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

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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

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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 *rendezvouz* point, the *rendezvouz* 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 $\mathrm{A}_n \in \Re^{n\times n}$ 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, $\mathrm{A}_n = [a_{ij}] \in \Re^{n\times n}$ 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_n^s, E_n^s) is a subgraph of (V_n, E_n) such that (V_n^s, E_n^s) is directed tree and $V_n^s = E_n^s$. A subgraph (V_n^s, E_n^s) of (V_n, E_n) is a graph such that $\left(V_n^s \subseteq V_n\right)$ and $E_n^s \subseteq E_n \cap \left(V_n^s \times E_n^s\right)$.

Definition 4. The group of robots is reached or achieved a consensus if, for all $x_i(0)$ and all $i, j = 1, \ldots, n, \left|x_i(t) - x_j(t)\right| \to 0$, 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:

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

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 NAO*i*. Thus, $\dot{x}_i$ is defined as angle velocity of a joint. Since NAO doesn't have an explisit variable to control the joint velocity, in this experiments, joint velocity $\dot{x}_i$ is approximated by $\frac{x_i[k] - x_i[k-1]}{\Delta T}$, where *k* is the discrete-time index and ΔT is the sample period. So, the equation (1) can be modified to:

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

Similar to the continues-time case, a discrete-time consensus is reached or achieved if, for all $x_i[0]$ and all $i, j = 1,\ldots,n, \left|x_i[k] - x_j[k]\right| \to 0$, 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]

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

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*, γ is a positive constant scalar, and $\eta_i(t) \equiv \sum_{j}^{n+1} a_{ij}(t)$. 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 $x_{(n+1)} \equiv x^r \in \Re^{((n+1)\times(n+1))}$, where x^r represents the consensus reference state.

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

$$x_i[k+1] = x_i[k] + \left(\begin{array}{l} \frac{1}{\eta_i[k]}\sum_{j=i}^{n} a_{ij}\left[\dot{x}_i[k] - \gamma(x_i[k] - x_j[k])\right] + \\ \frac{1}{\eta_i[k]} a_{i(n+1)}\left[\dot{x}^r[k] - \gamma(x_i[k] - x^r[k])\right] \end{array}\right)\Delta T \tag{4}$$

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 β, 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:

$$x_i[k+1] = x_i[k] + \begin{pmatrix} \frac{1}{\eta_i[k]} \sum_{j=i}^{n} a_{ij}\left[\beta \dot{x}_i[k] - \gamma(x_i[k] - x_j[k])\right] + \\ \frac{1}{\eta_i[k]} a_{i(n+1)}\left[\beta \dot{x}^r[k] - \gamma(x_i[k] - x^r[k])\right] \end{pmatrix} \Delta T \tag{5}$$

Proof: noting that equation (5) is applied for leader-follower topology, the communication topology among robots is defined by $G_{n+1} \equiv (V_{n+1}, E_{n+1})$, 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 $A_{n+1} = [a_{ij}] \in \Re^{(n+1)\times(n+1)}$, where n is the number of followers and $A_{n+1} = 0, \forall j \in 1,\ldots,n+1$. Let define $L_{n+1} = [l_{ij}] \in \Re^{(n+1)\times(n+1)}$ 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 $D_{n+1} = [d_{ij}] \in \Re^{(n+1)\times(n+1)}$, $d_{ij} = 0, i \neq j, d_{ii} = \sum_{j=1, j\neq i}^{n+1} a_{ij}$ for $i = 1,\ldots,n+1$. Using approximation, equation (5) can be written as :

$$\dot{x}_i = \frac{1}{\eta_i} \sum_{j=i, j\neq i}^{n+1} a_{ij}[\beta \dot{x}_j - \gamma(x_i - x_j)] \tag{6}$$

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

$$\sum_{j=i, j\neq i}^{n+1} a_{ij}[\dot{x}_i - \beta \dot{x}_j] = -\gamma \sum_{j=i, j\neq i}^{n+1} a_{ij}(x_i - x_j) \tag{7}$$

