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Master-slave hand system of different structures, grasp recognition by neural network and grasp mapping

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SUMMARY
This article is proposing a grasp recognition and grasp mapping method for a land mine clearance master-slave system. The system consists of a data glove and a powerful hydraulic hand. Because of the different structure of the master and slave hand a mapping from master grasp to slave grasp has to be implemented. The paper presents a grasp recognition method by Neural Network (NN) and a mapping method. The introduced mapping method allows the operator more intuitive grasping.

KEYWORDS: Master-slave; Robot hand; Grasp mapping; Grasp recognition.

1. INTRODUCTION

According to United Nations estimates, more than 100 million land mines lie buried around the world, causing 10,000 deaths and twice that many injuries annually. The most common demining technique used today is the manual method. It is a low-tech, high-risk, labor-intensive approach. There are different schemes for clearing a mine field. In Cambodia for example, two people traverse a mined field with slow, cautious steps. The first person, once alerted by the slow sweep of his metal detector, marks the spot where his partner will drop to the ground, delicately probing for whatever metallic object is buried below. It is very inefficient because battlefields are loaded with everything from tin cans to bombs. It is also very dangerous because a misstep can maim or kill. This manual method makes complete demining virtually impossible. New methods that increase demining safety and speed have to be found. We have focused on the development of mine detection robots since 1998[1–3]. Already four different robots were built in cooperation with the industry. The specialty of the newest robot that is currently being produced is the capability of mine removal. This particular robot will be equipped with a mine disposal robot hand that is being tested in our laboratory. The entire robot body as well as the robot hand is driven by a hydraulic system. The hand will be used to grasp mines and obstacles. The control strategy is preprogrammed or master-slave. The master-slave system is currently being tested. In this paper the master-slave system itself, the grasp recognition method and mapping are introduced.

Most master-slave hand systems presented in the literature like for example references [4] and [5] have the same or very similar structure and only direct mapping is applied. In contrast to this, in our laboratory we are using a master hand and a slave hand of much different structures and sizes. We found out that because of the structure differences between the master and the slave hand a direct mapping is not as effective. We introduce a new mapping method allowing the operator more intuitive grasping. In reference [6] an optical hand posture recognition was used for the purpose of robot control by human demonstration. In our research we are using the finger joint angular position information to identify the grasp. Our goal is to allow the human operator more intuitive grasping with a slave hand that is different to the operator own hand. Without applying the mapping presented the operator would have to move his hand in very inconvenient or physiologically almost impossible postures.

In the present paper we first describe the structure of the master and the slave system separately. Next the pulse modulation control Pulse Frequency Modulation (PFM) is presented only shortly since we have already described it in reference [7] at length. Next part of the present paper is the motivation for the grasp mapping. We explain why we use the mapping and what are its advantages. We give a brief description of different human hand grasps and possible robot hand grasps. Next, applying basic NN theory[8], the grasp recognition by NN is explained. The NN learning, its task and the grasp mapping is described at length. The problem of misclassification is tackled. Finally, experimental results are presented followed by conclusions.

2. MASTER-SLAVE SYSTEM

2.1. Master hand system

The master hand shown in Fig. 1 consists of a data glove and an exoskeleton. This data glove is equipped with 22 position sensors that allow detecting the angles of all human finger joints and also some angles of the palm. The position and orientation of the hand in space can be measured by a six d.o.f. sensor. The exoskeleton is equipped with five actuators

