Improving Human-Robot Object Exchange by On-line Force Classification

Wuwei He and Daniel Sidobre

CNRS, LAAS and Université de Toulouse, France

Robots are sometimes tasked with handing an object over to a human, which can be a challenging task for a robot to perform, especially when the human partner has no experience in interacting with robots. This paper presents our work to enable a robot to learn how to achieve this task with wrist force/torque sensing. Firstly, we present a device to record the data, then we discuss techniques used for teaching. We focused on the classification problem as defined in our paper to enable the robot to find the finger-opening movement. The main challenge is that the classification should be run online at a comparable rate to the controller. To achieve a computationally efficient classifier, we used the Wavelet Packet Transformation for feature extraction, and then we used the Fisher criterion to reduce the dimension of features. A Relevance Vector Machine is used for continuous classification procedure mainly for its sparsity. Some recorded data and results from dimension reduction are shown. We then discuss the accuracy and sparsity of classification by the Relevance Vector Machine in this application. The software of continuous classification on forces is then tested on the robot for interactive object exchange between human and robot, which gives promising results.

Keywords: Robotic, physical interaction, object exchange, relevance vector machine

1. Introduction

The exchange of objects between humans and robots is one of the elementary tasks that an interactive mobile manipulator has to perform. Either in daily life or industrial contexts, natural and intuitive object exchange is preferable for the human partner. To achieve this goal, a device is proposed to teach robots the ability to exchange objects naturally as humans do.

To achieve safe object hand-over, important challenges for the robot are to determine if it is safe to open the fingers and the right moment to open the fingers. In this paper, we show how to learn this skill from force signals recorded by an instrumented device during object exchange between people. This device, named the Bidule, uses a 6D force/torque sensor to record interaction forces during the exchanges. We model this force signal in classes identified by techniques based on a Relevance Vector Machine applied to information extracted from the force signal. The underlying objective is to identify information that is useful to people during human-to-human hand-over tasks.

In order to detect grasping, we use wavelet analysis and classification techniques to study object

Authors retain copyright and grant the Journal of Human-Robot Interaction right of first publication with the work simultaneously licensed under a Creative Commons Attribution License that allows others to share the work with an acknowledgement of the work's authorship and initial publication in this journal.

exchange between people. We also propose solutions to reduce the dimension of the classification model. This model, learned from human experience, is then used to teach the robot the capability to know if the human has grasped the manipulated object and to decide when to react.

We present experimental results obtained with one of our robots, which is capable to realize a complete task of object exchange (Sidobre et al., 2012). This task integrates results from human-aware motion planning, trajectory generation and control, and safety issues, such as online collision checking and external force monitoring on robot joints.

The objective of this paper is to present the object designed and the set of techniques used to efficiently extract patterns from the force signals during object exchange. Even if it is still a preliminary study, we show the possibility of learning a model from force signals during human interaction, aiming to improve physical human-robot interaction. We paid particular attention to choosing efficient tools for building our demonstrator and showing the approach’s capacities to extract relevant information from the transmitted force, therefore enhancing object exchanges.

Related works are presented in Section 2. The Bidule object, designed to study interaction forces during exchange, is presented in Section 3. The main part of the paper is Sections 4 and 5, which explain techniques for feature extraction and classification. We then give some results obtained with a robot in Section 6, followed by the conclusion.

2. Related Work

A solution to exchange objects between a human and a four-fingered robot hand was presented in Nagata, Oosaki, Kakikura, and Tsukune (1998). Authors used a six-axis force/torque (f/t) sensor mounted on each fingertip to control grasping force and evaluate modifications in the human grasp condition. Similarly, in the domain of cooperative manipulation with humans (Aggarwal, Dutta, & Bhattacharya, 2007; Takubo, Arai, Hayashibara, & Tanie, 2002), researchers tried to detect different stages of cooperation-like contact and slip.

The study of forces during object exchange can be done with a sensorized object (Kim, Nakazawa, & Inooka, 2002; Nakazawa, Kim, Inooka, & Ikeura, 1999, 2001). The object was designed to be grasped by the thumb and forefinger, so forces are only measured in two directions. When researchers designed the object, they proposed to answer a set of questions. The same questions can be used to define the objective of our learning-based approach, as follows:

- “How does the giver know the receiver’s contact?”
- “Which one starts to act first for the smooth hand-over?”
- “How do both of them control grasp forces during the hand-over?”

The authors also established that “the giver may feel slight vibrations on the fingertip and a change in the weight of the object as the receiver contacts the object.” They also showed that the grasp forces are adapted to the weight of the object.

A recent work using a sensorized baton to teach a Willow Garage PR2 robot demonstrates the validity of this approach (Chan, Parker, Van der Loos, & Croft, 2013). The authors built four controllers from the results of a study on human-human hand-overs using the baton. Then, they asked participants to compare the controllers. The results show that the controller directly derived from learned elements is the one preferred by participants. However, the conclusion of the paper states that tests were limited to one object exchanged in a vertical orientation. As the manual construction of a general controller will be very tedious, we propose to use analysis and classification tools. Likewise, grasping force measure is difficult in general case; in Chan et al. (2013), a particular grasp corresponding to the position of a Force Sensitive Resistor sensor is used. In our case, the robot does not control grasp force and simply opens the fingers of the gripper, so the users can use more natural and varied grasps.

