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# 2-Tier Control of a Humanoid Robot and Use of Sign Language Learned by Monte Carlo Method

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***Abstract*— In this research, an approach to implement a collaborative task between a humanoid robot (Hubo) and a human is presented. Velocity control using motion data generated from a motion capture system (MoCap) is used to control Hubo's lower body movement. The difference in moving direction and speed between the robot and a worker produced a step distance and turning angle of subsequent steps. For upper body control of Hubo, passive control enables the robot's arms to respond adaptively to human arm movements and diminishes undesired reaction forces from a human worker. For better interactive collaboration, several messages were chosen to assist communication between a human and Hubo. For each specific message, various kinds of sign language were initially designed and collected by MoCap. Captured signs were evaluated using Monte Carlo method and an optimized sign was determined based on the stability of carried objects and the robot itself. Finally, an experimental evaluation of the presented approach with the chosen signs was demonstrated through a real collaborative task between Hubo and a human worker which was carrying panels of various sizes.**

## I. INTRODUCTION

Since Honda unveiled their advanced robot ASIMO [1] in 2000, humanoid robots have gained growing popularities. As humanoids resemble to the appearance of a human body and approach high-level dynamic motions, people expect humanoids to execute increasingly complex tasks and to achieve human-level performances. In Steven Spielberg's famous science fiction drama film, *A.I. Artificial Intelligence* [2], it introduces various intelligent humanoid robots and describes how they can assist people in various tasks.

In spite of those rising hopes from people and academic advances in humanoid's manipulation skills [3],[4], many humanoid robots have stayed just in laboratory environment and have not provided solutions for real world needs. Various robots have been developed and used for rescue use [5] and home care [6]. They have proved of real service to people; however, most of the robot platforms were quadrupedal, hexapedal or wheeled robots. Humanoid robots have not been considered as helpful partners even for simple tasks such as carrying a large object or pushing a heavy object with human.

There have been several efforts to introduce humanoid robot to collaborative tasks with human. One humanoid platform, HRP-2, lifted objects with human using a probabilistic technique based on HMM and Gaussian Mixture Regression [7]. Based on repeated tasks which manipulated by tele-operation, a relationship between known parameters that can characterize tasks and desired motion pattern of HRP-2 was analyzed. However, the cooperative tasks were limited to movements in just one direction. In an experimentation using HRP, Olivier et al. showed a physical human and robot interaction (HRI) [8]. A human hold both hands of HRP and they walked together. Using measured values from tactile sensors, HRP re-planned its trajectories and generated motion patterns. Though this could be basic step for many tasks which let humanoids and human carry an object together, the movements of HRP remained in only one dimension at a time.

More general collaborative tasks between a humanoid and a human was demonstrated by Kazuhiko and Hiroyuki et al. [9]. HRP-2P and a human worker carried a wall panel together in real working environment. Utilizing the equipped stereo vision system and tactile sensors, HRP-2P grasped each side of the panel and moved with a desired velocity and heading direction. However, tactile sensor alone could not give enough data for HRP to decide whether it should move in lateral direction or rotate when a human worker made the corresponding movement. This ambiguity was also found in our experimentation and demonstrated in section VI. To solve the problem, a voice instruction was provided by a human supervisor or co-worker in their experimentations. Using spoken commands, an impedance controller model calculated a movement of the end effectors. Then, proper walking speed and heading direction of HRP were determined.

However, speech instruction is vulnerable to noises which may present in real working environments. Moreover, mistakes from the commander might be critical in some cases. Rather, if movement information of the co-worker whom a humanoid robot should follow can be sensed by external sensors, the robot and the human worker can carry an object with no necessities of speech command. In our previous study [10], an 18 camera Motion Capture (MoCap) system tracked the motions of both a human and a humanoid robot (Hubo). During the object-carrying task, MoCap continuously informed Hubo with an updated data of position, velocity and orientation of Hubo itself and of human. With the guidance of these motion data, walking information of the human worker was calculated and desired walking speed and heading direction for Hubo were generated. This resulted walking pattern of Hubo synchronized the movements of the humanoid with that of the human worker and enabled Hubo to collaboratively carry an object.