Equation (7) can be written in matrix form as $Q_{n+1}\dot{\mathbf{x}} = R_{n+1}\mathbf{x}$, with $\dot{\mathbf{x}} = [\dot{x}_1^T, \dot{x}_2^T, \dot{x}_3^T, \ldots, \dot{x}_{n+1}^T]$, and $\mathbf{x} = [x_1^T, x_2^T, x_3^T, \ldots, x_{n+1}^T]$. Matrix Q_{n+1} is defined as $Q_{(n+1)\times(n+1)} = [q_{ij}] \in \Re^{(n+1)\times(n+1)}$, 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 $Q_{n+1} = \begin{bmatrix} Q_{n\times(n+1)} \\ 0_{1\times(n+1)} \end{bmatrix}$ and $R_{n+1} = \begin{bmatrix} R_{n\times(n+1)} \\ 0_{1\times(n+1)} \end{bmatrix}$. Because $R_{n+1} = -\gamma L_{n+1}$, then L_{n+1} can also be written as $L_{n+1} = \begin{bmatrix} L_{n\times(n+1)} \\ 0_{1\times(n+1)} \end{bmatrix}$. 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 devide matrix $\boldsymbol{Q}_{n\times(n+1)}$ into $\boldsymbol{Q}_{n\times(n+1)}=[\boldsymbol{Q}_n \ \vdots \ \boldsymbol{b}]$ where $\boldsymbol{Q}_n=\boldsymbol{Q}_{n\times n}=[\boldsymbol{q}_{ij}]\in\Re^{n\times n}$, $\boldsymbol{L}_n=\boldsymbol{L}_{n\times n}=[\boldsymbol{l}_{ij}]\in\Re^{n\times n}$, where $\boldsymbol{b}=[-\beta\boldsymbol{a}_{1(n+1)},-\beta\boldsymbol{a}_{2(n+1)},\ldots,-\beta\boldsymbol{a}_{n(n+1)}]^T$ and $\boldsymbol{c}=[\boldsymbol{l}_{1(n+1)},\boldsymbol{l}_{2(n+1)},\ldots,\boldsymbol{l}_{n(n+1)}]^T$, respectively. Hence, equation (7) can be written as:

$$\sum_{j=i,\,j\neq i}^{n}\boldsymbol{a}_{ij}[\dot{\boldsymbol{x}}_i-\beta\dot{\boldsymbol{x}}_j]=-\gamma\sum_{j=i,\,j\neq i}^{n}\boldsymbol{a}_{ij}(\boldsymbol{x}_i-\boldsymbol{x}_j) \tag{8}$$

This equation implies that $\boldsymbol{Q}_n\dot{\mathbf{x}}=\boldsymbol{R}_n\mathbf{x}$, with $\dot{\mathbf{x}}=[\dot{\boldsymbol{x}}_1^T,\dot{\boldsymbol{x}}_2^T,\dot{\boldsymbol{x}}_3^T,\ldots,\dot{\boldsymbol{x}}_n^T]$, and $\mathbf{x}=[\boldsymbol{x}_1^T,\boldsymbol{x}_2^T,\boldsymbol{x}_3^T,\ldots,\boldsymbol{x}_n^T]$. So, matrix $\boldsymbol{Q}_{n+1}$ can be solved as $\boldsymbol{Q}_n=\boldsymbol{L}_n-(1-\beta)\boldsymbol{A}_n$. Further, equation (8) becomes:

$$[(\boldsymbol{L}_n-(1-\beta)\boldsymbol{A}_n)\otimes\boldsymbol{I}_m]\dot{\mathbf{x}}=-\gamma[\boldsymbol{L}_n\otimes\boldsymbol{I}_m]\mathbf{x} \tag{9}$$

Assuming that matrix $\boldsymbol{Q}_n$ is invertible, equation (9) can be written as:

$$\dot{\mathbf{x}}=-\gamma[(\boldsymbol{L}_n-(1-\beta)\boldsymbol{A}_n)\otimes\boldsymbol{I}_m]^{-1}[\boldsymbol{L}_n\otimes\boldsymbol{I}_m]\mathbf{x} \tag{10}$$

Because L_n satisfies property B.2 with $p=n$, and from Theorem C.1 in [5], all eigen values of $-\gamma[(\boldsymbol{L}_n-(1-\beta)\boldsymbol{A}_n)\otimes\boldsymbol{I}_m]^{-1}[\boldsymbol{L}_n\otimes\boldsymbol{I}_m]$ have negative real parts, consequenly, $[(\boldsymbol{L}_n-(1-\beta)\boldsymbol{A}_n)\otimes\boldsymbol{I}_m]^{-1}[\boldsymbol{L}_n\otimes\boldsymbol{I}_m]$ must be a positive definite, so it will follow that $\mathrm{x}(t)\to 0$. It implies that the proposed algorithm will achieve consensus asymtotically.