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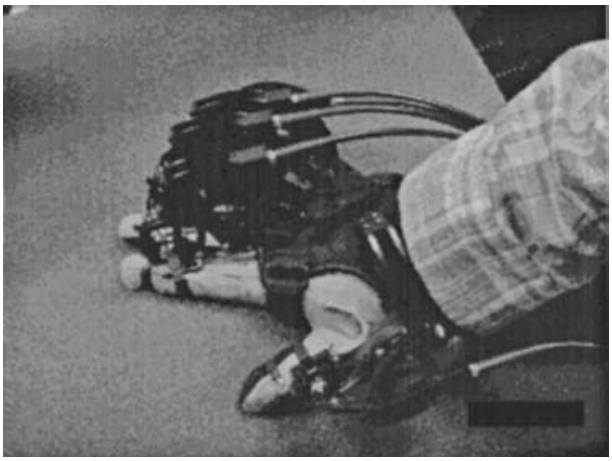


Fig. 1. Master hand system.

that, by applying traction on the pulleys, give the operator the sensation similar to touching an object. The master system can be accessed through *C++* routines. A virtual slave hand was programmed for visualization and VR (Virtual Reality).

2.2. Slave hand system

The slave hand shown in Fig. 2 is a four finger hand with all together nine d.o.f. Every finger has two joints. Additionally the palm can rotate around its normal. The ranges of the proximal and distal joints are 40° and 64°, respectively. The hand is driven by hydraulic cylinders. Four 2-position 2-way, solenoid, spring returned, normally closed valves connected in bridge, are used for every joint to allow abduction and adduction of the fingers. Each valve can only be switched ON or OFF and doesn't allow any other values. Linear valves were not used because of their heavy weight and size. Every joint of the hand is equipped with a linear potentiometer as position sensor. In the near future the fingertips will be equipped with force sensors. The position data of the potentiometer is read by an AD-converter and can be evaluated by a PC. The solenoid valves are connected to the PC by a digital output board. The needed electrical current is supplied by an external in-house made current amplifier. The AD-converter and the digital output board are PCI-interface boards. The oil pressure is supplied by a three-phase current hydraulic pump.

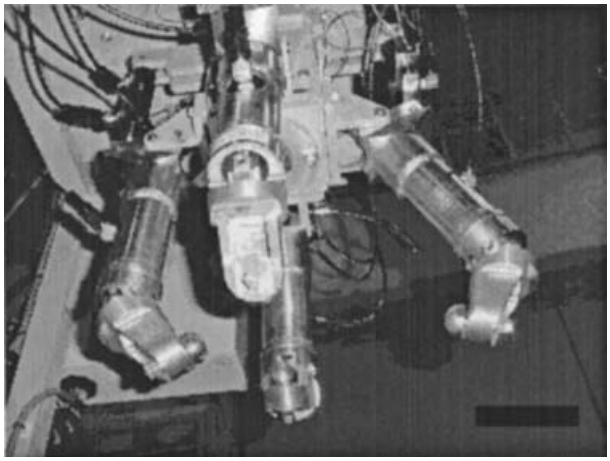


Fig. 2. Slave hand system.

The hand is controlled by a pulse frequency modulated (PFM) signal. To deal with the strongly nonlinear valve-cylinder system characteristics three PFM-converters are used. The first PFM converter is using a very short pulse width to allow smooth motion, however, it allows only low speed. The second PFM converter is using a bigger pulse width to allow fast motion. The resulting finger movement are, however, not as smooth as using the first PFM converter. The third converter is using even a bigger pulse width to allow high speed of the fingers.

3. GRASP MAPPING

The master hand and the slave hand have different structures. The master hand is a human hand equipped with a data glove with 22 position sensors. The slave hand is rotationally symmetric and has nine d.o.f. The structural differences don't allow a direct mapping from human hand sensors to robot hand actuators. For this reason we designed a NN grasp recognition and a grasp mapping unit as shown in Fig. 3.