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However, in the study, tactile sensors which attached to Hubo wrists were still a main controller for both movements of Hubo upper body and lower body. Though the motion of human was continuously calculated based on MoCap system data, moving velocity and heading direction of Hubo were calculated just for the initial step. Tactile sensors were then used to determine moving velocity for subsequent steps. In other words, MoCap provided just a guidance to reduce ambiguity of heading direction for Hubo's initial step. Posture of upper body also was adjusted mainly by measured forces which exerted on each wrist of Hubo.

However, the discontinuity of primal mover between MoCap system and tactile sensors generated instability of walking motions for Hubo. Therefore, in this paper, MoCap system became main controller for lower body movement of Hubo and was used for calculating the desired moving speed and direction for every steps during an object-carrying task. While the motion capture data may be an optimistic approximation and can work only in indoor lab environment, many ranging devices such as the Microsoft Kinect and BumbleBee stereo imaging system could provide similar motion data at a much lower cost even outdoor. In case of upper body, passive control method is used for generating adjustable upper body posture which can adapt to external forces acting on each hand. Besides 2-tier control for lower and upper body of Hubo, sign language is used for better interaction between Hubo and human in collaborative tasks and several necessary messages were chosen for the communication.

## II. OVERVIEW OF SYSTEM

Figure 1 shows 2-tier control of Hubo for generating stable walking trajectory during a carrying-object task with a human worker.

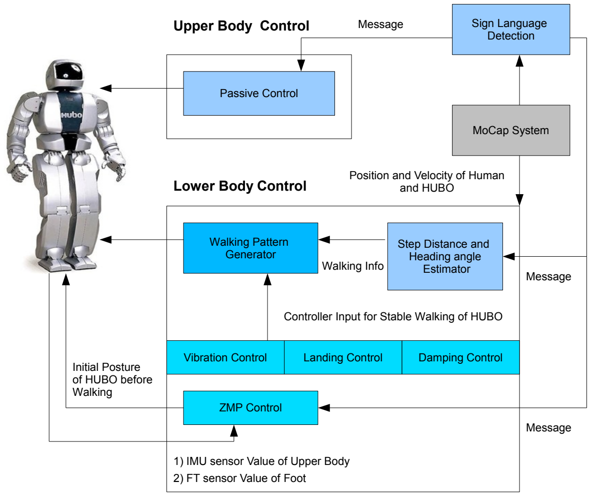

Fig. 1. 2-tier Control of Hubo for Collaborative Tasks

For control of lower body for Hubo, MoCap system is used and provided the relative position and rotation difference between the robot and a human worker. With the guidance of MoCap data, walking information of the co-worker could be calculated and proper walking speed and heading direction of Hubo were produced. Generated walking velocity and orientation of Hubo synchronized human movements with those of Hubo in real time. For a more stable walking trajectory, other control techniques such as landing, damping and vibration controller were also applied.

To control Hubo upper body, passive control is implemented. After grasping an object, servo controller for every joints of both arms was turned off and those joints could freely adapt to external forces. This passive state of upper body generated an adjustable posture which can fit to the forces acting on both arms while reducing computations.

2-tier control for upper body and lower body of a humanoid was already successfully applied by Alexander et al. in their previous study [11]. They used impedance control for upper body and velocity control for lower body. However, the humanoid robot, Justin, which they used, is a mobile based platform, not bipedal structure.

Through experimentations with Hubo, objects of various unknown sizes were used. Lower body control in our approach depends on relative difference between position and orientation of a robot and those of the human worker. Therefore, the length of each carried object should be determined before actual walking motion of Hubo. Likewise, some messages were necessary between Hubo and human for better interactive and autonomous collaborative performances. To support that, sign language of human was continuously detected using MoCap system and provided necessary messages to the robot. For example, when Hubo initially grasped a carried object with both arms, the relative position difference between Hubo and human was measured by MoCap system if the worker nodded. This position data calculated the length of the object and became threshold for determining how fast the worker moved in a certain direction.

The object's weight was also unknown in the collaborative task. To generate stable stance and walking trajectory, Hubo should adjust its posture when it initially grasped an object with both arms. To solve this problem, ZMP controller was activated at the same time when it determined the length of the object.

