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A Robot on the Shoulder: Coordinated Human-Wearable Robot Control using Coloured Petri Nets and Partial Least Squares Predictions*

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Abstract— **A wearable robot secured on the shoulder of a human is developed for assisting its wearer in the execution of tasks in the overhead workspace. Installing a ceiling panel is an example of such a task. During this task the robot can hold the panel or collaborate actively with the human in order to fix the panel with the appropriate equipment. This wearable robot, termed "Supernumerary Robotic Limbs", works closely with the human to streamline the operation and reduce the human workload. First, the design concept of the Robot-on-the-Shoulder system is described, and a new approach to the coordinated control between the wearable robot and the human is presented. A graphical task process representation based on Coloured Petri Nets (CPN) is used to model the concurrent and distributed nature of the human-robot system, which comprises two human hands and two robot hands. The CPN framework is then extended to a type of hybrid control system by imbedding local dynamic controllers in the Transition nodes of the CPN model. Each local dynamic controller collects sensor signals relevant to the target transition and makes a predictive control decision. This allows the robot on the shoulder to take a proactive and preemptive action as well as to confirm a successful Transition. The control parameters for these algorithms are tuned based on "teaching-by-showing" techniques using human demonstration data. Partial Least Squares is used for extracting significant sensor signals from high-dimensional sensor data in order to do real time predictions and control. A prototype robot-on-the-shoulder system is built, and the CPN hybrid control is implemented and tested for a ceiling panel installation task.**

I. Introduction

In our daily chores we often need an extra hand to hold an object temporarily while both of our hands are busy. When installing a lighting fixture on the ceiling, for example, we wish to have a third arm to hold the fixture while securing it with screws using a screwdriver. Such tasks in the overhead workspace result very laborious for the worker since the workspace between the shoulder and the waist is the comfort zone of the human. Installation, inspection, and repair of ceiling panels, cable wires, air ducts, and lighting fixtures are just a few examples of tasks that are ergonomically challenging for the human. The arm's strength as well as precision and dexterity of hand performance deteriorate sharply as the work area is elevated to the overhead space. Prolonged work in an inefficient and uncomfortable posture often leads to injuries at the neck, arms, and the back.

The goal of this work is to develop a wearable robot that is secured to the shoulder of a human and that assists the human in executing a task. Figure 1 shows a robot on the shoulder, called Supernumerary Robotic Limbs (SRL), assisting the wearer in installing a ceiling panel. It is expected that, with the extra arms coordinated with the human arms, the human can perform the installation task in an effective and productive manner with a reduced physical effort. One of the many ways the robot can aid the human is by holding the ceiling panel. This allows the human to use his or her, now free, hands to pick up a screw and a powered screwdriver in order to secure the panel. Tasks such as this one usually require two workers to perform the task, but the SRL on the shoulder allows a single worker to execute the task individually.

Figure 1. SRL prototype that is worn on the shoulders and aids the human worker in overhead tasks.

In the robotics and rehabilitation literature, there are two types of wearable robots that have been studied. One is prostheses for amputees [1, 2], and the other is exoskeletons for extending the strength of human limbs [3, 4]. SRL is a third type of wearable robots that has distinct features and functionality. Unlike prostheses, SRL provides the wearer with extra limbs rather than replacing lost limbs. Unlike exoskeletons, where powered joints are attached to the corresponding joints of the wearer, the SRL moves independently from them wearer's limbs. These properties allow the SRL to open up new possibilities for wearable robots, while creating unique technical issues and challenges.

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Communication and coordination between the SRL and its operator is the key to successful implementation of the SRL. The robot must understand the intentions of its wearer and plan its actions accordingly. Human-robot communication and coordination have been studied over the last 30 years, resulting in a number of effective techniques and methodologies. These include visual gesture understanding [5, 6, 7], voice recognition [8, 9], and other monitoring techniques [10]. Various human – robot communication techniques have also been developed in the fields of robotic surgery, tele – operation and virtual reality [11, 12, 13]. Other studies have focused on developing methods for modeling collaborative task processes. These methods include Markov processes [14, 15], probabilistic state machines [16], and a network of discrete events connected by indicators [17], all of which seek to achieve coordinated control of the robot and human activities.