3.1. Motivation for grasp mapping:

There are many situations where the operator is trying to control the hand in a way that is physiologically almost impossible if joint-to-joint mapping is used. An example is the two-finger grasp. If the operator tries to grasp an object with two fingers most naturally he uses his thumb and his index finger. Some people prefer to adduct the other fingers and some abduct the other fingers so as not to disturb manipulation. If joint-to-joint mapping is used this would mean that fingers F1 and F2 as in Fig. 4 of the slave hand would be used. This constellation is not optimal since these two fingers are acting at a 90° angle to each other. It is desirable to move fingers F1 and F3 or fingers F2 and F4. To move these two slave fingers F1 and F3 the operator has to use his thumb and his middle finger. This is maybe a little inconvenient but not impossible. The problem is that using fingers F1 and F2, one wishes to lift up the other two fingers so as not to disturb manipulation. This would mean that the operator has to move up his index and his ring finger which is not convenient and almost impossible to hold for long time. The other possibility to realize a two-finger grasp, that is to use fingers F2 and F4, is that the operator tries to grasp an object with his index and ring finger which is very unnatural and almost impossible. Some people prefer to adduct the fingers they don't need during the manipulation instead of stretching them out. This kind of posture is not possible with our slave hand since adducted fingers still disturb the object manipulation. To manipulate an object using the slave hand with a two-finger grasp without the operator needing to try unnatural or impossible human grasps, grasp mapping was introduced.

Another example of the usefulness of grasp mapping is when the operator is trying to grasp a circular object. From experiments with test persons we know that using a joint-to-joint mapping it is difficult to achieve a real circular grasp, because the operator has to adjust every finger

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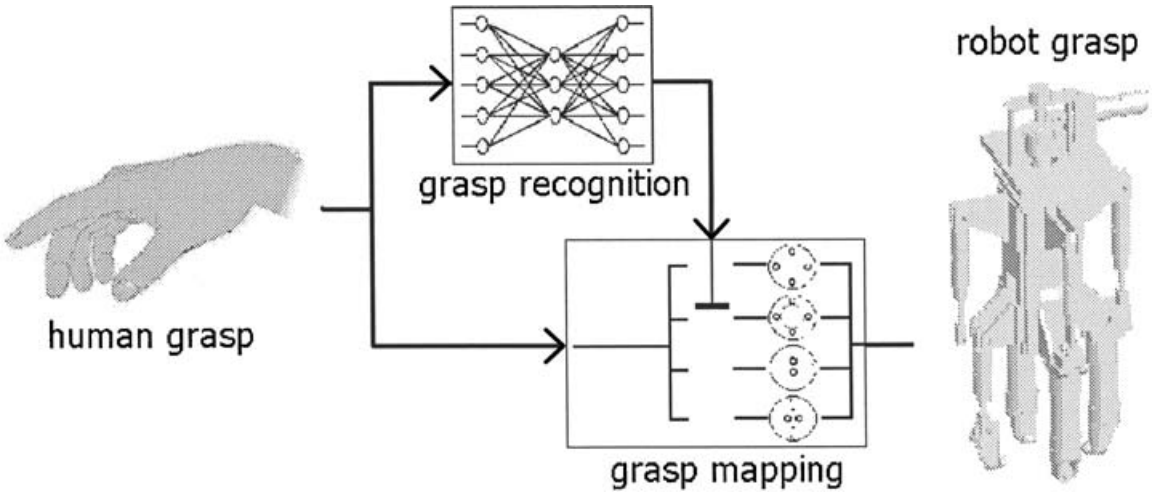


Fig. 3. Grasp mapping.

separately. Using mapping where every finger receives the same reference value consisting of mean values of the master hand joint values makes an exact circular grasp possible. Using this mapping the operator doesn't need to concentrate on every single finger but can focus fully on the task, the grasping. A circular grasp is especially important for mine grasping since most mines are round.

The grasp recognition unit automatically detects a grasp online. The mapping is also carried out online without operators intervention. This gives the operator the ability to intuitively grasp an object.

4. MASTER HAND GRASPS

The human hand is capable of many different grasps that were classified in reference [9]. There are only four human grasps used in this paper: *two-finger pinch grasp with other fingers adducted* as shown in Fig. 5a., *two-finger pinch grasp with other fingers stretched out* shown in Fig. 5b., *a square grasp with thumb on one side and other fingers on the other side of the square object* shown in Fig. 5c. and a *circular grasp* with all fingers grasping a round object.

