
\end{align*}
$$

where $w r_{i}$ and $w l_{i}$ are the right and left wheel of each robot, respectively, $L=0.25 \mathrm{~m}$ is the distance between two wheels and $r=0.03 \mathrm{~m}$ is the radius of the wheels. Finally, the desired angular velocities are sent via a wireless Bluetooth transmitter to every robot. The image processing and the control law were developed in a software application using the real-time programming of Matlab R2013a.

Note that the experimental set-up becomes a flexible platform for emulating different formation-tracking systems, from centralized to decentralized schemes, by selecting the adequate information obtained from the vision system to be used in the local control laws of each robot.

To complement the control laws, a reactive secondary control law for the avoidance of inter-robot collision was programmed into the experiments. Although the prevention of possible collisions was achieved using a simple reactive control law, in the experiments, none of the robots were in danger of collision due to their initial conditions. The analysis of non-collision in formation tracking is not studied in this paper and will be addressed in further research.

### 6.1 Experiments with exact velocities

Figure 8 shows an experiment of the control law $\Gamma_{1}$ given in (4) using the exact information of the derivative of $m(t)$, with $n=3, k=1, k_{m}=1$ and $\ell=0.15 m$. The marching path is the circle given (in metres) by $m(t)=\left[0.5+0.4 \cos \left(\frac{2 \pi}{40} t\right), 0.5+0.4 \sin \left(\frac{2 \pi}{40} t\right)\right]$. The vectors of the relative positions are $c_{21}=c_{32}=[0.6 \mathrm{~m}, 0]$ (a straight-line shaped formation). The initial conditions, also given in metres and radians, are given by $\left[x_{1}, y_{1}, \theta_{1}\right]=[2.23,0.68,1.56]$, $\left[x_{2}, y_{2}, \theta_{2}\right]=[1.69,0.68,1.50]$ and $\left[x_{3}, y_{3}, \theta_{3}\right]=[1.14,0.66,1.65]$. The trajectories of the coordinates $\alpha_{i}$ that are recorded by the vision system are presented in Figure 8(a). The leader robot $R_{3}$ converges to the desired marching path whereas the follower robots converge to the desired formation. The evolution of $x_{i}, y_{i}$ and $\theta_{i}$ is depicted in Figure 8(b). Note that the experimental results are very close to the simulation signals. Finally, the control outputs $v_{i}$ and $w_{i}$ are shown in Figure 8(c).

The second experiment is given in Figure 9, which is now dedicated to the control law $\Gamma_{2}$ given in (5) using the exact information of the robots' velocities. The value of the control gains $k$ and $k_{m}$ are similar to the ones used in the previous case. Now the robots are formed in a triangular shape, given by the vectors $c_{21}=[0.6,0.6]$ and $c_{32}=[0.6,-0.6]$. The initial conditions are $\left[x_{1}, y_{1}, \theta_{1}\right]=[2.26,0.70,1.68]$, $\left[x_{2}, y_{2}, \theta_{2}\right]=[2.03,1.45,2.85]$ and $\left[x_{3}, y_{3}, \theta_{3}\right]=[1.03,0.65,0.68]$. The trajectories of the coordinates $\alpha_{i}$ that are recorded by the vision system are presented in Figure 9(a). The evolution of $x_{i}, y_{i}$ and $\theta_{i}$ is depicted in Figure 9(b). The control outputs $v_{i}$ and $w_{i}$ are shown in Figure 9(c). Similar to the previous

(a) Position of the robots in the workspace.

(b) Coordinates $x_{i}, y_{i}, \theta_{i}$.






(c) Linear and angular velocities

Figure 8. Experiment 1 using the control law $\Gamma_{1}$
case, the graphs show a good performance of the control law, in which the robots converge to the desired formation tracking and the experimental results are close to the numerical simulation.

(a) Position of the robots in the workspace.

(b) Coordinates $x_{i}, y_{i}, \theta_{i}$.






(c) Linear and angular velocities

Figure 9. Experiment 2 using the control law $x_{i}$
In both experiments, the orientation angles converge to the same value although they are not controlled by the control laws. In addition, note that the linear and angular velocities
shown in Figures 8(c) and 9(c) converge to a positive value; therefore, the robots after the transitory regime, continue to move in an antoclockwise direction while facing the front. It is shown in Figures 8(b) and 9(b) where the trajectories of coordinates $y_{i}$ and $\Gamma_{2}$, respectively, describe the parametric functions of the circumference, and that the orientation angles are positive and increasing.