As mentioned above, a passive control was used for Hubo's arm movements. Since passive control should act on both arms after grasping a carried object, the sign, which was used for determining the length of the object, also activated passive control for upper body. In short, one sign from human in the initial stage activated the 2-tier control and ZMP controller concurrently. Section V describes how several sign candidates were initially designed for the message and a certain optimized sign was determined using Monte Carlo method. In the section, other messages which might be necessary for collaborative tasks were also demonstrated.

## III. MoCap System based Velocity Control for Lower Body

A MoCap system which used for our experiments consists of 18 different V100:R2 cameras of OptiTrack company and its capturing area is 144 square feet. Since MoCap system can produce position and rotation data of each rigid body in global coordinate in MoCap system, we assigned individual marker for a human worker and Hubo each.

To calculate relative position differences both in fore/aft and lateral direction, global position values of origin point in each local coordinate for a human worker and Hubo were earned first. For invariance with rotation, both position values were rotated by a yaw angle which is heading direction of Hubo. Then, relative differences were calculated by subtracting origin point of Hubo from origin point of human worker. More details can be found in [10].

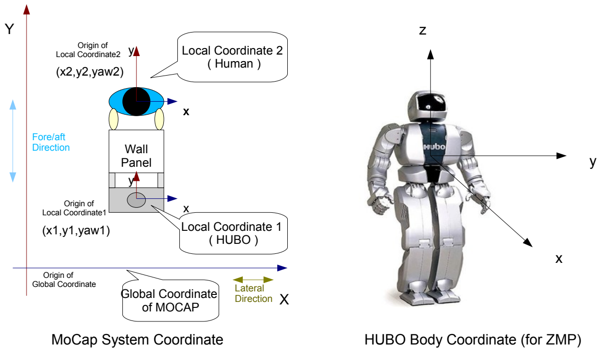

Fig. 2. Left: A Human Worker and Hubo in MoCap System Coordinate [10], Right: Hubo Body Coordinate for ZMP measurement

Each difference value was used for determining forward and side step distance and turning angle of Hubo's walking step. Walking trajectory of Hubo is designed by a cycloid algorithm which uses a reference ZMP trajectory and a foot trajectory [12]. While fixing hold time, DSP time and SSP time, velocity of a Hubo is decided only by step distances for translational movement and by a turning angle for rotational movement. Sway distance each for initial, during walking and last step should be adjusted to each different walking velocity. More details of generating a walking trajectory with a certain walking speed and heading direction were presented in the previous study on Hubo [13].

## IV. Passive Control for Hubo Upper Body

In case of upper body control for Hubo, passive control method [14] is applied. After grasping an object, Hubo waits a sign which indicates a start of carrying task from a human co-worker. After recognizing the sign, servo controllers for every joint of both arms were turned off and those joints of upper body could be adjusted freely by external forces.

Figure 3 shows passive movement of Hubo's upper body against forces which acted on tip of both hand. This passive state of upper body generated an adjustable upper body pose which can fit to external forces which generated from human. This reduced computations which other control techniques such as an impedance control method require for calculation of inverse kinematics and etc.

Fig. 3. Passive Movement of Upper Body of Hubo

## V. Sign Acquisition using Monte Carlo Control

For more autonomous and efficient interaction between Hubo and a human co-worker, several messages were necessary for communication between human and the robot. As described in Section II, length of a carried object should be recognized before walking movements of Hubo. ZMP controller and passive controller for upper body also should be activated at the same time before actual motions of Hubo for carrying task. To make Hubo recognize a proper time for implementing those tasks, it was necessary for human to send the message at a specific time.

Since MoCap based control lets Hubo just follow a trajectory of a human worker passively, Hubo can not lead the worker during a collaborative task. When the co-worker wants for Hubo to make an independent motion regardless of human's movement, a certain message or an order should be provided from the worker.

Likewise, several messages which are necessary for communication between Hubo and human were chosen and various sign candidates were designed for each chosen message. For initial generation of candidates, three important features, 1) visibility, 2) stability and 3) non-accidentality were considered. Signs which are not easily visible by robot and can damage stability of a carried object were excluded from candidates. And signs which can happen by human worker's accidental movement were also not considered.

Using MoCap system, various initially designed signs were recoded while Hubo and human are carrying an object together.