5. SLAVE HAND GRASPS

Our slave hand is in comparison to the human hand very simple and therefore only few grasp types can be implemented. We concentrate on finger tip grasps only. In this paper we implement three grasps. These are *two-finger grasp using opposite fingers F1 and F3* as in Fig. 6c., *two-finger grasp using opposite fingers F2 and F4* as in Fig. 6d., and *all finger circular/square grasp* as in Fig. 6a,b.

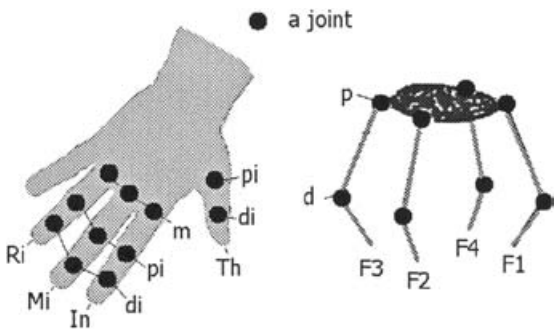


Fig. 4. Master and slave hand joint nomenclature.

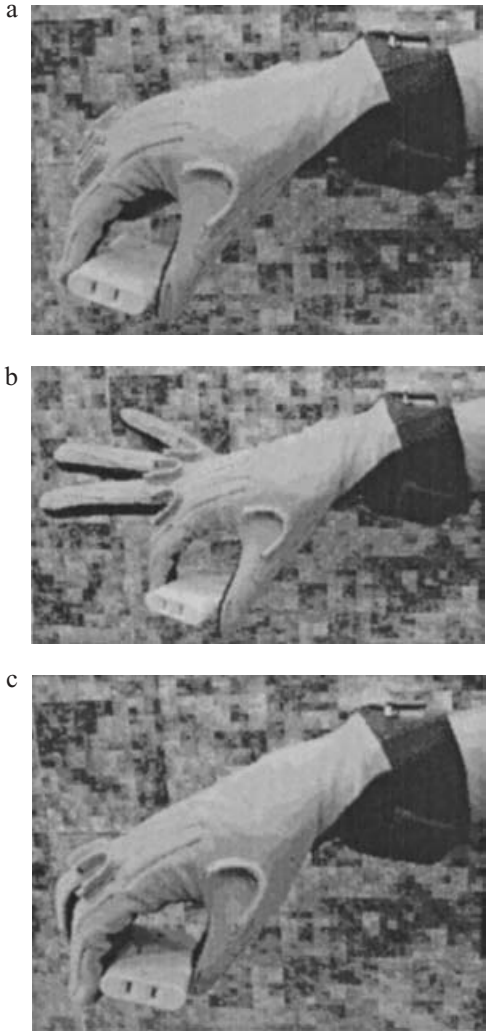


Fig. 5. Master hand postures.

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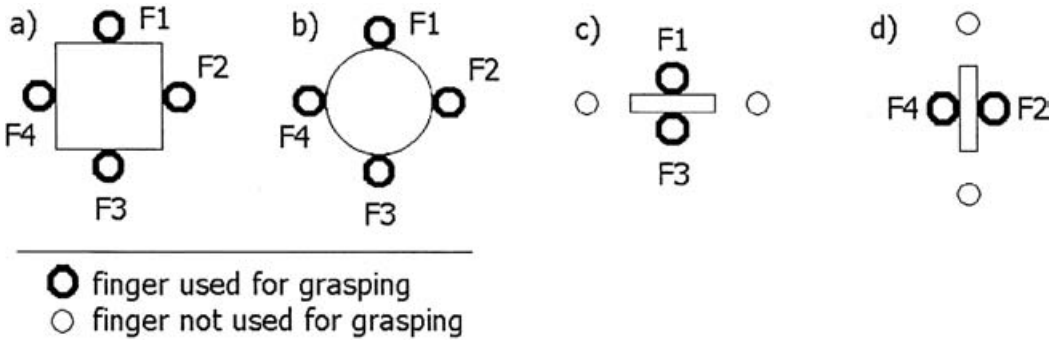


Fig. 6. Slave hand grasps.

