The Implementation of Consensus Algorithm on a Group of Humanoid Robots with Varying Network Topologies

Ali Sadiyoko¹, Harry Septanto², Oetomo Sudjana³ and Bambang Riyanto T.⁴

¹Industrial Engineering Department, Universitas Katolik Parahyangan,
²Center for Spacecraft Technology, National Institute of Aeronautics and Space,
³Electronics Engineering, Institut Teknologi Harapan Bangsa,
⁴School of Electrical Engineering & Informatics, Institut Teknologi Bandung,
INDONESIA

Abstract: The purpose of this paper is to present experiment results on the implementation of consensus algorithm on a group of humanoid robots. The experiment in this work is based on some previous works on distributed control of robotic networks and distributed consensus in multi-vehicle cooperative control. According to Ren, a consensus may occur if communication topology between the robots forms a spanning tree. The existence of some shared informations is a necessary condition for this algorithm. Further, a consensus may occur if the topology of communication among the robots forms a spanning tree. However, to apply the algorithm on a group of humanoid robots we need some modification on the original algorithm. A new algorithm is proposed by adding a new damping variable (β) on original algorithm to make a group of humanoid robots move synchronously. The experiment of the new consensus algorithm is tested on two topologies, which are leader-follower and leaderless topology. This research concludes that consensus in a group of humanoid robot can be achieved by inducing damping variable in original equation.

Keywords: consensus algorithm; experimental platform; humanoid robots; communication network topology.

1. Introduction

The idea to form a group of humanoid robots that can move together synchronously is always a challenge for engineers. An efficient, simple and stable algorithm is the main goal of the research. In 2004, Fax and Murray [1] proposed an algorithm to control a multi-agents networked system with an emphasis on the role of information flows among the agents. Since then, such applications include mobile robots formation control, UAV formation flying, wireless sensor networks, multipoint surveillance were developed [2-4]. This algorithm provides rapid agreement and cooperation among all agents to do a task together. This is inspired by collective animal behaviors, such as swarming of insects, flocking of birds or schooling of fish. Any individual animal in the group shares information to the other members of the group. In the case of flocking, birds share their positions and velocities to other birds behind of them. Based on this behavior, we believed that an individual animal in a group tends to navigate relative to its nearby neighbors. Any individual animal in the group seems to make an agreement/consensus to its neighbors. So, the algorithm is known as agreement/consensus algorithm. From this phenomenon, it can be concluded that necessary condition for a group of agents (or birds) to reach consensus is the availability of shared information. The shared information that is necessary for cooperation is called coordination information or coordination variable. Cooperation will occur if each member in the team has access to consistent, accurate and complete coordination information. According to [5], a consensus may occur if the topology of communication between the agents forms a spanning tree.

Experiment in [5] and most of consensus algorithm experiments had always been tested on a group of mobile robots. To expand the possibility use of this algorithm in other system, this
research is trying to apply the algorithm on a group of humanoid robots. The humanoid robot
used in this experiment is NAO H-25, a 25 degree of freedom (DoF) humanoid robot made by
Aldebaran Robotics, France. The first step in the experiment is to build a suitable experiment
platform for simulating some tasks on a group of humanoid robots and then observe the
performance of a group of robots to achieve consensus. The experiments start with the
manipulation of NAO’s head and then manipulating the movement of NAO’s arm. Experiment
is carried out on two topologies: leader-follower and leaderless topology.

On the leader-follower topology, a leader robot acts as a command generator, which
generates the desired movement and ignores information from the other robots. All other robots
attempt to follow the movement of the leader robot. This problem is known as leader-following
consensus, model reference consensus or synchronized tracking control. On the leaderless
topology, distributed controllers are programmed for all robots, such that all robots eventually
driven to an unprescribed common value. This value may be a constant, or may be time
varying, and is generally a function of the initial states of the robots in the communication
network [6].

In a multi-robots system, a consensus situation is reached if all robots in system agreed on
the value of a variable of interest. Information consensus guarantees that robots share
consistent information that is critical to the coordination task information over a network
topology. There must be existed a shared variable of interest over a network topology for all
robots in the group, so that all robots can achieve consensus. The shared variable of interest is
called the information state. This information state is critical to the coordination task of the
group, represents an instantiation of the coordination variable for the team, e.g: the shape of a
formation, the rendezvous point, the rendezvous time, the direction of motion, the length of a
perimeter being monitored, or the direction of motion for a multi-robot swarm. The goal of
consensus algorithm is to design an update law so that the information states of all of the robots
in the network converge to a common value.