Another important consideration is related to the localization of the information in both time and frequency domains. *Vibration* condition, defined as a threshold on the high-frequency hand acceleration signal, can be used to detect contact with environment when the robot places an object (Romano, Hsiao, Niemeyer, Chitta, & Kuchenbecker, 2011). Here again, the threshold is determined by manual trial and error, which would be especially difficult when multiple contact types should be classified.

The methods used in this paper are wavelet-analysis based. Readers can refer to Mallat (2008) for a detailed discussion on wavelets and comparison to Fourier analysis and its variants. Linear Discriminant Analysis was used to select features, and a clear explanation of this can be found in Bishop (2006). Relevance Vector Machine, used as a classifier in this work, was initially introduced in Tipping (2001). Frequency information based classification, although with different feature formation, was also reported with successful application on touch classification (Sato, Poupyrev, & Harrison, 2012), and especially on image classification, such as in Rehman, Gao, J. Wang, and Z. Wang (2013).

3. Bidule: A Device for Manipulation Learning

The first objective of this research was to design an autonomous object for being able to record contact forces and motion. We designed an object, called the Bidule, to learn useful information during object exchange-like force and motion signals. The goal is that learned information can be directly used on robots equipped with a wrist f/t sensor. The f/t sensor is common for mobile manipulators, and the wrist f/t can often be estimated for robots without an f/t sensor. The device was also designed to help to learn trajectories and force control policies; however, details of these last two parts will not be covered in this paper.

Figure 1. Left: The Bidule design with the 6D force/torque sensor (orange); the handles (blue) are fixed on rings screwed to the sensor; the computer is on the left side and the battery with the power supply board is on the right side. Right: Bidule, the device used during this research.

The Bidule was built up around an embedded Gumstix microcomputer, a WiFi link, and a 6D force/torque sensor. An Inertial Measurement Unit (IMU) was used to compensate inertial forces and to record the motions of the Bidule. The shape and the size were designed to better fit the human hand (Fig. 1). Two tubes can be grasped by humans and transmit external forces to the sensor. The force signals are amplified, filtered, and re-scaled before an analog-to-digital converter (ADC) digitizes these signals. The link between the computer board and the acquisition board was done via an SPI link running at 3 M bits per s available on a 60-pins connector. Two additional bronze rings, each weighing 0.227 kg, can be added around the Bidule object weighing 0.529 kg. This enables us to study different exchange forces when the mass of exchanged objects varies.

Figure 2. The frame F_1 is located at the mass center of the Bidule object's upper part. The frame F_s is located at the center of the force/torque sensor. G_1 represents the inertial model of the upper part and G_2 that of the lower part.

During manipulation, the f/t sensor records not only the contact forces of the Bidule with the environment, but also the inertia of the Bidule. Dynamic compensation needs to estimate firstly the inertial parameters (the mass, center of mass, and all elements in the inertia matrix) of the upper and lower parts of the Bidule. This problem can be illustrated by Fig. 2. The whole set of inertial parameters of the upper part of the Bidule was named G_1 :

$$G_1 = (m \ c_x \ c_y \ c_z \ I_{xx} \ I_{xy} \ I_{xz} \ I_{yy} \ I_{yz} \ I_{zz})^T \quad (1)$$

Where m is the mass of this part, vector $(c_x \ c_y \ c_z)^T$ represents the position of the center of mass in the frame F_s of the force sensor, and $(I_{xx} \ I_{xy} \ I_{xz} \ I_{yy} \ I_{yz} \ I_{zz})^T$ includes all the terms in the inertial matrix I , which can be written as:

$$I = \begin{bmatrix} I_{xx} & I_{xy} & I_{xz} \\ I_{xy} & I_{yy} & I_{yz} \\ I_{xz} & I_{yz} & I_{zz} \end{bmatrix} \quad (2)$$

Inertia matrix I is represented in the frame F_1 located at the center of mass (see Fig. 2). Details of the inertial model and how Kalman Filters are used to achieve online estimation can be found in He (2013). The same method was used for the lower part, G_2 . It should be noted that G_3 and different coordinate transformation need to be handled carefully. We will omit the details in this paper because of limited space. Kubus, Kroger, and M.Wahl (2008) proposed a recursive approach to solve a similar problem. Although we used an Unscented Kalman Filter instead of Recursive Least Square, the readers can refer to the paper for more discussion on the topic. Once the whole set of inertial parameters were estimated, the inertial forces ($f_{inertia}$ and $\tau_{inertia}$) were simulated and removed from the sensed signals (f_{sensor} and τ_{sensor}), and we obtained contact forces ($f_{contact}$ and $\tau_{contact}$).

$$f_{contact} = f_{sensor} - f_{inertia} \quad (3)$$

$$\tau_{contact} = \tau_{sensor} - \tau_{inertia} \quad (4)$$

The structure of this calculation can be summarized as:

Figure 3. Contact Forces/Torques Computation. The gravitational vector g , acceleration a , and angular velocity ω can be computed from an inertial measurement unit (IMU). f_s and τ_s are measured forces/torques vectors. The same strategy can be used for a wrist force sensor on the robot’s arm to achieve online estimation of contact forces/torques.

The Bidule was designed to learn three aspects of object manipulation for a service robot:

- How to classify events from the rich information coming from the f/t sensor during exchange or when the robot end effector contacts environment, either for human grasp or collision with different obstacles.
- Trajectories for hand-over motions adapted to the mass and types of the manipulated object.
- Force control policies for a robot during object exchange with a human partner.