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.

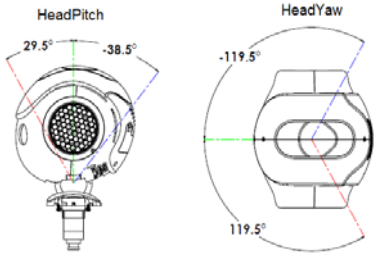


Figure 2. Information on NAO's head joint [7].

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.

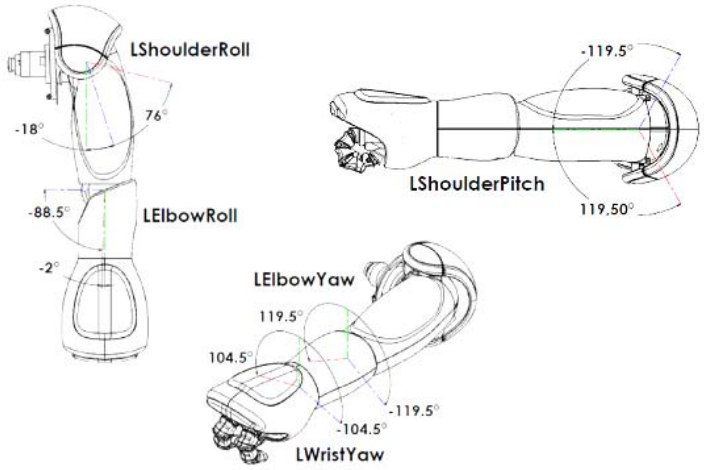
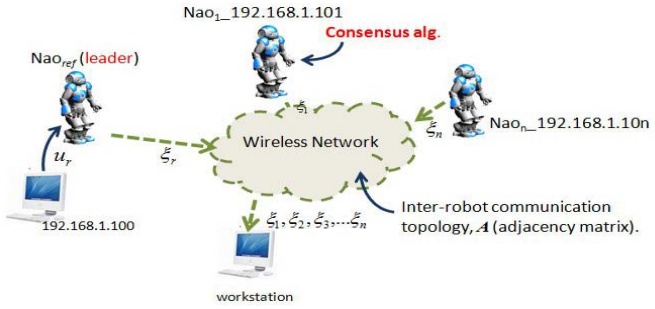


Figure 3. Information on NAO's left arm joint [7]

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.



(a)

(b)

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

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.

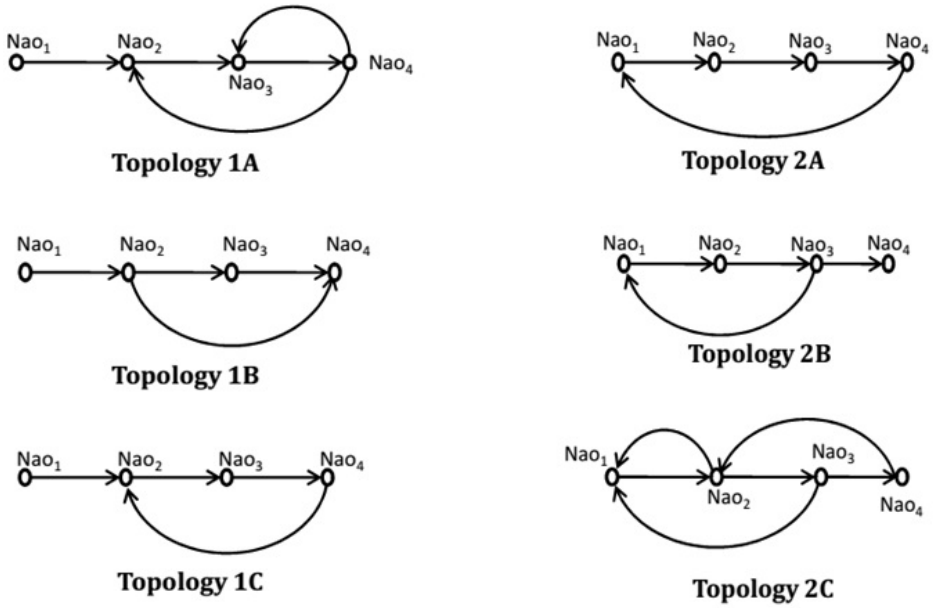


Figure 7. (a) Leader-follower and (b) leaderless communication topology among robots.