2. Consensus Algorithm

In this article we adopt some of the notations and experiments described in [5] and in
addition present the application of consensus algorithm on a group of humanoid robots.

Let $n$ is number of robot in team, $a_{ij}(t)$ is the $(i, j)$ entry of adjacency matrix $A_n \in \mathbb{R}^{n \times n}$
associated with graph $G_n$ at time $t$ and $x_i$ is the information state of $i$-th robot.

**Definition 1.** Graph $G_n$ is a directed graph representing robot team’s communication topology,
defined by $G_n \equiv (V_n \times E_n)$, where $V_n = \{1, ..., n\}$ is the node set and $E_n \subseteq V_n \times V_n$ is the
edge set.

**Definition 2.** The adjacency matrix, $A_n = [a_{ij}] \in \mathbb{R}^{n \times n}$ of a directed graph $G_n$ is defined such
that $a_{ij}$ is a positive weight if $(j, i) \in E_n$, and $a_{ij} = 0$ if $(j, i) \notin E_n$. Value of $a_{ij} = 0$
denotes the fact that robot $i$ does not received information from robot $j$.

**Definition 3.** A directed spanning tree $(V^s_n, E^s_n)$ is a subgraph of $(V_n, E_n)$ such that
$(V^s_n, E^s_n)$ is directed tree and $V^s_n \subseteq V_n$. A subgraph $(V^s_n, E^s_n)$ of $(V_n, E_n)$ is a graph such
that $(V^s_n \subseteq V_n)$ and $E^s_n \subseteq E_n \cap (V^s_n \times V^s_n)$.
Definition 4. The group of robots is reached or achieved a consensus if, for all $x_i(0)$ and all $i,j = 1,\ldots,n$, $|x_i(t) - x_j(t)| \to 0$, as $t \to \infty$. Consensus is reached if the topology of communication between the robots forms a spanning tree [5]. According to [5] the most common continuous-time consensus algorithm is given by:

$$\dot{x}_i = -\sum_{j=1}^{n} a_{ij}(t)[x_j(t) - x_i(t)], \quad i = 1,\ldots,n$$  \hspace{1cm} (1)

The experiments in this research follow the study of consensus tracking algorithm for single-integrator dynamics in [5]. The shared state variable $x_i$ in equation (1) is defined as angle position of a joint in NAOi. Thus, $\dot{x}_i$ is defined as angle velocity of a joint. Since NAO doesn’t have an explicit variable to control the joint velocity, in this experiments, joint velocity $\ddot{x}_i$ is approximated by $T_k x_k i j i i_\Delta$ $\ldots$, $\lbrack \ldots \rbrack$, where $k$ is the discrete-time index and $\Delta T$ is the sample period. So, the equation (1) can be modified to:

$$x_i[k+1] = x_i[k] - \sum_{j=1}^{n} a_{ij}[x_j[k] - x_i[k]] \Delta T$$ \hspace{1cm} (2)

Similar to the continuous-time case, a discrete-time consensus is reached or achieved if, for all $x_i[0]$ and all $i,j = 1,\ldots,n$, $|x_i[k] - x_j[k]| \to 0$, as $k \to \infty$. However, for more complex scenarios in this experiment, more fundamental form of consensus algorithm is needed. The experiments use fundamental consensus algorithm as shown in equation (3) [5]:

$$u_i = \frac{1}{\eta_i(t)} \sum_{j=1}^{n} a_{ij}(t)\left[\dot{x}_i - \gamma(x_i - x_j)\right] + \frac{1}{\eta_i(t)} \sum_{i=1}^{n} a_{i(n+1)}(t)\left[\dot{x}_r - \gamma(x_i - x_r)\right]$$ \hspace{1cm} (3)

where $a_{ij}(t), i=1,\ldots,n$, $j=1,\ldots,n+1$, is the $(i,j)$ entry of adjacency matrix $A_{(n+1)}(t)$ at time $t$, $\gamma$ is a positive constant scalar, and $\eta_i(t) = \sum_{j=1}^{n+1} a_{ij}(t)$. Variables $x_r$ and $\dot{x}_r$ are the information states of an additional robot or can be virtual, which acts as the unique virtual leader of the team. The robot $n+1$ is called the leader and robot $1,\ldots,n$ is called the followers. The information state of robot $n+1$ is $x_{(n+1)} = x_r \in \mathbb{R}^{(n+1)}$, where $x_r$ represents the consensus reference state.