In this paper, we focus on the first part, while learning of the trajectory and of force control policies will be the subject of future research.

4. Force Signal Monitoring by Classification

The control of our robot was centered around a trajectory controller based on Online Trajectory Generation (OTG) (Broquère, 2011; Broquère, Sidobre, & Herrera-Aguilar, 2008; Kroger & Wahl, 2010). During the hand-over, several situations concerning contact forces will occur:

- To give an object to a person, the robot approaches and tracks the exchange point, which is computed in a frame attached to the human partner. When the person grasps the object, the robot detects the event and opens the gripper. If still moving, the robot stops its movement and then retracts the arm along the same path. This enables a dynamic and reactive object exchange.
- During the hand-over motion, the manipulated object can collide with the human hand or with the environment. The human can also fail to grasp the object. As a safety measure, the robot should react differently, depending on the type of collision or failed grasps.

Two such events are shown in Fig. 4. Our first objective for learning was to use continuous classification to monitor the force signal history; for example, to clearly identify the situation in the previous second. We wanted the robot to be able to use classification to distinguish different contact types, and more importantly, to open the fingers or stop motion at the right moment. We first defined three classes: collision, grasp, and all remaining cases: pure noise or grasp/collision but not yet the moment to react. In this paper, we limit the environment to rigid bodies, such as a table, chair, and other rigid objects in the robot’s working space. The signals would be different collisions

Figure 4. Left: The manipulated object collides with the green box. Right: Human takes the object given by the robot.

happening between compliant bodies, and continuing study for more environment types will be part of our future work.

The examination of the forces/torques time series showed that forces and torques depend on the human partner and the manipulated object. For example, a larger object will be handled more slowly and grasped more firmly, so the contact forces should be bigger in magnitude and last longer. Although some simple statistics on the f/t signals could also gain useful results, we preferred machine learning techniques to take advantage of the rich time-frequency information in the signals and obtain robust control policies for the robot.

In Fig. 5, we see several examples of the forces/torques produced when the object was grasped by a person or during typical collision between the Bidule and a table; they showed different forms of vibration. We can see that grasp exhibited more variation, and collision had a higher-frequencies pattern. For either of the two classes, neither the magnitude nor the duration of the vibration could be easily used to identify the signal. However, some characteristics could be used to achieve classification, which is what we tried to extract by machine learning. The choices of techniques were oriented to obtain a computationally efficient and hence fast classifier, so it could be run at a high rate together with other algorithms, such as Online Trajectory Generation and online collision checking.

5. Feature Extraction and Learning

5.1 Wavelet Packet Transformation

The contact forces are transient signals, for which wavelet-based methods had been established to be a reasonable choice for extracting time-frequency information. Compared to Fourier analysis, wavelets capture not only frequency information, but also time localization. The Wavelet Packet Transformation (WPT) used for feature extraction has been reported in various works relating to myoelectric signal (Englehart, Hudgins, Parker, & Stevenson, 1999) or underwater acoustic signal (Learned & Willsky, 1995). Wavelet Packet Transformation is an algorithm used to decompose discrete signals into subbands with different time-frequency resolutions (Mallat, 2008). Each step of decomposition was implemented as being filtered by a two-channel filter bank, together with downsampling operations. Fig. 6 shows an example of a signal of size sixteen decomposed by a Haar filter bank (Jensen & Cour-Harbo, 2001). The original signal is represented at level zero of the

tree. At level $j = 1$, the blue part was obtained by lowpass-downsampling operations of the signal, while the pink part was obtained by highpass-downsampling operations. The same computation was then executed on these two signals, decomposing the signal into four subbands (level $j = 2$). The signal was decomposed until $j = 4$, which is the maximum level J for a signal of size 16. If the size of the original signal was D , we had $J = \log_2 D$.

Notice that in Discrete Wavelet Transformation (DWT), only the high-frequency part was recur-

Figure 5. Forces/torques signals during several exchange and collision events. On the left, we see three different object exchanges between two people, when the object mass changes too. On the right, forces/torques of three different collisions between object and rigid environment happened. The scale for time, force, and torque are set to be the same for all the plots.

Figure 6. Wavelet Packet Transformation decomposes the original signal recursively into a tree structure, here through the Haar wavelet filter bank. Each subband is decomposed into a high-frequency part (pink) and a low-frequency part (blue).

sively decomposed. It could then be seen as one subset of WPT. The problem with DWT is that it may lose the possibility to highlight some features. As reported in Coifman and Wickerhauser (1992), only some signals have the information focused in this fixed representation. Additionally, Learned and Willsky (1995) show a clear example of a transient signal where some patterns are captured by a WPT, but they will not appear in the results of a DWT.

In our system, as the transformation should be computed in real-time, we chose to implement each step of wavelet transformation in a lifting scheme. The lifting scheme reduces computational complexity, requires less memory, and maintains ever-perfect reconstruction. For implementation details, readers may refer to Sweldens (1995).

To illustrate the time-frequency pattern of a signal, we computed the WPT of a linear chirp signal $y(t) = \sin(k\pi t^2)$ by Daubechies wavelets ($db4$). Then, the fifth level was chosen from the tree and ordered by frequency. The results are presented in Fig. 7, in which the coordinates of time and frequency are shown without units because they lost the physical meaning, and magnitude plots the function $\log(1 + x^2(i))$ in which $x(i)$ are the wavelet coefficients in level 5. We can see clearly an increasing frequency pattern. The ridges that appear perpendicular to the main diagonal line of increasing frequency are artifacts, which will not influence the results of pattern recognition.