Then, every captured signs for a given message were evaluated based on stability of the carried object and a robot itself using Monte Carlo method. Figure 4 demonstrates a learning agent which was used for evaluation of initial designed signs. Using a set of candidate signs for each message, penalty grades were saved in value table in the agent based on stability of the object and Hubo. Stability of the object is measured by variation of Center of Mass (COM). A sign which caused a bigger COM oscillation got

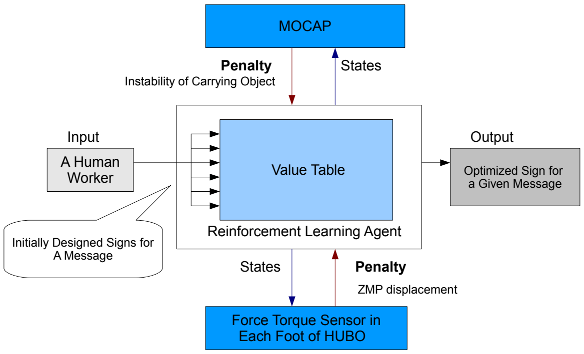

Fig. 4. Calculation of an Optimized Sign for a Given Message using Monte Carlo Learning

Fig. 5. Examples of Initially Designed Sign Languages for a Message indicating Start Carrying-Task: 1) Nodding Forward, 2) Nodding Backward, 3) Bending Arms, 4) Swaying Waist

more penalty values. Stability of Hubo was calculated by difference between reference ZMP and real ZMP which was earned by tactile sensors on both foot of Hubo. If ZMP is on the inside of foot, a robot would not fall down [16]. Since reference ZMP is designed initially to be located inside supporting zone of Hubo's foot, measured ZMP should be closely located to reference ZMP. Therefore, displacement between those two ZMP could indicate instability of Hubo effectively.

As an illustrative example, 4 different signs in Figure 5 were tried by a human worker for a message which make Hubo detect the length of a carried object through several experimental runs. Since the message should be conveyed in initial stage of carrying task, human gave signs when Hubo stood on the ground and was ready for the task. Figure 6 demonstrates ZMP displacements of Hubo which each was generated by sign 1 (Nodding Forward) and sign3 (Bending Arms). Since sign3 (Bending Arms) generated bigger oscillation of Hubo's ZMP in both X and Y axis of Hubo body coordinate, it got more penalties in the corresponding bin of value table in learning agent.

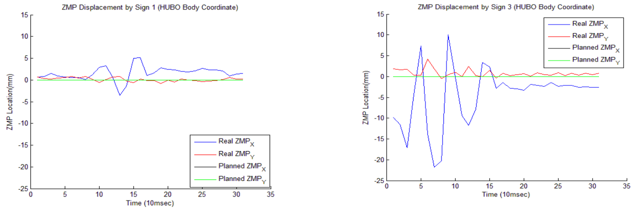

Fig. 6. ZMP Displacement of Hubo by Sign1: Nodding Forward(Top) and by Sign3: Bending Arms(Bottom)

Figure 7 demonstrates COM variations of a carried panel which each was generated by sign 1 and sign3. Since a sign3 (Bending Arms) generated bigger oscillations of the object's COM in both X and Y axis of MoCap system coordinate, it got more penalties.

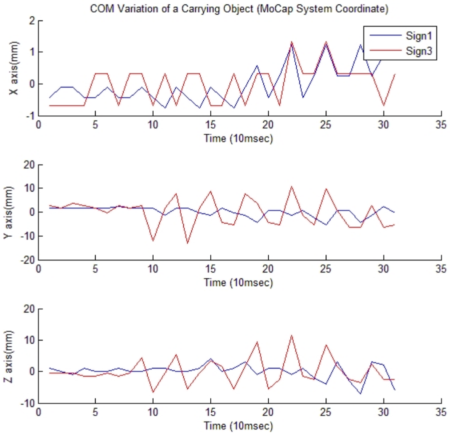

Fig. 7. COM Variation of a Carried Object by Sign1 and Sign3

Likewise, bins of value table in Monte Carlo agent got updated by penalty values based on stability of Hubo and an object. After several iterations of update, Nodding Forward sign which had a minimum penalty value was chosen as a sign for the message which order Hubo to detect the length of a carried object.