Similar to the continuous-time case in equation (1), equation (3) should be modified to:

$$x_i[k+1] = x_i[k] + \left[ \frac{1}{\eta_i[k]} \sum_{j=1}^{n} a_{ij}[\dot{x}_j[k] - \gamma(x_i[k] - x_j[k])] + \frac{1}{\eta_i[k]} \sum_{i=1}^{n+1} a_{i(n+1)}[\dot{x}_r[k] - \gamma(x_i[k] - x_r[k])] \right] \Delta T$$ \hspace{1cm} (4)

3. Proposed Algorithm

During experiments, the implementation of equation (4) directly to robots will make Nao’s arm joints saturated. We propose a new parameter $\beta$, defined as damping parameter, to reduce
the influence of \( \dot{x}_i \) (velocity) on the performance of system to reach consensus. Hence, the original equation (4) is modified into:

\[
    x_i[k+1] = x_i[k] + \left[ \frac{1}{\eta_i[k]} \sum_{j=i}^{n} a_{ij} \left[ \beta \dot{x}_j[k] - \gamma (x_i[k] - x_j[k]) \right] \right] + \frac{1}{\eta_i[n+1]} \sum_{i=1}^{n} a_{i(n+1)} \left[ \beta \dot{x}'[k] - \gamma (x_i[k] - x'[k]) \right] \Delta T
\]

(5)

**Proof:** noting that equation (5) is applied for leader-follower topology, the communication topology among robots is defined by \( G_{n+1} = (V_{n+1}, E_{n+1}) \), where \( V_{n+1} = \{1, \ldots, n\} \) is the node set and \( E_{n+1} \subseteq V_{n+1} \times E_{n+1} \) is the edge set. Also let \( A_{n+1} = [a_{ij}] \in \mathbb{R}^{(n+1)\times(n+1)} \), where \( n \) is the number of followers and \( A_{n+1} = 0, \forall j \in 1, \ldots, n+1 \). Let define \( L_{n+1} = [l_{ij}] \in \mathbb{R}^{(n+1)\times(n+1)} \) as a Laplacian matrix associated with \( G_{n+1} \) where \( l_{ij} = -a_{ij}, i \neq j \), \( l_{ii} = \sum_{j=1, j \neq i}^{n+1} a_{ij} \), for \( i = 1, \ldots, n+1 \). We also need to define a degree matrix, where \( D_{n+1} = [d_{ij}] \in \mathbb{R}^{(n+1)\times(n+1)} \), \( d_{ij} = 0, i \neq j \), \( d_{ii} = \sum_{j=1, j \neq i}^{n+1} a_{ij} \) for \( i = 1, \ldots, n+1 \). Using approximation, equation (5) can be written as:

\[
    \dot{x}_i = \frac{1}{\eta_i} \sum_{j=1, j \neq i}^{n+1} a_{ij} \left[ \beta \dot{x}_j - \gamma (x_i - x_j) \right]
\]

(6)

where \( \eta_i = \sum_{j=1, j \neq i}^{n+1} a_{ij} \). Using \( \eta_i = \sum_{j=1, j \neq i}^{n+1} a_{ij} \), equation (6) can be written as:

\[
    \sum_{j=1, j \neq i}^{n+1} a_{ij} \left( \dot{x}_i - \beta \dot{x}_j \right) = -\gamma \sum_{j=1, j \neq i}^{n+1} a_{ij} (x_i - x_j)
\]

(7)

Equation (7) can be written in matrix form as \( Q_{n+1} \dot{x} = R_{n+1} x \), with \( \dot{x} = [\dot{x}_1^T, \dot{x}_2^T, \ldots, \dot{x}_{n+1}^T]^T \), and \( x = [x_1^T, x_2^T, \ldots, x_{n+1}^T]^T \). Matrix \( Q_{n+1} \) is defined as \( Q_{n+1} = [q_{ij}] \in \mathbb{R}^{(n+1)\times(n+1)} \), where \( q_{ij} = -\beta a_{ij}, i \neq j \), \( q_{ii} = \sum_{j=1, j \neq i}^{n+1} a_{ij} \) and \( q_{i(n+1)} = -\beta a_{i(n+1)} \).