For this signal with a clear increasing frequency, it is easy to illustrate its pattern by constructing a time-frequency plot, but to classify complex and variant contact forces, we needed tools to help us find the best pattern representation from the WPT.

5.2 Feature Formation and Selection

From the WPT tree, several types of feature representations exist: part of the decomposition coefficients, statistical information of the coefficients, or the energy map (Birbaumer et al., 2000; Fatourehchi, Mason, Birch, & Ward, 2004; Xue, Zhang, Zheng, & Yan, 2003). The whole coefficients set captures all the in-class variations and noise, which would otherwise need a large data set to achieve convergence of the learning optimization process.

Feature selection was a critical step to minimizing classification error (Peng, Long, & Ding, 2005). In many applications, increasing the data set would also minimize classification error, but in our case, building a large data set from manipulations with different candidates and different situations was a tedious task. On the other hand, the classifier will run online at a comparable frequency as the controller, so reducing the dimension of the learned model was also important. Given these reasons, we decided to differentiate time and frequency separately by combining a part of the coefficients and the energy map, instead of keeping all the coefficients. As shown below, feature selection can significantly reduce feature size.

Figure 7. Linear chirp (top) and its time-frequency pattern (bottom), constructed from level 5 of a WPT tree structure. We see that the WPT tree captured the information in time and in frequency.

The *Relative Energy Map* was used to capture frequency information. Each level of the WPT decomposed the signal into a time-frequency representation with different time-frequency precision. For each subband in the tree, an energy value was computed from all the coefficients in the subband. If we name one subband b and its coefficients $x(k)$, then its energy e_b is computed as:

$$e_b = \sum_k (x(k))^2 \quad (5)$$

By this definition, e_0 , which is computed on the subband S_0 in Fig. 8, is the total energy of the signal, and e_1^L is the energy in subband S_1^L . The energy was calculated through the whole tree. Then, all data was normalized to the total energy of the signal in the time window, which means:

$$E_b = \frac{e_b}{e_0} \quad (6)$$

For a sample to learn, we can write this feature set as $\mathbf{E} = \{E_b\}$, which includes the relative energy in all selected subbands. We notice that a large part of the feature produced by this method is zero, which is no surprise since wavelets produce a sparse representation of the original signal (see Mallat, 2008 for more details about the sparsity of WPT). We should then choose the most discriminative features from $\mathbf{E}$ to further reduce the size of the feature vector.

The energy map is independent of the magnitude and the duration of vibration in the original force signal, and the time information is lost. It can be noted that the relative energy map is already scaled to between 0 and 1.

Figure 8. Three subbands for the WPT tree. L means that the subband has been filtered by a low-pass filter and then downsampled; H means filtered by a high-pass filter and downsampled. The subbands in blue are the low-frequency part at each level.

Coefficients of One Subband were selected to capture the global form of the signal. The objective was twofold: to record information of the changing weight when the receiver started to hold the exchanged object and to deduce the right time for the robot to open its fingers or react. The robot should differentiate two signals, as shown in Fig. 9, where the same signal was shifted in time. We chose the coefficients from the first subband of a level in the WPT tree, which contained information of the signal's low frequency part and with a reduced size. We wrote this feature set as S . In Fig. 8, the candidates are shown in the blue-colored areas. Since each level contains such a low frequency subband, the level choice was decided by compromising the classification error and the feature size produced. The higher level we chose for this subband, the less precise it was in time. The coefficients were then normalized to between 0 and 1 as the relative energy map.

The choice of the first subband of a level was based on prior knowledge that for signals in all classes of the problem at hand, this subband indeed captured the peaks of the original force signals well, as shown by Fig. 10. For some signals that contain only high frequency components, the subband choice needed to be made by feature selection algorithms.

Figure 9. The classifier should be able to tell a difference between the two signals above to find the right time to react to an event detected by the forces/torques sensor.

Fisher Linear Discriminant Analysis was then used to select features and to further reduce the dimension of the classification model. Fisher-LDA is a tool used for classification and dimension

Figure 10. Part of the WPT tree plotted for the signal F ($F = F_x + F_y + F_z$) in Fig. 9. The first subbands (highlighted by red rectangles) captured the peak in signal (peaks are white in color). The WPT was computed with Symlets 5 wavelets (*sym5*). The zeros in the tree also show the WPT’s sparsity. The unit for the horizontal axis is omitted, since the time measurement unit varies for different levels in the WPT, while level 0 is the original time signal.

reduction of features (Welling, 2005). Detailed discussion for this tool can be found in Bishop (2006). Fisher-LDA considers finding the best weight $\mathbf{w}$ by maximizing the objective:

$$J(\mathbf{w}) = \frac{\mathbf{w}^T S_B \mathbf{w}}{\mathbf{w}^T S_W \mathbf{w}} \quad (7)$$

where S_B is the “between classes scatter matrix,” and S_W is the “within classes scatter matrix” (Welling, 2005). The value of J means the separability of classes for a set or a subset of features. Here, we used the criterion to select the best features in our feature set of the relative energy map $\mathbf{E}$. The criterion was reformulated as defined in Eq. (8). It was calculated for every feature in $\mathbf{E}$ to evaluate the separability measure (Gu, Li, & Han, 2011) of that feature. As WPT produced a sparse representation of the signal, which means many terms in the tree were nearly zero, it was reasonable to not include those features that were invariant between classes.