6. NN CONTROLLER DESIGN

6.1. Grasp recognition and NN training

The data glove is equipped with 22 sensors out of which we send 9 signals to the slave hand. Eight signals feed the finger joints and one the rotatory wrist joint. In joint-to-joint mapping the human operator can move every robot finger independently. In this case the mean value of the human distal interphalangeal joint and the proximal interphalangeal joint is mapped to the distal joint of the robot hand. The human metacarpophalangeal joint is mapped to the proximal joint of the robot hand. In case of the thumb the human distal interphalangeal joint is mapped to the distal robot hand joint and the proximal interphalangeal joint is mapped to the proximal joint of the robot hand. The human little finger is not used for the control. Two sensors in the wrist of the data glove are mapped to the wrist of the robot hand.

The data of all data glove sensors for a particular hand posture defines this hand posture. This data can be written in a vector $V = [s_1, s_2, \ldots s_{22}]$. Since our program is using only eight data channels to move the fingers we use a reduced vector to represent a hand posture $V_R = [s_1, s_2, \ldots s_8]$. A human grasp type can be represented by a set of hand posture vectors. This set will differ from person to person. Even the same person will get a little bit different data every time he puts on the glove because the relative position between the operators hand and the data glove is a little bit different each time. To assure the universal validity of a data to represent a particular grasp a data set, i.e. a set of hand posture vectors $D_R = [V_{R1}, V_{R2}, V_{R3}, V_{Rn}]$ was taken. Taking a big set of vectors still doesn't cover all possibilities that might arise during operation. The operator may move his fingers slightly to another position that was not contained in the set but is not much different from a vector in the set. Our controller has to be able to generalize. To be able to provide generalization we used an NN as a controller. The vector set of hand postures was used to train the NN. The NN has eight inputs which is the length of the V_R vector. The output of the NN is a vector of the length three which is the number of grasps that the network should discriminate between. We distinguish between three different grasps as described in section 4.

The NN used is a two-layer network using log-sigmoidal neuron transfer function. There are eight inputs, five neurons in the hidden layer and three in the output layer. The learning algorithm is backpropagation.

6.2. NN controller usage and Grasp mapping

After the NN was trained it was used to switch the controller of the robot hand fingers. This switching can be called grasp mapping. A particular human posture V_R will be translated to a robot hand grasp R. Since the number of the human hand grasps is bigger than the number of the robot hand grasps the mapping is not injective.

There is a probability that the neural network misclassifies a grasp. If the misclassification is only temporary it can be prevented. This is implemented by time delaying the grasp classification signal by a first order element. There is also another situation when this signal delay is helpful. This is when the operator changes his hand posture from a grasp A to a grasp B and has to move his fingers through positions that constitute a different grasp C. Since the desired grasp is B and not C an immediate grasp mapping would cause unnecessary movements of the slave hand. If the operator moves his fingers fast enough the grasp C will be ignored.

In Fig. 4. the hand nomenclature is presented. The measured joints are marked with a black circle. The master hand consists of the Th (= thumb), In (= index finger), Mi (= middle finger) and Ri (= ring finger). The joints are m (= metacarpophalangeal), pi (= proximal interphalangeal) and di (= distal interphalangeal).

Table I shows the joint-to-joint mapping. Table II shows the two-finger grasp mapping and Table III shows the all-finger rotationally symmetric grasp mapping. To express the mean values of two or more joint angle values a function μ(jointA & JointB) was used.