By focusing on interaction topology among robots, matrix \( Q_{n+1} \) can be written as:

\[
    Q_{n+1} = \begin{bmatrix} Q_{n+1}(n+1) & 0_{n\times(n+1)} \\ 0_{(n+1)\times n} & 0_{(n+1)\times(n+1)} \end{bmatrix} \quad \text{and} \quad R_{n+1} = \begin{bmatrix} R_{n+1}(n+1) \\ 0_{n\times(n+1)} \end{bmatrix}.
\]

Because \( R_{n+1} = -\gamma L_{n+1} \), then \( L_{n+1} \) can also be written as \( L_{n+1} = \begin{bmatrix} L_{n+1}(n+1) \\ 0_{n\times(n+1)} \end{bmatrix} \). Noting that all entries of the row \( Q_{n+1} \) are zero and \( G_{n+1} \) has a directed spanning tree, it follows that the other rows of \( Q_{n+1} \) do not have all zero entries. This condition follows that \( \sum_{j=1, j \neq i}^{n+1} a_{ij} \neq 0, i = 1, \ldots, n \). Also note that matrix \( L_{n+1} \) satisfies the property of \( l_{ij} \leq 0, \sum_{j=1, j \neq i}^{n+1} l_{ij} = 0, \) where \( i = 1, \ldots, n \). (Property B.2 in [5]).
By keep focusing only on interaction topology, we can divide matrix $Q_{n \times (n+1)}$ into $Q_{n \times n} = [q_{ij}] \in \mathbb{R}^{n \times n}$, $L_n = I_{n \times n} = [l_{ij}] \in \mathbb{R}^{n \times n}$, where $b = [-\beta a_{1(n+1)} \ldots -\beta a_{2(n+1)} \ldots -\beta a_{m(n+1)}]^T$ and $c = [l_{1(n+1)} \ldots l_{2(n+1)} \ldots l_{m(n+1)}]^T$, respectively. Hence, equation (7) can be written as:

$$
\sum_{j=i, j \neq i}^{n} a_{ij} [x_i - x_j] = -\gamma \sum_{j=i, j \neq i}^{n} a_{ij} (x_i - x_j)
$$

This equation implies that $Q_n \dot{x} = R_n x$, with $x = [x_1^T, x_2^T, x_3^T, \ldots, x_n^T]^T$, and $x = [x_1^T, x_2^T, x_3^T, \ldots, x_n^T]^T$. So, matrix $Q_{n+1}$ can be solved as $Q_n = L_n - (1-\beta)A_n$. Further, equation (8) becomes:

$$
[(L_n - (1-\beta)A_n) \otimes I_m]x = -\gamma [L_n \otimes I_m]x
$$

Assuming that matrix $Q_n$ is invertible, equation (9) can be written as:

$$
\dot{x} = -\gamma [(L_n - (1-\beta)A_n) \otimes I_m]^{-1} [L_n \otimes I_m]x
$$

Because $L_n$ satisfies property B.2 with $p = n$, and from Theorem C.1 in [5], all eigenvalues of $-\gamma [(L_n - (1-\beta)A_n) \otimes I_m]^{-1} [L_n \otimes I_m]$ have negative real parts, consequently, $[(L_n - (1-\beta)A_n) \otimes I_m]^{-1} [L_n \otimes I_m]$ must be a positive definite, so it will follow that $x(t) \rightarrow 0$. It implies that the proposed algorithm will achieve consensus asymptotically.

4. Experiments

The first step in this experiment is to design an experimental platform. The main hardware components are composed of: 4 humanoid robots (Aldebaran’s Nao), a computer and a router. The next step is to design a program that will be embedded in NAO. The programs have 2 main tasks. The first task is providing information states, joints position for adjacent NAO, and to perform consensus. The second task is to acquire and record joints position of robot in a file. To start NAO’s behavior and to get data from robots are carried out manually using command lines from a Linux workstation. These programs are written in Python programming language. Python is used because it is already embedded in NAO.

Our first experiment observes the movement behavior of group in a leaderless topology. The experiments were conducted by moving the NAO’s head in 2 DoF (head yaw and head pitch). It is considered easier to be done, so it is a good start to understand the behavior of NAO’s dynamic. The 2 NAO’s head joints variables, HeadYaw and HeadPitch, are shown in Figure 2.