$$J = \text{tr}(S_W^{-1} S_B) \quad (8)$$

During the object exchange manipulation, the orientations of f/t changed in different situations: the posture of the robot and of the people, the exchange positions, and more. Not including orientations for the event detection simplified the problem. In fact, the f/t is expressed in the local frame of the sensor, which made the orientations more difficult to use for the classifier. Learning a model with orientations will also be much more complex and produce a model of much higher dimension, resulting in a slower classifier. While f/t orientations were excluded from the feature set, the feature set building process can be summarized as:

- The WPT tree representation was built from force F and from torque T , F was computed as $F = \|F_x + F_y + F_z\|$, and T was computed as $T = \|T_x + T_y + T_z\|$.

- The relative energy map was computed for the WPT.
- The result was then combined with a subband from the tree. The subband was also scaled to range, from 0 to 1, matching the same as that of the relative energy map.
- Fisher LDA criterion was used to reduce the feature set size of energy map E and the level from the subband S selected as a trade-off between classification accuracy and feature size.

5.3 Relevance Vector Machine and Classification

Once the features were well defined, the problem was formulated as a classification of multiple-classes. In the previous section, the f/t signals were transformed into the feature space of the energy map and a subband from the WPT tree. If we write the whole feature vector as $\mathbf{x}$, then this problem is: given $(\mathbf{x}_i, d_i)_{i=1,2,\dots,N}$, a set of N training data where d_i is the class label, how to determine a classifier $y(\mathbf{x})$ that correctly classifies the force signals? The Support Vector Machine (SVM) established itself as a state-of-the-art algorithm with strong theoretical foundations for classification and regression (Burges, 1998; Vapnik, 1999). However, the new Relevance Vector Machine (RVM) approach is promising, and we chose it for this work. Compared to SVM, RVM has some advantages, as discussed in Tipping (2001), which will not be repeated in this paper.

We show how a sparse model is achieved by RVM. For clarity, the simple case of a binary classification problem is discussed, which means $d_i \in \{0, 1\}$. Given a new input vector $\mathbf{x}_*$, the probability of its class label is given as:

$$p(d|\mathbf{x}_*) = \frac{1}{1 + \exp(-y(\mathbf{x}_*))} \quad (9)$$

the RVM classifier function y is given by:

$$y(\mathbf{x}) = \sum_{i=1}^N w_i K(\mathbf{x}_*, \mathbf{x}_i) \quad (10)$$

In which $K(\cdot, \cdot)$ is a kernel function; $\mathbf{x}_i (i = 1, 2, 3, \dots, N)$ are the N training data. As discussed in Tipping (2001), the parameters w_i in Eq. (10) are determined by Bayesian estimation, and a sparse prior is introduced on these parameters, forcing them to be highly concentrated around 0. Then, they are computed by maximizing the posterior distribution of the class labels given in the inputs. Very few nonzero terms of w_i means that very few samples in the training data are used in the classifier function given by Eq. (10), achieving a sparse model. Like for SVM, the kernel trick is used to expand the basic functions for $y(\mathbf{x})$. In this work, the RBF kernel function is used, which is:

$$K(\mathbf{x}_*, \mathbf{x}) = \exp\left(-\frac{\|\mathbf{x}_* - \mathbf{x}\|^2}{2\sigma^2}\right) \quad (11)$$

In which the optimized $\sigma > 0$ defines kernel width. The choice of the RBF kernel was made by trying different kernels, and RBF gave satisfying results. Readers can refer to Bishop (2006) and Tipping (2001) to see how RVM is generalized for multiclass problems and for information for other kernels. RVM has been successfully applied for fault diagnosis (Widodo et al., 2009), supervised hyperspectral classification (Mianji & Zhang, 2011), and for recovering 3D human body pose by regression (Agarwal & Triggs, 2004).

6. Data Acquisition and Results

6.1 The Experimental Protocol

The experiments were carried out with nine pairs of volunteers, all adults and inclusive of both genders. We selected people who had worked around robots and also four pairs who had no work

experience around robots. Three qualitative velocities were chosen: slow, normal, and fast. We then explained the experiment to each participant. First, the Bidule was presented to volunteers as a precious and fragile object that needed to be handled with care. These exchanges defined the slow velocity exchanges. The Bidule's real solidity was then revealed, and participants were asked to carry out natural exchanges, namely, normal velocity exchanges. Then, the volunteers were asked to do fast exchanges.

Figure 11. Configurations of Bidule used for the experiments.

We defined four different orientations for the Bidule, the two vertical ones (antenna up and upside down), one horizontal, and one tilted. One-third of the experiments were done with additional mass. Fig. 11 presents the seventeen different cases of exchange, while Fig. 12 shows one such exchange experiment. Each couple of volunteers performed each case of exchange two times, once as giver and once as receiver. Each record lasted three to five seconds, depending on the speed of object exchange.

Figure 12. Two persons equipped with markers and exchanging the Bidule.