These prior studies have primarily focused on a human-robot system where the robot is physically separated from the human. In contrast, SRL is attached to the human body, which leads to the creation of a communication channel that substantially differs from the cases with separate robots. The reaction force and moment induced by the robot's motion, as well as the ones that the environment exerts on the robot's end-effector, are transmitted to the human body as haptic feedback. For example, considering the scenario in Figure 1: as the robot holds the ceiling panel and presses it against the ceiling frame, the human feels the reaction force on his or her shoulder. In fact, the human can use this haptic feedback as a measure of how securely the ceiling panel is being held and to coordinate better his or her motion with the robot.

Having the SRL working in close proximity to the human, both pairs of human and robotic arms concurrently share the same workspace. One of the new technical challenges of this problem is the coordination and synchronization among the four arms, which is essential for the successful and efficient implementation of the SRL. It is imperative to employ an effective modeling method for representing a collaborative task process, where multiple arms and hands are working concurrently.

This paper presents the novel design concept of the wearable supernumerary robotic limbs and also addresses the coordination and communication issues between the robot and its human wearer. Coordination will be planned using Coloured Petri Nets (CPN) [18, 19, 20] and communication will be handled using Partial Least Squares (PLS) [25] based predictions. Petri Net is a powerful tool for representing distributed, concurrent, and discrete event processes [21]. The tasks performed by four arms, including two human arms and two SRLs robot arms, are a distributed system consisting of both human and robot control systems. It is also a concurrent event system, since the four arms make state transitions in parallel. However, describing the discrete nature of state transitions alone cannot capture important dynamics of the system required to perform real-time coordination control. To address this issue, local dynamic controllers are built for a few selected transitions, where the robot takes proactive and preemptive actions by observing the human and the task process status. This can increase the level of human-robot coordination from static step-by-step transitions to dynamic, prediction-based transitions.

This paper presents the basic design concept description of the Robot-on-the-Shoulder system, followed by CPN modeling of human-robot-task processes. Using PLS and teach by demonstration data, we embed local, dynamic controllers in several transitions of the CPN model. This extends the CPN model to a real-time hybrid system. We use a prototype system to demonstrate the features of the proposed approach.

II. PROTOTYPE DESIGN

The primary objective of developing a Robot-on-the-Shoulder system is to alleviate the overhead workload. The robot can assist the human in performing laborious work such as raising, holding, and securing an object in the overhead area, thus reducing fatigue and the possibility of injuries. Furthermore, the Robot-on-the-Shoulder can streamline the task execution by serving as a co-worker. As described previously in the installation of a ceiling panel, the human and the robot can work concurrently to expedite the execution of multi-step operations.

Figure 2. Example of a person carrying a heavy load through the use of a rod aligned across the shoulders.

Wearing a robot may represent an additional burden for the human. However, carrying a robot on the shoulder is indeed not a significant load. As long as the center of mass of the robot is aligned with or near the centerline of the human spine, the weight of the robot is directly borne by the backbone thus decreasing the bending moment acting on the back. For example, people can carry heavy loads, such as buckets of water, with a rod aligned with the shoulder (Figure 2). Figure 3 shows the overall view of the Robot-on the-Shoulder system. It consists of two arms, each with five degrees of freedom (DOF), a shoulder mount, and an electronics unit and various sensor modules that are attached to the back of the mount. Details of our prototype implementation are included in Chapter V, Section A.

III. COLOURED PETRI NET AND TASK MODEL

We consider the ceiling panel installation task as an exemplary case study to build a task model, since it contains many steps of actions that need high-level skills and coordination. In the case in which the SRL performs the roles of a helping worker, we will consider a ceiling panel installation task. Figure 4 illustrates each step of this case:

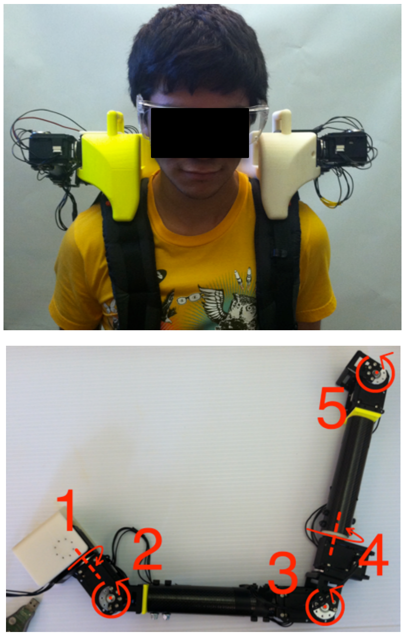

Figure 3. The top figure shows the front view of the robot mount. The shoulder mount is placed directly over the shoulder line, just like in Figure 2. When in rest position, the robot arms are folded backward and inward. This minimizes its inertia and keeps the robot outside the range of motion of its wearer. The bottom figure shows the robot's right arm. Red arrows and axes indicate the arm's five degrees of freedom.