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 $A_{(n+1)} = [a_{ij}] \in \Re^{(n+1)\times(n+1)}$, where n is number of all follower robots and $a(n+1, j) = 0, \forall j = 1,\ldots,n+1$. In this case, consensus algorithm is conducted in all follower robots (NAO_2, NAO_3 and NAO_4).

In topology 2A to 2C, all robots has equivallent 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 $A_n = [a_{ij}] \in \Re^{n\times n}$, 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 NAO_1. 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 experimentis available on Youtube Channel [13].

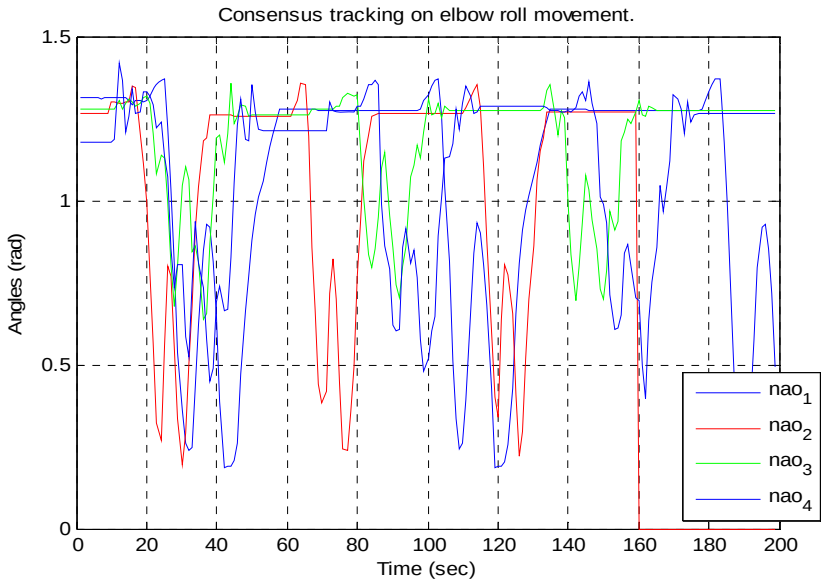


Figure 8. Consensus tracking on elbow roll movement using original consensus algorithm (4).

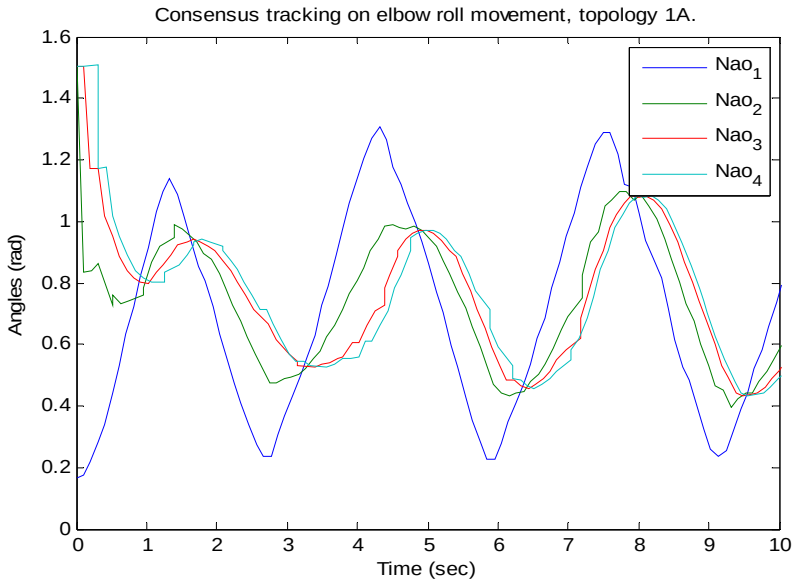


Figure 9. Consensus tracking on elbow roll movement using modified consensus algorithm (5) and topology 1A.