6.2 The Data Set

Firstly, the time window was fixed to approximately 1 second, because we observed that the slowest manipulation lasted about 1 second, which gave 2048 data points, as the acquisition rate was set to 1 kHz (1024 for force data points and 1024 data points for torque). By discarding failed data records because of various reasons such as communication failure, 213 experiments for each type of events (“collision” and “grasp”) were selected. For class “collision,” we recorded data of class

collision between the Bidule and different environments: human hand, table, bottles, and video tapes. We limited the environment to the working space of the robot, which included only rigid bodies. Including soft bodies in the “collision” database would have changed how the classifier identified events, and how that works on the robot needs further investigation. As we needed to model the correct time to release the object for the giver, samples for class “noise” were simply cut from the data that could be pure noise, or just signal at a different instant from the reaction time, shifted by 0.05, 0.1, and 0.15 s, etc. We used a random process to segment data samples of “noise” from recorded noise signals, with the smallest time difference of 0.05 second. The total data set for training was of size 639. Then, 240 data of the three classes were selected in the same way to test the model.

6.3 Feature Selection Results

In this section, we will discuss the choice of features by some results. Table 1 shows the result of classification with different feature sets: the full energy map (E), the subband from level 1 S , and the two combined. The choice to combine two different feature sets was justified by the results in the classification errors.

Table 1: Error rate for different feature sets. RVM with a RBF kernel was used as the classifier.

Features	E	S	$\{E S\}$
Error(%)	15.42	21.67	2.5

To reduce the feature size of the relative energy map E and the subband S , we conducted two studies: We evaluated E by the Fisher LDA criterion, and then we fixed E to evaluate the different choices on S by directly comparing the classification error. Firstly, we calculated the energy map from the WPT until level 6, which produced a total of 126 features for force and 126 for torque. The relative energy of level 0 (original signal) was omitted, since it was 1 for all instances. We examined the separability J of the relative energy map feature set E . The results can be seen in Fig. 13 for the forces F . Several terms in the feature set dominated the discriminative measure, which enabled us to reduce largely the size of the feature set without losing too much of the feature set’s discriminative information. The final set of features was chosen from the most discriminating terms from the combination of the WPT results of force and of torque.

Figure 13. The separability measurement of features in the relative energy map E of forces. J was calculated by Eq. (8) through all features in E . The zeros in this measurement were largely due to the sparsity of the WPT tree. Similar results were also obtained for torques. The features were sequenced by the separability measurement J in decreasing order.

Figure 14. The trade-off between feature size (blue curve) and classification error (red curve). The small feature size meant a faster model for online prediction. Level 5 was chosen, as it gave a satisfying balance between number of features and error rate.

For the choice of the level from which to extract the low frequency subband, we used RVM with RBF kernel and directly compared the classification error rate. During this study, the energy map was reduced to the first 13 most discriminative features. Firstly, we chose S at the first level, and we evaluated the classification error. We then evaluated at level 2 and until the error rate of classification increased significantly at level 6. Losing of time precision in the higher level of the WPT tree explains this phenomenon. The subband was fixed to level 5 to keep the error rate low with a low number of features.

Table 2: For this application, RVM produces a much sparser model than SVM along with a comparable classification accuracy rate.

	Dimension	Accuracy(%)
SVM	151	97.92
RVM	9	97.5

For this study, we finally chose the first 13 features out of 252 of the relative energy map E . The subband of level 5 gave 64 features. After dimension reduction, a classification accuracy rate of 97.5% was obtained, with a compact model having a dimension of 9 (the nonzero weighed in RVM), while feature size was 77. When the whole WPT tree was used directly to train an RVM, the learning did not converge because of the in-class variations and due to the training data set's small size, and the whole WPT tree decomposed until level 6 was of size 12288 (each level had 1024 elements for forces and 1024 elements for torques).

6.4 Comparison to SVM

Similar classification accuracy was given when the same feature set was used for SVM. As shown in Table 2, RVM produced a much sparser model (and hence, faster classification). In the table, the dimensions are the number of Support Vectors or of Relevance Vectors. Since we want to run the classifier online at a comparable speed of the controller with other resource-consuming computations, reduced model complexity is important. Notice that only the used features but not the whole WPT tree need to be computed for online classification. The results for SVM are obtained by running LIBSVM (Chang & Lin, 2011) (RBF kernel).

The 2.5% classification error happened when the classifier gave the label “collision” and the object was grasped by a person. In this case, the robot did not open the gripper when the object was

grasped. Although we believe that a 2.5% error rate is acceptable, we will investigate how we can improve this in the future.

Figure 15. Time delay between the moment when the object came in contact (shown by “event” and classified as type “collision”) and the moment when the robot reacted (shown as “detect” and the reaction is “stop”). The event happens at time a, and the robot reacts at time b. At time b, the system monitors the past 1 second of f/t. The time window monitored by the system is illustrated by the black line.

6.5 Firsts Results With a Robot

The classifier was implemented on the robot for the wrist f/t sensor, which is capable of using the learned model from human experience. The classifier ran at 50Hz, together with other perception and planning software on the robot. Fig. 15 demonstrates interaction forces and time delay before the robot reacted. For this experiment, the object was held by the robot and a person grasped the object, but not firmly. The event given by the classifier is not “grasp” but “collision,” showing the ability to tell if the object was properly grasped. The figure shows the time delay between the grasp event and the time for the robot to react (here, it is not to open the gripper but to stop the motion, since “collision” is detected instead of “grasp”), with detection by force signals.