- Step 1: The human worker picks up and positions the panel.
- Step 2: After the panel is properly positioned, the SRL holds the panel for the human.
- Step 3: The human proceeds to pick up and place a screw and operate a powered screwdriver (PSD) to fix the panel.
- Step 4: Human can repeat step 3 until the panel has been secured. Note that as more screws are fixed to the panel, the robot's load is decreased and eventually it can remove one or even both arms from the panel.

This scenario presents ideal circumstances since the human performs the complex parts, e.g. placing the screw and operating the PSD, while the robot holds the panel once its wearer has placed it. Note that the panel must be held against the ceiling frame at all times, and two hands, either the human or the robot hands, or even a combination of these is needed to securely hold it. However, assignment of hands, i.e. which hands to hold the panel, may change dynamically as such is the nature of collaboration between coworkers. For example, the human worker may have difficulty using the PSD due to environmental constrains. He can exploit the SRL's unconstrained arm mobility by switching roles with the SRL. That way he can hold the ceiling panel while the SRL takes care of fine – positioning and operating the PSD. This section will focus on showing the advantages brought on by using a CPN model to plan the robot's actions. For detailed information on how to design, model and analyze a CPN, please refer to [18].

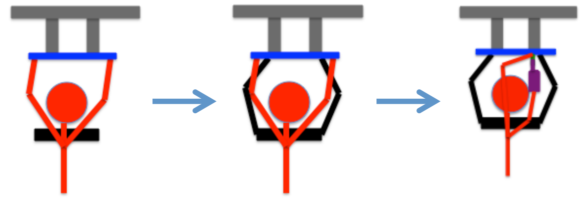

Figure 4. Schematic for each of the task's steps of transitions. The red color represents the human wearer, black represents the SRL, blue is the ceiling panel, green is a screw and purple represents the powered screw driver.

We consider a case relevant to the ceiling panel installation task and to the possible scenarios presented in the previous paragraph. This task process contains multiple events that occur concurrently and in a distributed manner. For the ceiling panel installation task, the following discrete static states, termed Places P, and dynamic state paths, termed Transitions T, are defined:

P = {Standby, SRL holds panel in position, Screw in Position, PSD in position, Fastened Screws}

T ={Prepare screw and PSD, Fastened screw}

The Places or Transitions occurring on the system are controlled by Tokens, which represent the availability of resources. In the human-robot system, multiple types of resources, e.g. human arms vs SRLs, must be distinguished. We use Coloured Petri Nets (CPN) in order to employ Colour Tokens containing diverse information that allows us to identify them and assign them their roles accordingly. The Colours, or properties for the system's tokens, used for our model are:

$\sum$ = {No, Re, NoxRe, status, TR},

where the colours No, Re, NoxRe, status and TR are integer, string, product of integer and string, Boolean and a list of integer and strings products respectively. These colours serve as labels that are used to distinguish each token and allow us to group and use them as we want. Using state space analysis for our CPN model we concluded that it has only one possible end state (completed task) but various manners of achieving it. Figure 5 shows a simplified CPN model representation of one part of the panel installation task. Numbers in the circles represent their respective Places P, Letters in the rectangles represent their respective Transitions T and the small circles in the Places are the Tokens. This schematic will be used to explain how CPN modeling matches our system's concurrent and collaborative demands.