7. EXPERIMENTS

To train the neural network a set of 200 master hand posture vectors was taken for each grasp type. The vector

Table I. Joint-to-joint master to slave mapping.

Master hand joint		Slave hand joint
Th_p Th_d	← →	$F1_p$ $F1_d$
In_m $\mu(In_{pi}$ & $In_{di})$	← →	$F2_p$ $F2_d$
Mi_m $\mu(Mi_{pi}$ & $Mi_{di})$	← →	F3p $F3_d$
Ri_m $\mu(Ri_{pi}$ & $Ri_{di})$	← →	$F4_p$ $F4_d$

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Table II. Grasp mapping: two-finger grasp.

Master hand joint		Slave hand joint
$\mu(Th_p \,\&\, Mi_m)$	$\leftarrow\rightarrow$	$F1_p$
$\mu(Th_d \,\&\, \mu(Mi_{pi} \,\&\, Mi_{di}))$		$F1_d$
$Const_{max}$	$\leftarrow\rightarrow$	$F2_p$
$Const_{max}$		$F2_d$
$\mu(Th_p \,\&\, Mi_m)$	$\leftarrow\rightarrow$	$F3_p$
$\mu(Th_d \,\&\, \mu(Mi_{pi} \,\&\, Mi_{di}))$		$F3_d$
$Const_{max}$	$\leftarrow\rightarrow$	$F4_p$
$Const_{max}$		$F4_d$

set consists of expected posture vectors in this grasp. The grasp data $D_R = [V_{R1}, V_{R2}, V_{R3}, \ldots, V_{Rn}]$, where $V_{Rn} = [s_{n1}, s_{n2}, \ldots s_{n8}]$, is shown in Fig. 7: *Two-finger grasp with other fingers adducted* in Fig. 7a, *two-finger grasp with other fingers abducted* in Fig. 7b, circular grasp in Fig. 7c, square grasp in Fig. 7d. The vertical (z) axis shows the angular displacement of a joint s_{nm}. The joints from 1 to 8 are marked along the x-axis. The y-axis shows the vector number from 1 to $n = 200$. As we can see the data of the circular and the square grasp are similar. Both grasps were regarded as the same grasp and mapped into the same rotationally symmetric grasp of the slave hand. After the neural network was trained with this data its values are not changed any more. During the actual operation the hand posture is read by the NN-controller, classified into a grasp and then a robot hand grasp is generated.

In the experiment the operator is first trying to pick up an object with his thumb and index finger. During this operation all other operator fingers are adducted. The robot hand is expected to use fingers F1 and F3 for grasping and abduct completely fingers F2 and F4 as to not to disturb. Next the operator releases the object and tries to grasp with all his fingers another object, this time a round one. The NN is recognizing a new hand posture and changes the master-to-slave mapping. This time all robot hand fingers receive the same reference and form a rotationally symmetrical grasp. Finally, the operator releases the object and grasps again using his thumb and index finger. Other fingers are abducted. The NN recognizes the hand posture and the robot hand fingers F1 and F3 abduct to their full extension as not to disturb the manipulation. The operator can move fingers F2 and F4 freely.

To prove the correct classification of the NN a different set of master hand data was taken for every grasp. The biggest possible noise that can occur is half a bit. The angle resolution

Table III. Grasp mapping: four-finger grasp.