![Figure 2. Information on NAO’s head joint [7].](image-url)
Further, the experiments are conducted on NAO’s left arm to observe the movement behavior of group in order to achieve consensus. There are 5 information states that must be shared over network, i.e: left shoulder pitch, left shoulder roll, left elbow roll, left elbow yaw, and left wrist yaw. Joint information on NAO’s left arm can be shown in Figure 3.

![Figure 3. Information on NAO’s left arm joint [7]](image)

A. Experiment Platform
The hardware experimental platform in this research is inspired by the works of [10], [11] and [12]. A sketch of the experiment platform configuration and the implementation platform are depicted in Figure 4.

![Figure 4. (a) Conceptual design of the experiment and (b) experiment platform for implementing consensus algorithm on a group of humanoid robots [9].](image)
B. Communication Topology

Some experiments are conducted to study the correlation between communication topology and group performance to achieve consensus. Several topologies which are examined in this study are depicted in Figure 7.

In leader-follower topology 1A to 1C, NAO 1 is acted as virtual leader of the group. It implies that information states from NAO 1 is set as reference state. The adjacency matrix \( A_{n+1} \) is defined as

\[
A_{n+1} = \begin{bmatrix}
0 & a_{12} & a_{13} & a_{14} \\
a_{21} & 0 & a_{23} & a_{24} \\
a_{31} & a_{32} & 0 & a_{34} \\
a_{41} & a_{42} & a_{43} & 0
\end{bmatrix},
\]

where \( n \) is number of all follower robots and \( a_{ij} \), \( i,j=1,2,3,4 \). In this case, consensus algorithm is conducted in all follower robots (NAO2, NAO3 and NAO4).

In topology 2A to 2C, all robots has equivalent role. There are no leaders or followers in group. It implies that there are no reference states to be followed, so the adjacency matrix \( A_n \) can be defined as

\[
A_n = [a_{ij}] \in \mathbb{R}^{n \times n},
\]

where \( n \) is number of all robots in group.

5. Results

A. Leader-follower Topology

The experiment to observe the movement behavior of group in a leader-follower topology, or also known as consensus tracking, is carried out using robot’s arm joints. Robot that acted as the leader in this experiment is NAO1. The other robots are acted as the followers. The results of the experiment are shown in Figure 8 to Figure 11. A video to illustrate the result of this experiment is available on Youtube Channel [13].
Figure 8. Consensus tracking on elbow roll movement using original consensus algorithm (4).

Figure 9. Consensus tracking on elbow roll movement using modified consensus algorithm (5) and topology 1A.
B. Leaderless Topology

The experiment to observe the movement behavior of group in a leaderless topology is conducted on robot’s head joint. The result of the experiment is shown in Figure 12. It is shown that all robots has reached consensus at 5 seconds.

To examine robustness of the algorithm, a disturbance was induced to the system. As seen in Figure 13, all robots reached consensus at $t \approx 4$ seconds. To simulate disturbance, we change the head yaw angle on NAO$_1$ manually, as we did at $t \approx 12$ seconds in the experiment. The
observation showed that all robots are immediately seeking a new consensus state. In this case, all robots reached consensus approximately after 5 seconds.

Figure 12. Consensus on head yaw movement using leaderless topology.

Figure 13. Consensus on head yaw movement using leaderless topology, with disturbance.

Some further experiments were conducted to examine the performance of the algorithm when applied to more complex systems. To obtain a higher level of complexity, experiments
were performed on NAO’s arm joints. The experiment results are depicted on Figure 14 to Figure 18.

Figure 14. Leaderless consensus on elbow roll movement using topology 2A.

Figure 15. Leaderless consensus on elbow roll movement using topology 2B.
6. Discussion

As observed on experiments, the best performance is shown in a topology which the followers formed a directed spanning tree and not strongly connected, as depicted in Figure 11. By using discrete-time algorithm in equation (5), it is shown that all robots achieve consensus asymptotically, \( x_i[k] \to x^r[k] \) as \( k \to \infty \), if and only if directed graph \( G_n \) has a directed spanning tree. A directed graph is strongly connected if there is a directed path from every node to every other node.

By comparing Figure 14, 15 and 16, it is shown that in leaderless topology, using equation (5), all robots are achieved consensus, \( |x_i[k] - x_j[k]| \to 0 \), as \( k \to \infty \). However, the fastest consensus time is found on a multi-cycle topology. A multi-cycle topology is a directed graph \( G_n \) that has more than one cycle in it. A cycle is a directed path that starts and ends at the same node.