Given that the SRL is holding the panel (red tokens are assigned to place 2) the human worker can proceed to grab a screw from the standby place, move it into place (Place 3) and use his or her other hand to grab the PSD (Place 4). After both tools are in position the worker can proceed to fix the screw and repeat the process. After the first screw has been positioned, both hands of the human worker return to standby. At this point, the robot can choose to keep holding the panel with both arms, or, since the load has been greatly reduced, can choose to bear the entire load on one arm and return the other to standby. This arm can assume the role of positioning the screw or operating the PSD given the right conditions, or even doing both in case the human worker decides to hold the panel and switch roles entirely with the SRL. Some conditions that may be evaluated by the CPN when deciding which tokens should proceed to Places 3 and 4 might be muscle fatigue, environmental constrain, poor performance, etc. By adding sensors to the system or establishing certain criteria we can decide how to establish our priorities when assigning roles. One example would be the implementation of electromyography to determine when the worker's fatigue levels are high enough. The CPN model would proceed to assign the passive tasks to the worker and the more demanding ones to the SRL.

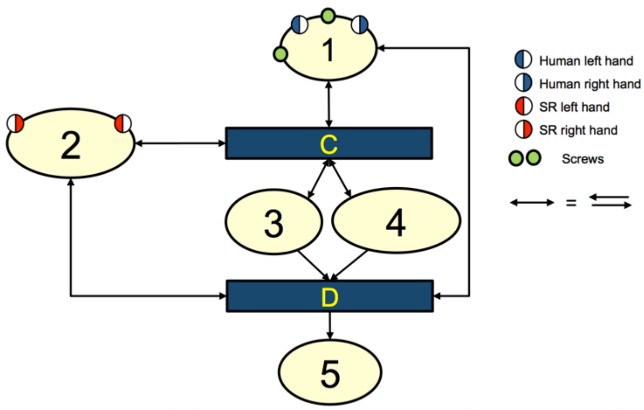

Figure 5. Simplified section of our CPN model's places and transitions. Places 1 through 5 correspond to Places P, transitions C through D to Transitions T. Tokes have been simplified as to be identifiable using the colors shown in the legend to the right of the schematic.

It is important to clarify that the CPN model shown in Figure 5 is a simplified version of our complete model that is used to show how the places and transitions are connected. Each arc has a unique expression that determines the behavior of the tokens during the execution of each transition. Each transition has guard expressions that also indicate which tokens are needed in order to trigger each transition. This results in a very complex model that is not included in this paper. The CPN-based task modeling helps examine whether transitions can occur properly without leading the task process into a dead lock. The CPN Tools software was used for validating the execution of the task process.

IV. Partial Least Squares Predictions And Control

Experienced co-workers execute the ceiling panel installation task in a much more dynamic and efficient manner than the step-by-step discrete transitions depicted by the standard CPN model. Each worker observes the co-worker's action and makes a proactive, or even preemptive, action based on "prediction". This prediction-based, proactive/preemptive transition can be generated by combining the CPN model with "teach through demonstration" data.

Human skill acquisition is an effective method for extracting human skills from teaching-by-showing data [5, 22, 23, 24]. In this work we observe coordinated actions of two co-workers and extract dynamic predictors for triggering transitions that are made in a proactive/preemptive manner. The identified dynamic predictors are embedded in the CPN model and used for controlling SRLs in real-time.

A challenge in applying human skill acquisition is the difficulty in finding the right "structure" of skill model to predict the observed behavior. It is not clear which signals and what sort of traits the human uses in his/her skills. To ease this fundamental difficulty, we employ a multivariate data analysis technique, referred to as Partial Least Squares (PLS) regression. PLS is an extension of Principal Component Analysis to input-output data, where most significant latent variables are determined to maximize the correlation for predicting outputs. In this section we describe the methods, experiments and equipment used to prove that the PLSR algorithm can be successfully used to find a relationship between the sensors worn by the human worker and the preemptive action taken by his or her coworker.

In this work, a number of signals are observed from human demonstrations, and a high-dimensional input space is formed by aggregating the data over a certain time window. Human demonstration will take place at a test rig that resembles a ceiling structure (Figure 6). During these tests the main worker (wearing the SRL) will pick up a ceiling panel, each time from a different location, and proceed to position the panel with the correct orientation against the test rig. During this time, the second worker will be manually operating the SRL in order to help the main worker position and hold the panel. The goal of this second worker is to minimize the amount of time that the main worker has to hold the panel. With that in mind, for this experiment the second worker cannot assume leadership and cannot interfere directly with the main worker's workspace. The test subject that wears the SRL will wear 3 inertial measurement units (IMUs). Each will record gyro and accelerometer information. These are worn in two different locations: one is worn in each wrist (also shown in Figure 6) and one at the base of the robot's shoulder mount. This last IMU ensures that the overall orientation and motion of the robot's base (affected by human motion) is taken into account for our prediction algorithm. In its simplest form the input data space recorded at any time t contains the gyro and accelerometer data from 3 IMU's. This accounts for 18 data points. However, given the spacial-temporal aspect of the task at hand, we'll use the PLSR algorithm to make predictions based on time-series data.