Master hand joint		Slave hand joint
$\mu(Th_p \,\&\, In_m \,\&\, Mi_m \,\&\, Ri_m)$		$F1_p$
$\mu\{Th_d \,\&\, \mu(In_{pi} \,\&\, In_{di}) \,\&$	$\leftarrow\rightarrow$	$F1_d$
$\mu(Mi_{pi} \,\&\, Mi_{di}) \,\&\, \mu(Ri_{pi} \,\&\, Ri_{di})\}$		
Same as $F1_p$	$\leftarrow\rightarrow$	$F2_p$
Same as $F1_d$		$F2_d$
Same as $F1_p$	$\leftarrow\rightarrow$	$F3_p$
Same as $F1_d$		$F3_d$
Same as $F1_p$	$\leftarrow\rightarrow$	$F4_p$
Same as $F1_d$		$F4_d$

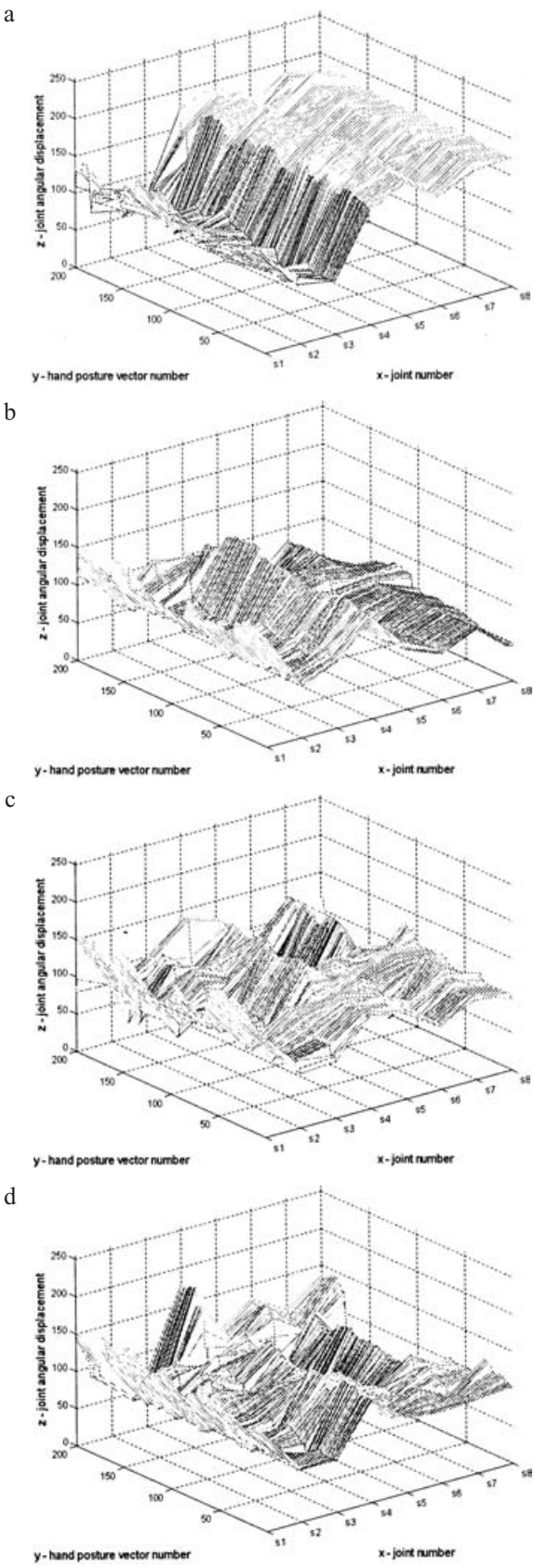


Fig. 7. Grasp data.

is 8 bit. The test set with a 3 bit noise was used to feed the NN and no misclassification occurred.

In another experiment the operator has to change from one grasp through another to a third grasp. Figure 8 shows the

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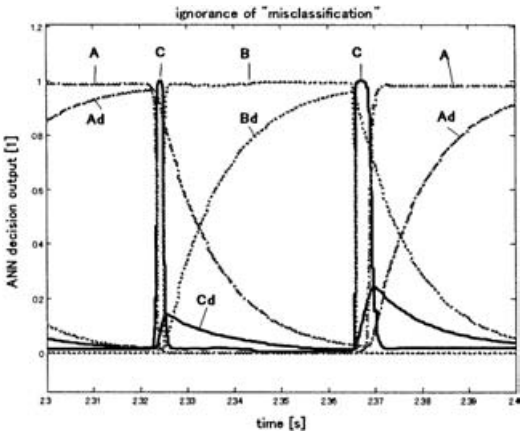


Fig. 8. Prevention of a temporal misclassification.