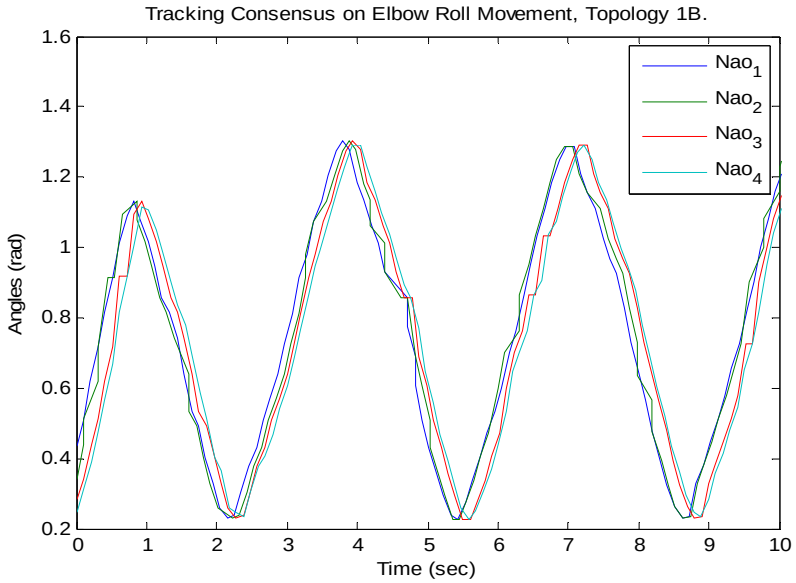


Figure 10. Consensus tracking on elbow roll movement using modified consensus algorithm (5) and topology 1B.

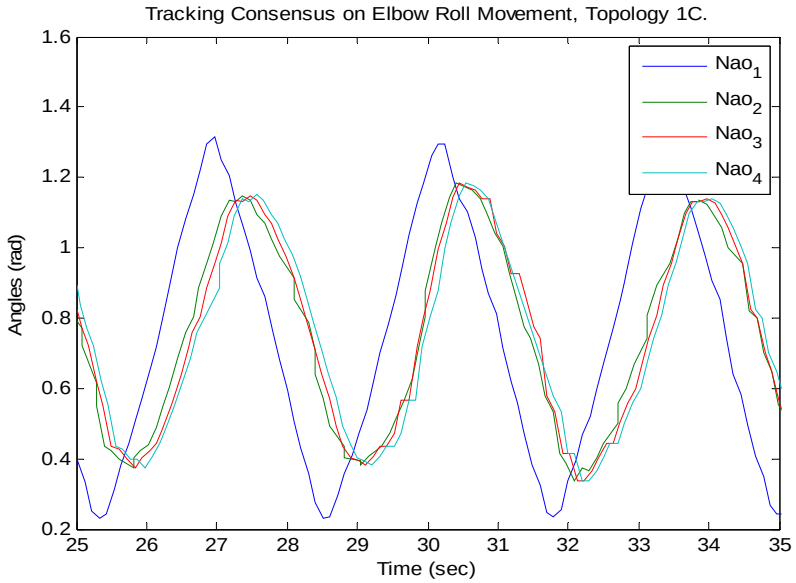


Figure 11. Consensus tracking on elbow roll movement using modified consensus algorithm (5) and topology 1C.

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.