The output space is formed by observed data of the co-worker's movements, which can be used for controlling the SRL. In these tests, the co-worker's actions are presented as all the joint angles for the robot, therefore the output matrix at any time t consists of 10 readings corresponding to the 5 joints of both robot arms. The objective of PLS data analysis is to find the most significant factors of both data groups and identify which factors from the input data can describe best the output [25, 26, 27, 28].

Taking into consideration all data recorded at time t we can proceed to build the input and output matrices used for the PLSR predictions. We had 5 test subjects that, arranged in 5 different worker #1 – worker #2 configurations, each repeated the experiment 25 times under different conditions.

Figure 6. Figure to the left shows the test rig where the ceiling panel has to be installed. Figure to the right shows one of the trials where test subject #2 (wearing red) helps test subject #1 during the ceiling panel instalation task. As shown in the figure to the right, two IMUs are located at the test subject #1's wrists.

Out of these trials, 20 were used as training data for the algorithm and 5 were used for data validation. The trials used for data validation were chosen at random and excluded from the training algorithm. From each trial we will evaluate a number of 160 data points, which corresponds to the amount of samples during the slowest task completion + 20 samples.

Using data recovered at time *t* we can build:

$$x(t) = (x_1(t), x_2(t), \ldots, x_{18}(t)) \quad (1)$$

$$y(t) = (\theta_1(t), \theta_2(t), \ldots, \theta_{10}(t)) \quad (2)$$

Storing data from time *t* – 19 up to *t* we can build the following matrices:

$$X_n(t) = [x(t-19), x(t-18), \ldots, x(t)] \quad (3)$$

$$Y_n(t) = y(t) \quad (4)$$

Where $n = t$ and goes from 1 to 160 correspond to the respective time sample in the trial data point. Notice that for point $n = 1$ from the trial data, (3) will include up to the x(t – 19)th term. In order to include such data in our analysis we prohibited the test subject from starting to perform the task until a period of 5 seconds has gone by. During this time the test subjects are free to do as they will as long as the helping worker maintains the SRL's arms at the rest position. This allows us to have a variety of initial conditions for our evaluated data sets. The output matrix (4) is straightforward to build as it only contains the joint angles at time *t*. Taking into account our M = 20 training data sets, and J = 5 configurations of test subjects, we can build our X and Y matrices which will be used for the PLSR algorithm:

$$XX_m = \begin{bmatrix} X_1(t) \\ \vdots \\ X_N(t) \end{bmatrix}, XXX_j = \begin{bmatrix} XX_1(t) \\ \vdots \\ XX_M(t) \end{bmatrix}, X = \begin{bmatrix} XXX_1(t) \\ \vdots \\ XXX_J(t) \end{bmatrix} \quad (5)$$

$$YY_m = \begin{bmatrix} Y_1(t) \\ \vdots \\ Y_N(t) \end{bmatrix}, YYY_j = \begin{bmatrix} YY_1(t) \\ \vdots \\ YY_M(t) \end{bmatrix}, Y = \begin{bmatrix} YYY_1(t) \\ \vdots \\ YYY_J(t) \end{bmatrix} \quad (6)$$

Before implementing the PLSR algorithm, both X and Y were column normalized. In order to mimic using the PLSR for real-time predictions, the validating data sets were normalized using the averages and standard deviation from the training data sets. Using the normalized matrices as our input and output matrices respectively for the PLSR algorithm allowed us to calculate the actions that the robot must make at time *t* in order to help its wearer in a proactive and preemptive manner. By predicting the joint angles for the SRL at each instant in time, then we can employ Adaptive or Sliding control to ensure that the SRL follows our predicted trajectory [29].