3 outputs of the NN that are representing the recognition level of three different grasps A, B and C. Also the same three delayed signals Ad, Bd and Cd are shown in this figure. Here the operator is changing from grasp A to B. The change implies an undesired temporal classification to grasp C. To avoid this ''misclassification'' a first order element delays the signal preventing it from growing bigger than other grasp signals unless the signal is present for longer time. We can see from the picture that indeed the delayed grasp Cd signal remains at all times smaller than the other delayed signals and therefore a ''misclassification'' doesn't affect the hand control.

In the next experiment that is similar to the previous one the operator is trying to change his grasp and move back to the grasp before. A fast change from one grasp to the other and back is an example of when the operator in a real manipulation makes a ''mistake''. The operator might unintentionally move his hand because of tiredness and or any other reason. The mistake was ignored by the system. The grasp type didn't change because of the built in time delay.

8. CONCLUSIONS

In this article we presented our master-slave system consisting of a data glove and an hydraulic robot hand. A master hand grasp recognition method using NN and a grasp mapping method were developed and successfully implemented. The motivation for using this kind of mapping was explained. Applied human grasps and possible robot grasps were introduces. The NN training was explained and experiment results discussed.

The concept can be extended to more grasp types as long as they aren't too similar. Training the NN with grasps that are too similar decreases the robustness of the system. Generally, the concept of grasp recognition and mapping can be applied to any master-slave system where the master and slave systems differ in structure.

LIST OF SYMBOLS

V	master hand posture vector
V_R	reduced master hand posture vector
D_R	set of reduced master hand posture vectors, master hand grasp
R	slave hand grasp
F1, F2, F3, F4	finger 1, 2, 3, 4 of the slave hand
Th	thumb
In	index finger
Mi	middle finger
Ri	ring finger
m	metacarpophalangeal
pi	proximal interphalangeal
di	distal interphalangeal
$\mu()$	mean value function

References

1. K. Nonami et al., "Humanitarian mine detection six-legged walking robot", *Proc. of the Third Int. Conf. on Climbing and Walking Robots (CLAWAR2000)* Madrid (October 2–4, 2000) pp. 861–868.
2. Q. Huang and K. Nonami, "Humanitarian mine detecting six-legged walking robot and hybrid neuro walking control with position/force control", *Mechatronics* **13**, 773–790 (2003).
3. K. Nonami et al., "Development and control of mine detection robot COMET-II and COMET-III", *JSME International Journal, Series C*. **46**, No. 3, 881–890 (2003).
4. T. Mouri and H. Kawasaki, ''Anthropomorphic robot hand: Gifu hand III", *ICCAS, 16–19*, Muju Resort, Jeonbuk, Korea (October, 2002) pp. 1288–1293.
5. M. Bouzit, "Design, implementation and testing of a data glove with force feedback for virtual and real objects telemanipulation", *Dissertation* (University of Pierre et Marie Curie, Nov 29, 1996).
6. S. B. Kang, "Robot instruction by human demonstration", *Dissertation* (Carnegie Mellon University Pittsburgh, Pennsylvania, December 1994).
7. T. Wojtara, K. Nonami et al., "Hydraulic master-slave land mine clearance robot hand controlled by pulse modulation" (submitted to *Mechatronics*).
8. C. M. Bishop, *Neural Networks for Pattern Recognition* (Oxford University Press, 2003).
9. M. R. Cutkosky, "On grasp choice, grasp models, and the design of hand for manufacturing Tasks", *IEEE Transaction on Robotics and Automation* **5**, No. 3, 269–279 (June, 1989).

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