The time delay is normally less than half a second between the event happening and the reaction, with an average of 0.37 seconds; therefore, the choice of a one-second observation window seems adequate. One important aspect is that the result did not show the fastest speed at which the classifier can detect the event, but it showed the right moment to react. This delay was learned by the model, which was decided by the instances acquired from human-to-human manipulations. It is possible that volunteers tend to exchange the Bidule slower than how they do in daily life with familiar objects, but we do not have strong results for this hypothesis. The classifier, on the other hand, can achieve faster detection if only fast training data is selected. We achieved a model that gave a 0.2-second reaction by a smaller set of selected fast data, but we decided that reaction speed should be determined by a user study instead of by hand-selected training data.

We would like to mention that external force monitoring was implemented on joint space when collision detection was needed for safety issues, so this reaction time did not introduce a safety issue for the robot.

First manipulations between robots and people have been carried out with promising results. Fig. 16 shows how the software, from signal processing to classification, were used for manipulations. During this manipulation, the robot decided to open the gripper. A user study of this approach to see how it can improve the quality of object exchange for human users in interactive manipulation is yet to be finished. Such a study will include many aspects, including human preference for the

robot's reaction speed. Another example would be to compare the false negatives and false positives for grasp detection and see which one has a greater influence on users' experience.

Figure 16. Software tested during manipulation. (a) Robot Jido, the human partner, and objects to manipulate. (b) The robot decided to take the object on the table. (c) The person asked for the object. (d) The robot gave the object to him, and he took the object. (e) Detecting that the object is taken by the person, the robot opened the gripper. (f) Object exchange successfully finished.

7. Conclusion and Future Work

The device proposed to teach the robot how to exchange objects as humans do is very promising, as rich information can be extracted. Force signal classification is the focus of this paper. Wavelet Packet Transformation is chosen, from which the energy map and a subband are used to extract features, and Fisher Linear Discriminant Criterion is used to reduce the dimension of the feature set. Furthermore, the Relevance Vector Machine is employed as a classifier, because it produces a sparse model. Some results for feature selection and for classification are shown. It can be noted that by constructing a classifier, robust control policies can be achieved with no thresholds to choose by trial and error, which becomes especially difficult when more classes should be considered.

Our experimental device, named the Bidule, has been designed to learn more than what we discussed in this paper, such as force control policies during exchange and associated movements.

Those topics deserve further research and another paper for discussion. For the classification problem, more classes can be added to make a difference between the collisions (soft surface against hard surface) or further separate different grasp types. On the other hand, the user study about event detection is the next work to finish. We also need to investigate possibilities of using the same set of classification techniques for other manipulations (e.g., putting objects on a table or grasping a handle). At this time, we want to mention that the collision detection by f/t sensor is also to be used for other tasks, such as for the robot to properly place an object on the table. For example, touching of an object's bottom surface with a table's edge would surely produce different patterns on the force signals. In this case, it would be reasonable to also include torques into the feature set. With new methods discussed in this paper used to build compact and efficient models, online classification can improve many aspects of robotic manipulations.

Acknowledgements

This work has been supported by the European Community's Seventh Framework Program FP7/2007-2013 SAPHARI under grant agreement no. 287513 and by the French National Research Agency project ANR-10-CORD-0025 ICARO.

References

- Agarwal, A., & Triggs, B. (2004). 3d human pose from silhouettes by relevance vector regression. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (Vol. 2, pp. II-882). doi:10.1109/CVPR.2004.1315258
- Aggarwal, P., Dutta, A., & Bhattacharya, B. (2007). Cooperation between a 4 DOF robotic hand and a human for carrying an object together. In *Proceedings of the SICE Annual Conference* (pp. 2354-2359). Takamatsu, Japan. doi:10.1109/SICE.2007.4421382
- Birbaumer, N., Kubler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., ... Flor, H. (2000). The thought translation device (ttd) for completely paralyzed patients. *IEEE Transactions on Rehabilitation Engineering*, 8(2), 190-193. doi:10.1109/86.847812
- Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer: New York. Retrieved from <http://www.springer.com/us/book/9780387310732>
- Broquère, X. (2011). *Planification de trajectoire pour la manipulation d'objets et l'interaction homme-robot* (Unpublished doctoral dissertation). LAAS-CNRS and Université de Toulouse, Paul Sabatier.
- Broquère, X., Sidobre, D., & Herrera-Aguilar, I. (2008). Soft motion trajectory planner for service manipulator robot. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems* (pp. 2808-2813). doi:10.1109/IROS.2008.4650608
- Burges, C. J. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2(2), 121-167.
- Chan, W. P., Parker, C. A., Van der Loos, H. M., & Croft, E. A. (2013). A human-inspired object handover controller. *The International Journal of Robotics Research*, 32(8), 971-983.
- Chang, C.-C., & Lin, C.-J. (2011). LIBSVM: A library for support vector machines. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 2(3), 27.
- Coifman, R. R., & Wickerhauser, M. V. (1992). Entropy-based algorithms for best basis selection. *IEEE Transactions on Information Theory*, 38(2), 713-718.
- Englehart, K., Hudgins, B., Parker, P. A., & Stevenson, M. (1999). Classification of the myoelectric signal using time-frequency based representations. *Medical Engineering & Physics*, 21(6), 431-438.
- Fatourech, M., Mason, S., Birch, G., & Ward, R. (2004). A wavelet-based approach for the extraction of event related potentials from eeg. In *Proceedings of the IEEE Interna-*