Integrating these predictions with the CPN model brings another interesting aspect to how the tasks are executed. Instead of having executed every task after the previous has been completed, now we can have both the robot and the human working concurrently and in the same workspace. This behavior is not a part of the CPN model, and forces our CPN model to form a super transition where concurrent actions of this nature can happen. This concept is shown in Figure 7.

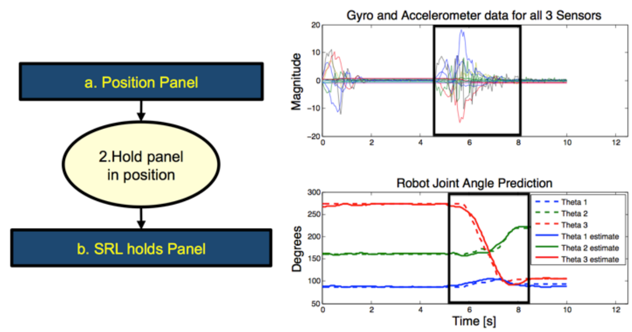

Figure 7. Figure on the left is a simplified version of the CPN model of the task section performed in the experiment. Figure on the right shows sensor data of both X (top) and Y (bottom). The black square in the top graph represents transition *a* and the one in the bottom graph transition *b*.While a CPN model would not allow the robot to start moving until the human has finished positioning the panel, PLSR allows the robot to act in a preemptive manner.

Using traditional Transitions and Places does not allow the robot to act preemptively. However, in order to employ the PLSR algorithm to perform highly coordinated and concurrent actions we can combine various transitions and places into a single, broader transition: a super transition. In this case, the super transition would absorb transitions *a* and *b*, as well as Place 2. The resulting super transition would then utilize the PLSR algorithm to control the robot.

V. Prototyping And Experimental Results

A. Prototyping

We wanted this robot to be tightly attached to its operator's upper body. Also, the human's current arm movement should interfere as little as possible with this mount. Because of this, the part that is in direct contact with the human should be as close as possible to the cervical region, resting on the trapezius. This is the area that remains most static when a person extends his or her arms upward. The contact area is extended to the clavipectoral triangle in the front and to the middle of the trapezius in the back. We use hiking backpack straps to ensure that the mount is strongly attached to the user. These straps are attached to the bottom part of the mount and also serve as padding. They are in direct contact with the wearer from the trapezius to the pectoral muscles and the axillary fold. The straps are crossed in the back as to ensure that the mount remains attached to the upper chest and back area and does not shift its support to the shoulders and arms. This design aligns the center of mass of the robot with that of its operator. This adds the weight of the robot directly to the human's, thus this added weight does not create a torque about the back. This greatly reduces the possibility of wear-induced back problems as the load goes directly to the legs. In addition, having the arms produce reaction torques directly to the operator's upper body is more natural to the human. This aids in achieving the goal of having this robot feel as an extension of the human body.

Each of the SRL's arms has five degrees of freedom (DOF), which enables us to have full position control in 3D space and allows us to control two DOF for the orientation of the endpoint. The servoed joints are torque-controllable and provide position, speed, and torque information. These servos are also fully back drivable, a property that is used to obtain the "teach by demonstration" training data. We also include sensors for monitoring the state of a tool, such as the ones for measuring the spindle speed and torque of a powered screwdriver. All the data was recorded using LabView as our interface.

B. *PLSR Experimental Results*

In this section we will present the results obtained from using PLSR to determine the SRL's joint angles in real time. Figure 8 shows the percent variance of the data sets as a function of components to be used for the PLS regression. Using the first 3 components we can describe 85% of the output data variance.

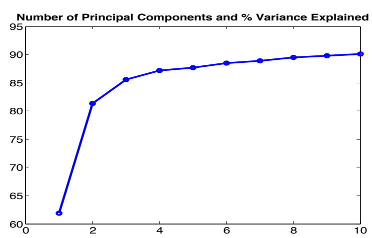

Figure 8. Variance of the data sets in percent as a function of the number of components used for the PLS regression.