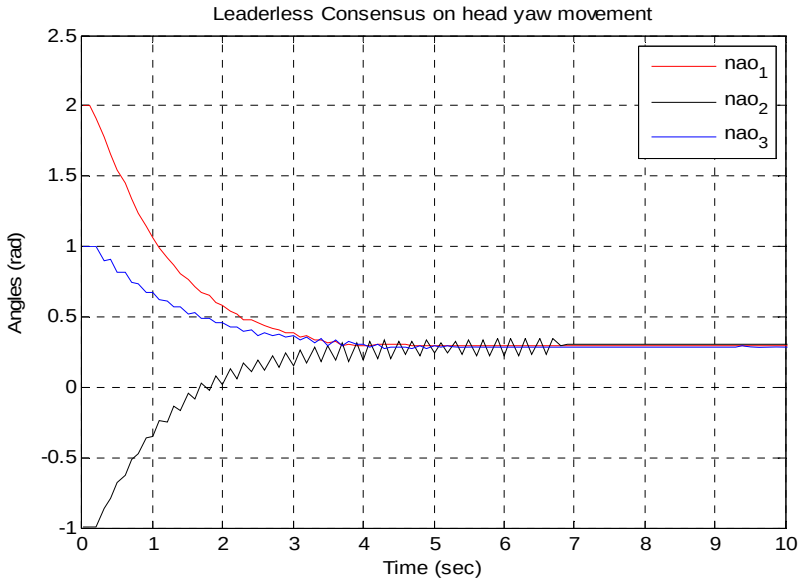


Figure 12. Consensus on head yaw movement using leaderless topology.

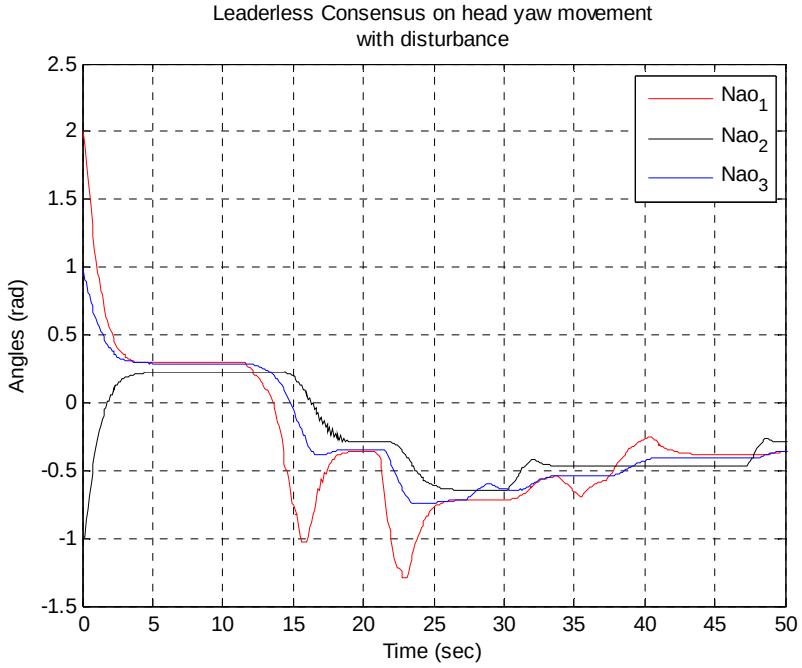


Figure 13. Consensus on head yaw movement using leaderless topology, with disturbance.

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.