- tional Conference on Acoustics, Speech, and Signal Processing* (Vol. 2, pp. ii–737). doi: 10.1109/ICASSP.2004.1326363
- Gu, Q., Li, Z., & Han, J. (2011). Linear discriminant dimensionality reduction. *Machine Learning and Knowledge Discovery in Databases*, 549–564.
- He, W. (2013). *Reactive control and sensor fusion for mobile manipulators in human robot interaction* (Unpublished doctoral dissertation). LAAS-CNRS and Université de Toulouse, Paul Sabatier.
- Jensen, A., & Cour-Harbo, A. (2001). *Ripples in mathematics: The discrete wavelet transform*. Springer: New York.
- Kim, I., Nakazawa, N., & Inooka, H. (2002). Control of a robot hand emulating human’s hand-over motion. *Mechatronics*, 12(1), 55–69.
- Kroger, T., & Wahl, F. M. (2010). Online trajectory generation: Basic concepts for instantaneous reactions to unforeseen events. *IEEE Transactions on Robotics*, 26(1), 94–111.
- Kubus, D., Kroger, T., & M.Wahl, F. (2008). Improving force control performance by computational elimination of non-contact forces/torques. In *Proceedings of the IEEE International Conference on Robotics and Automation*. doi:doi:10.1109/ROBOT.2008.4543607
- Learned, R. E., & Willsky, A. S. (1995). A wavelet packet approach to transient signal classification. *Applied and Computational Harmonic Analysis*, 2(3), 265–278.
- Mallat, S. (2008). *A wavelet tour of signal processing: The sparse way* (3rd ed.). Springer: New York.
- Mianji, F. A., & Zhang, Y. (2011). Robust hyperspectral classification using relevance vector machine. *IEEE Transactions on Geoscience and Remote Sensing*, 49(6), 2100–2112.
- Nagata, K., Oosaki, Y., Kakikura, M., & Tsukune, H. (1998). Delivery by hand between human and robot based on fingertipforce-torque information. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems* (Vol. 2). doi: 10.1109/IROS.1998.727283
- Nakazawa, N., Kim, I., Inooka, H., & Ikeura, R. (2001). Force control of a robot gripper based on human grasping schemes. *Control Engineering Practice*, 9(7), 735–742.
- Nakazawa, N., Kim, I.-H., Inooka, H., & Ikeura, R. (1999). Force control of a robot hand emulating human’s grasping motion. In *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics* (Vol. 6, p. 774–779). doi:10.1109/ICSMC.1999.816649
- Peng, H., Long, F., & Ding, C. (2005). Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(8), 1226–1238.
- Rehman, A., Gao, Y., Wang, J., & Wang, Z. (2012). Image classification based on complex wavelet structural similarity. *Signal Processing: Image Communication, Special Issue on Biologically Inspired Approaches for Visual Information Processing and Analysis*, 28(8), 984–992. doi: 10.1016/j.image.2012.07.004
- Romano, J. M., Hsiao, K., Niemeyer, G., Chitta, S., & Kuchenbecker, K. J. (2011). Human-inspired robotic grasp control with tactile sensing. *IEEE Transactions on Robotics*, 27(6), 1067–1079.
- Sato, M., Poupyrev, I., & Harrison, C. (2012). Touche: Enhancing touch interaction on humans, screens, liquids, and everyday objects. In *Proceedings of the ACM Annual Conference on Human Factors in Computing Systems* (pp. 483–492). doi:10.1145/2207676.2207743
- Sidobre, D., Broquère, X., Mainprice, J., Burattini, E., Finzi, A., Rossi, S., & Staffa, M. (2012). Human-robot interaction. In B. Siciliano (Ed.), *Advanced bimanual manipulation* (Vol. 80, p. 123–172). Springer-Verlag: Berlin Heidelberg. doi:10.1007/978-3-642-29041-1_3
- Sweldens. (1995). The lifting scheme: A new philosophy in biorthogonal wavelet constructions. *Wavelet Applications in Signal and Image Processing*, 3, 68–79.

- Takubo, T., Arai, H., Hayashibara, Y., & Tanie, K. (2002). Human-robot cooperative manipulation using a virtual nonholonomic constraint. *International Journal of Robotics Research*, 21(5), 541–553.
- Tipping, M. E. (2001). Sparse Bayesian learning and the relevance vector machine. *The Journal of Machine Learning Research*, 1, 211–244.
- Vapnik, V. (1999). *The nature of statistical learning theory*. Springer: New York.
- Welling, M. (2005). Fisher linear discriminant analysis. *Department of Computer Science, University of Toronto*. Retrieved from <http://www.cs.huji.ac.il/~csip/Fisher-LDA.pdf>
- Widodo, A., Kim, E. Y., Son, J.-D., Yang, B.-S., Tan, A. C., Gu, D.-S., ... Mathew, J. (2009). Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine. *Expert Systems With Applications*, 36(3), 7252–7261.
- Xue, J.-Z., Zhang, H., Zheng, C.-X., & Yan, X.-G. (2003). Wavelet packet transform for feature extraction of eeg during mental tasks. In *Proceedings of the International Conference on Machine Learning and Cybernetics* (Vol. 1, pp. 360–363).

Wuwei He and Daniel Sidobre; CNRS, LAAS, 7 avenue du colonel Roche, F-31400 Toulouse, France; and Univ de Toulouse; UPS, LAAS; F-31400 Toulouse, France. Email: wuwei.he@laas.fr and daniel.sidobre@laas.fr.