## VI. EXPERIMENTAL RESULTS

Within capturing area of MoCap system (144 square ft), a human worker and Hubo carried a panel (0.51 m x 0.29m) together. During the task, Hubo was informed the movement of human who led carrying from MoCap and it followed the human while holding the panel. After grasping the panel, human gave a sign to Hubo for letting the robot recognize the size of the panel. As soon as recognizing the sign, Hubo also activated ZMP and passive controller as described in section II. ZMP controller was activated only when Hubo stands on the ground. When Hubo starts its initial stepping after a given time, ZMP controller was deactivated to reduce any effect in generated walking trajectory of Hubo.

Figure 8 shows movements of Hubo which followed the human co-worker who led carrying a panel in our experiment. Figure 9 provides their each COM location which was captured from MoCap system. Movements of Hubo in Figure 8 and MoCap data show that Hubo successfully followed the movement of the human who led a carrying task.

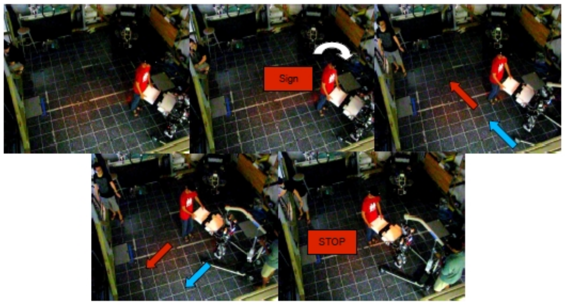

Fig. 8. Exp 1: Movements with Long Distances in MoCap Capturing Area.

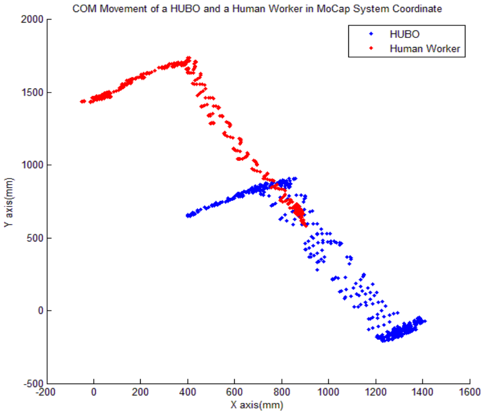

Fig. 9. Exp 1: COM Location of Hubo and a Human Worker in Mocap System Coordinate.

Figure 10 demonstrates difference of trajectory between human and Hubo for each X and Y direction in MoCap System coordinate. In both directions, it was found that Hubo synchronized its movement with motion of a human worker without visible time delay.

Figure 11 shows displacement of measured ZMP values from their initially targeted values in x and y axis of Hubo' body coordinate. Humanoid robots do not fall down when ZMP is on the inside of foot [16]. Since reference ZMP value is designed to be located on inside Hubo's foot, measured ZMP value should be closely located to its reference value. Therefore, displacement between those two ZMP indicates instability of Hubo. Real ZMP value was measured from force/torque sensors which were attached to both foot of Hubo. Those measured values were not much differ from reference ZMP values during a carrying task. It was also found that the measured ZMP value was stable when a human worker gave a sign to Hubo in initial stage of carrying task.

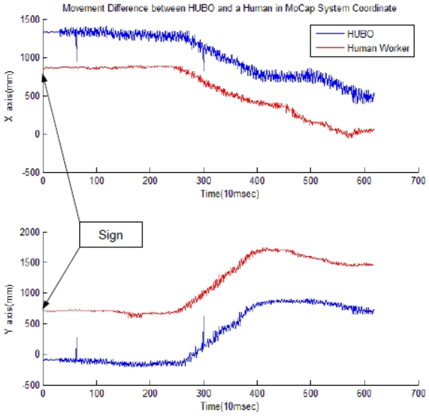

Fig. 10. Difference of Movement between Hubo and a Human (Exp 1)