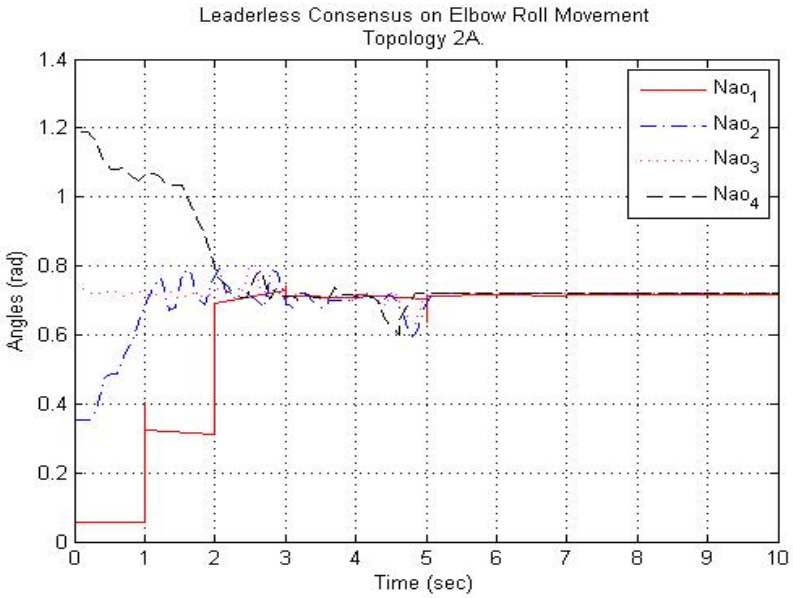


Figure 14. Leaderless consensus on elbow roll movement using topology 2A

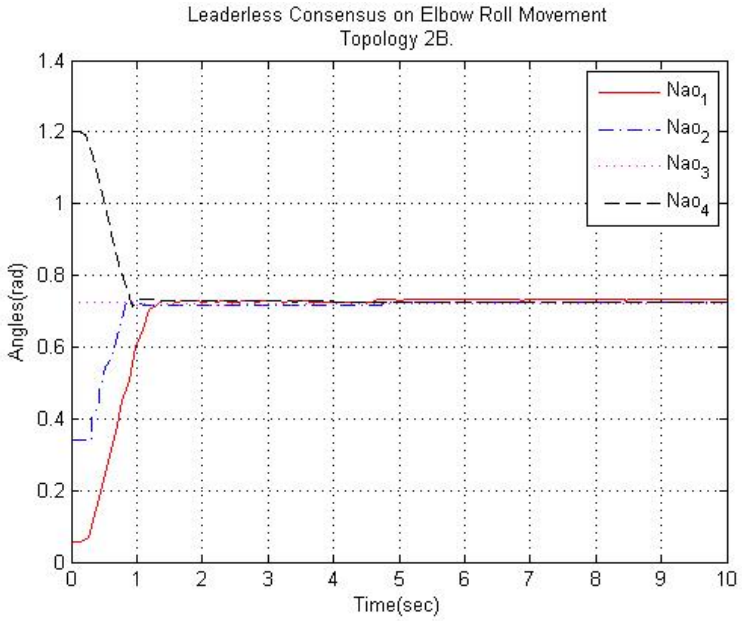


Figure 15. Leaderless onsensus on elbow roll movement using topology 2B.

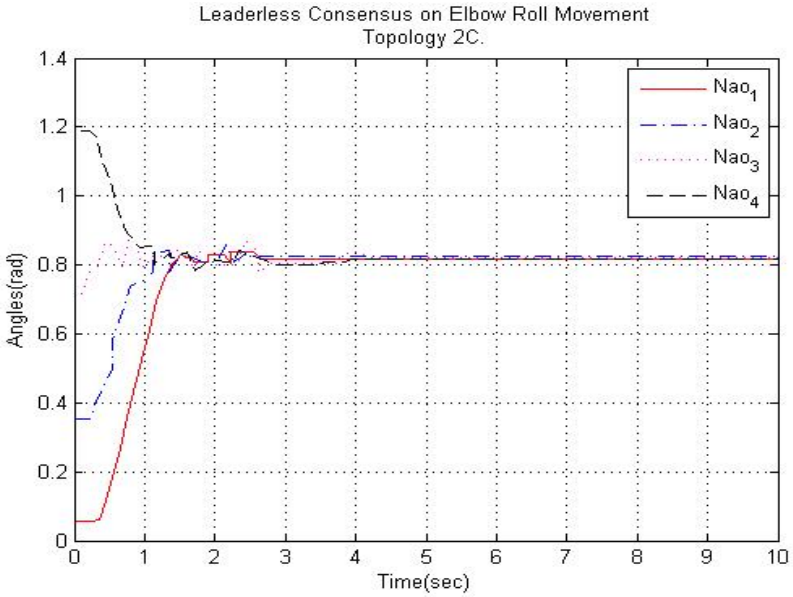


Figure 16. Leaderless consensus on elbow roll movement using topology 2C

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 achieves 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, $|\boldsymbol{x_i[k] - x_j[k]}| \to 0$, 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 β in original equation. The application of the proposed algorithm shown that all robots achieved consensus asymtotically, as long as value of $[(\boldsymbol{L_n} - (1-\beta)\boldsymbol{A_n}) \otimes \boldsymbol{I_m}]^{-1}[\boldsymbol{L_n} \otimes \boldsymbol{I_m}]$ 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 $x^r - x_i$, all followers follow the leader at the smallest error, $\boldsymbol{x_i[k] \to x^r[k]}$, as $\boldsymbol{k \to \infty}$. 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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