7. Conclusion

As observed on experiments, the best performance is shown in a topology which the followers. Some interesting findings on this research are:

1. Consensus in a group of humanoid robot can be achieved by inducing parameter \( \beta \) in original equation. The application of the proposed algorithm shown that all robots achieved consensus asymptotically, as long as value of \( [I_n - (1 - \beta)A_n] \otimes I_m \) is positive definite.
2. In leader-follower topology, continues tracking, all the robots are able to follow the movement of the leader. While error is defined as \( x^r - x_1 \), all followers follow the leader at the smallest error, \( x_i[k] \to x^r[k] \), as \( k \to \infty \). The best performance was obtained when the network topology is not cyclic.
3. In leader-follower topology, larger error emerges in a topology which has many loops.
4. In leaderless topology, the more loops in the topology will make the system reach consensus faster. This is conflicting to our intuition, in the sense that more loops will need more computing time and lead to instability for the whole team.
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9. References
[13] http://www.youtube.com/watch?v=De7k7K5_rTIG

Ali Sadiyoko was graduated from Electrical Engineering Department in 1995 and Master Degree from Development Studies in 1999, both from Institut Teknologi Bandung (ITB), Indonesia. Currently, he is a doctoral student of School of Electrical and Informatics ITB. He works as a lecturer at Industrial Engineering Department, Universitas Katolik Parahyangan. He experienced for over than 10 years as information system consultant and developer to some organizations. His research interests include system modelling and simulation, information systems & technology, computer networking, multi-agent systems and robotics. He held CCNA and CCDA from Cisco System and also member of IEEE.
Harry Septanto was graduated from Engineering Physics, ITB in 2002. He obtained his Master Degree from Electrical Engineering, ITB in 2010, supported by LAPAN scholarship. Currently, he is a doctoral student of School of Electrical and Informatics ITB, supported by Beasiswa Unggulan - Kemdiknas scholarship. His permanent affiliation is National Institute of Aeronautics and Space (Lembaga Penerbangan dan Antariksa Nasional, LAPAN), Indonesia. From Dec 2013 till Feb 2014, he was a visiting research fellow at Josaphat Microwave Remote Sensing Laboratory, Chiba University under TWINCLE Program. His research interests include nonlinear control, collaborative control, robotics and spacecraft attitude control system.

Octomo Sudjana was graduated from Electrical Engineering, Universitas Udayana, Bali in 2010. He obtained his Master Degree from Electrical Engineering, ITB in 2014. Currently, He is a lecturer at Computer System and Electrical Engineering, Institut Teknologi Harapan Bangsa (ITHB), Bandung. His research interests include control system, robotics, vision and signal processing.

Bambang Riyanto Trilaksono was born in Banyuwangi, Indonesia, on November 15, 1962. He was graduated from Electrical Engineering Department, Institut Teknologi Bandung (ITB), Indonesia, in 1986. He obtained his Master and Doctoral Degree both from Electrical Engineering Department, Waseda University, Japan, in 1991 and 1994, respectively. He is a lecturer at School of Electrical Engineering and Informatics, ITB. His research interests include robust and intelligent control & signal processing, multi-agent systems and robotics. From 1995 until 1998 he involved in the development of total aircraft simulator and in ground flight control test for N250 aircraft at Indonesian Aircraft Industry. He is currently involved in the preliminary design of avionics and flight control systems for R80 aircraft. He published over 250 papers in journal and conferences. He received several awards including Toray Science Foundation Research Award, in 2004. He is a member of advisory committee of Asian Control Association. He served as Vice Chair of Asian Control Conference in 2006, and of International Conference on Intelligent Unmanned Systems in 2007. He served as member of Program Committee of a number of conferences in control and intelligent systems. He serves as Chief Editor of Journal of Engineering and Technological Sciences, and of Journal of ICT Research and Applications. He is serving as editorial board member for International Journal of Electrical Engineering and Informatics, Emerald International Journal of Intelligent Unmanned Systems, Journal of Unmanned Systems Technology, and Internetworking Indonesia Journal. He is editor of a book entitled “Intelligent Unmanned Systems : Theory and Applications”, Studies in Computational Intelligence, Vol. 192, Springer, 2009. He is a research fellow of University of New South Wales, Australia. He is a member of IEEE.