Using these three components for our algorithm results in the desired behavior of having the SRL act proactively in aiding the human worker. By further examining the loading vectors from our input matrix we can determine which sensor data is the most important when making predictions. The first component relies heavily on the acceleration data from all three axis of the IMUs, this is related to both motion and posture of the human worker. By examining the temporal aspects of the input matrix we can see that the acceleration values from our IMUs remain equally important without regards to that point's place in time (wether it is x(t-19) or x(t-3)). However, when taking a look at the loadings of the second and third principal component we see complex combinations of both acceleration and velocity measurements that vary with time. Considering these three components we can determine that the sensor information most relevant to making the predictions are the accelerometer readings from all 3 IMUs, the angular velocities in z from the IMUs located in the wrists and the velocity in y from the IMU at the base of the robot. An average result of our prediction on the validating data set is shown in Figure 9. We can see that the joint prediction (only showing 3 joint angles for simplicity) is quite accurate, as this algorithm can be used to control the general behavior of the SRL while implementing other systems, such as vision, to perform fine positioning in the environment. One of the advantages of using PLSR as our control algorithm is that although the human operator is active before the execution of the task, this algorithm does not recognize that moving pattern as the one that corresponds to the transition in question. Another advantage is that the input matrix X used for the PLSR algorithm is taking into account the orientation and movement properties of the robot's base, thus the joint angles predicted are already accounting for a part of human induced disturbances.

Combining PLSR predictions together with super transitions in a CPN model can be used in order to control the SRL in a proactive manner. Using these super transitions removes idle time, thus accelerating the execution of the process and greatly reducing the worker's fatigue.

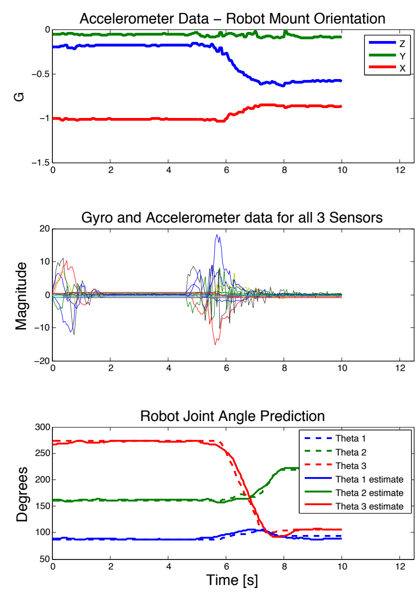

Figure 9. Top figure shows the accelerometer data recorded from the IMU located in the robot's shoulder mount. Figure in the middle shows all the recorded data from all IMUs in our validating data set. The figure in the bottom shows the recorded position joint angles for the SRL's right arm (solids) and our PLSR predicted values (dashed).

One interesting aspect is that this algorithm cannot only be used to determine the robot's actions based on the human's behavior, but also vice versa. For example, after the robot hands are confirmed to be holding the panel, the human's hands are free and briefly resume the standby position. By changing our X and Y matrices, we can use this PLS to predict the human's actions based on the torque exerted by the joints of the SRL. This is the equivalent of using the reaction forces felt by the human operator to predict when the human has determined that the SRL has secured its hold on the ceiling panel. Once again, this algorithm can be used to preemptively trigger other dynamic transitions that require the SRL and its operator to work in a coordinate manner while executing concurrent tasks that are dependant of one another.

VI. Conclusion And Future Works

A wearable robot secured to a human's shoulders is developed and presented. The design constraints were presented in order to have a wearable robot that does not create torques about its operator's back and that minimally interferes with the operator's actions. This wearable robot, termed Supernumerary Robotic Limbs (SRL), works in a highly coordinated manner with the human during the execution of such tasks. Coloured Petri Nets (CPN) is used to model the concurrent and distributed nature of a ceiling panel installation task. This model assigns to the robot the roles that result more laborious for the human, thus lessening the workload on the human worker. The CPN framework is then extended to a hybrid control system by grouping several transitions and places into a super transition, which is then imbedded with dynamic controllers. Each dynamic controller collects sensor signals from the human operator and the robot mount. Using this data and a Partial Least Squares Regression (PLSR), we are able to predict the SRL's trajectory based on the human's actions in a 20 sample window. Using a rough prototype and teach by demonstration experimental data we tuned the PLS algorithm to allow the SRL to take proactive action during the execution of the task. This algorithm proved to be a very strong solution to both determining when the robot can start to execute its role and for determining in real time the trajectory that the SRL has to follow during each transition.

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