The quantization error is considered to be sufficiently small for this experiment, due to the precision of the camera and the insignificance of its influence. This can be seen in Figures 8 and 9 , where the results show a ripple in the order of the instrument's resolution.

### 6.2 Experiments with approximate velocities

Figure 10 shows an experiment 3 using the control law $\bar{\Gamma}_{1}$ with $\tau=0.5$. The marching path and desired vector of the positions are similar to those of the experiment 1 shown in Figure 8. Now, the initial conditions are $\left[x_{1}, y_{1}, \theta_{1}\right]=[2.3679,1.1637,1.8659]$,
$\left[x_{2}, y_{2}, \theta_{2}\right]=[1.7655,1.1773,1.9130]$
and $\left[x_{3}, y_{3}, \theta_{3}\right]=[1.1632,1.1920,1.9660]$. The trajectories of the coordinates $\alpha_{i}$, which are recorded by the vision system, are presented in Figure 10(a). The evolutions of $x_{i}, y_{i}$ and $\theta_{i}$ are depicted in Figure 10(b). The control outputs $v_{i}$ and $w_{i}$ are shown in Figure 10(c).
Finally, the fourth experiment is given in Figure 11, using the control law $\bar{\Gamma}_{2}$ with $\tau=0.5$. The marching paths and desired vectors of the positions are similar to those of Experiment 2 as shown in Figure 9. The initial conditions are $\quad\left[x_{1}, y_{1}, \theta_{1}\right]=[1.8747,0.7022,1.3280]$, $\left[x_{2}, y_{2}, \theta_{2}\right]=[1.3245,1.3362,1.6792] \quad$ and $\left[x_{3}, y_{3}, \theta_{3}\right]=[0.6352,0.6170,1.4002]$. The trajectories of the coordinates $\alpha_{i}$ recorded by the vision system are presented in Figure 11(a). The evolution of $x_{i}, y_{i}$ and $\theta_{i}$ is depicted in Figure 11(b). The control outputs $v_{i}$ and $w_{i}$ are shown in Figure 11(c).

Note that the trajectories in Experiments 3 and 4 are modified due to the approximations of the velocities and the performance of the robots deteriorating with respect to the ideal case. The transient response of the control inputs, as shown in Figures 10(c) and 11(c), exhibits a larger overshoot with respect to the control inputs of Experiments 1 and 2, as presented in Figures 8(c) and 9(c), respectively, with the worst being Experiment 4. Similar to Experiments 1 and 2 , the linear and angular velocities converge to a positive value; therefore, the robots continue to move in an antoclockwise direction while facing the front, which is verified by the trajectories depicted in Figures 10(b) and 11(b), respectively.
According to the main result detailed in Section 4, the errors remain oscillatory around zero. These effects are shown in Figure 12 for Experiments 3 and 4, respectively. Note that due to propagation of the inexact measures of velocities

(a) Position of the robots in the workspace.

(b) Coordinates $x_{i}, y_{i}, \theta_{i}$.

(c) Linear and angular velocities

Figure 10. Experiment 3 using the control law $\bar{\Gamma}_{1}$ and $\tau=0.5$
along the chain of robots, the behaviour of the errors worsen in robots that move away from the leader. Thus, the robot $R_{1}$ exhibits the worst performance in the formation tracking.


Figure 11. Experiment 4 using the control law $\bar{\Gamma}_{2}$ and $\tau=0.5$

## 7. Conclusion

This paper shows that, assuming perfect knowledge about the positions and velocities of the robots and the marching


Figure 12. Graphics of errors using approximate velocities
path, it is possible to guarantee the preservation of a rigid formation and the group trajectory tracking of the robots. However, during a decentralized formation tracking, the robots measure only positions and the velocities must be approximated. This paper incorporates the analysis of the variables of approximate velocities within the closed-loop systems, and some conditions are determined in order to ensure that the errors are bounded. The desired outcome occurs if the trajectory is sufficiently smooth and the bound of the errors' performance improves when the bandwidth approximation increases for the velocities, recovering the ideal case in the limit. The control laws were extended for the case of unicycle-type robots with numerical simulations and real-time experiments. In further research, the analysis
of control strategies with other formation-tracking topologies and collision avoidance applied to different nonholonomic mobile robots will be studied.

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[^0]:    Figure 4. Formation-tracking scheme, with approximate information about the velocities of robots and the trajectory