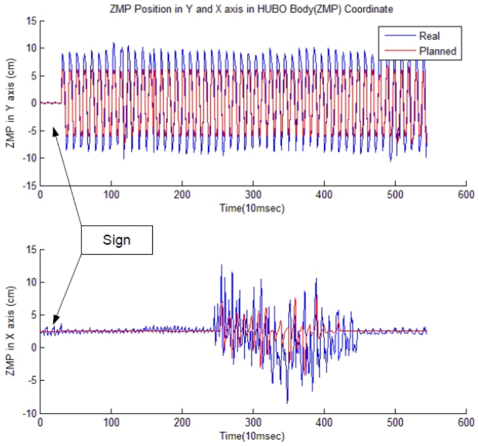

Fig. 11. ZMP Displacement of Hubo (Exp 1)

Figure 12 shows another example of movements for Hubo which followed the human who made small steps through a carrying task. Imagining a working area which is very crowded with obstacles, human made walking steps with very small step distances and changed his walking direction quickly. Figure 13 shows that Hubo also could follow the movement of human in this case.

Figure 14 demonstrates difference of trajectory between human and Hubo each for both X and Y direction in MoCap System coordinate. Overall, Hubo could synchronize its motion with movement of human without significant delay. Compared to Figure 10, there is little more time delays (500 msec) when human made a lateral movement through y axis of Hubo's body coordinate. To make Hubo not become too sensitive to subtle movement of a human worker, dead zone was initially set and Hubo did not make a responsive movement while a human was staying inside the zone. Since a human worker made steps with vary small step distances,

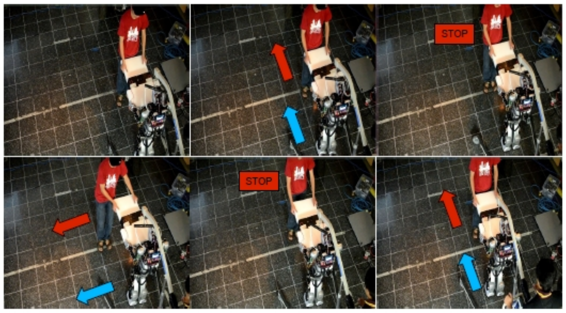

Fig. 12. Exp 2: Movements with Short Step Distances in MoCap Capturing Area

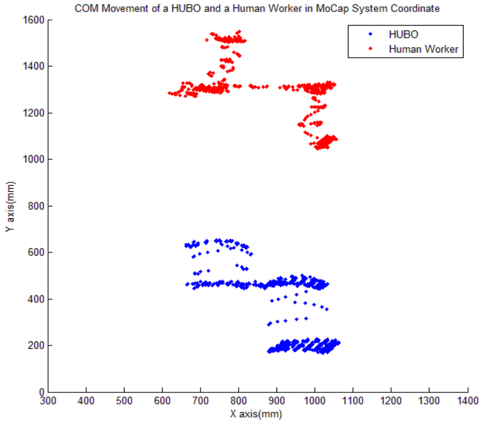

Fig. 13. Exp 2: COM Locations of Hubo and a Human Worker in MoCap System Coordinate

Hubo waited until the human worker egress from dead zone and it resulted in little delay.

## VII. CONCLUSION

In this paper, a 2-tier control for a collaborative task between an adult sized humanoid robot (Hubo) and a human worker is presented. Using data from a MoCap system, velocity control which modifies step distance and heading angle of the robot is used to control lower body movements. For upper body, passive control is implemented to enable robot's arms to adapt to external forces from human. To achieve better interactive performance, several messages are communicated via sign language between human and the robot. For each specific message, various kinds of designed signs were initially gathered by MoCap and each captured sign was evaluated using Monte Carlo learning agent. Finally, an experimental evaluation of the presented approach was demonstrated through a collaborative task. Through different runs, it was proved that our presented approach enabled Hubo to successfully follow a human co-worker who led the task.

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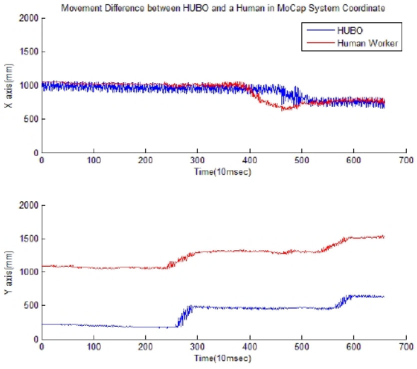

Fig. 14. Difference of Movement between Hubo and a Human (Exp 2)

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