ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Fast calibration of hand movement-based interface for arm exoskeleton control

Hugo Martin[1], Sylvain Chevallier[1] and Eric Monacelli[1]

1- Université Versailles Saint-Quentin
Laboratoire d'Ingénierie des Systèmes de Versailles
78140 Velizy, France
{firstname.lastname}@lisv.uvsq.fr

Abstract. Several muscular degenerative diseases alter motor abilities of large muscles but spare smaller muscles, e.g. keeping hand motor skills relatively unaffected while upper limbs ones are altered. Thus, hand movements could be be used to control an arm exoskeleton for rehabilitation and assistive purpose. Using an infra-red sensors (IR) based interface for the exoskeleton control, this paper describes the learning part of the system, endowing the system with a fast online calibration and adaptation abilities. This learning component shows good results and have been successfully implemented on the real system.

1 Introduction

Exoskeleton for upper limb could be used to enhanced or augment muscular capacity of the user [1]. They also offer a useful technology for rehabilitation [2] and assistance robotics [3], as described in this paper. In an assistive robotic context, arm exoskeletons aims at compensating the lack of mobility for persons with various muscular diseases, such as muscular dystrophy or neuro-degenerative disorders.

There is two key components: the exoskeleton technology and the interface. Most of the existing exoskeleton are not designed and suited for providing an assistive system. This paper uses the ESTA exoskeleton project [4], which provides a suitable orthosis for disabled persons. It had been design to compensate for motor deficiency in the upper limb, i.e. shoulder and elbow muscles. Several degenerative diseases affect the large muscles but leave the small ones with some motor capacities, such as wrists, hands and fingers.

Several control interfaces have been proposed in the literature. The most promising solution is to use direct recording of the muscle activity with surface electromyogram [1]. This approach overcomes the electro-chemical-mechanical delay, allowing very fast responses, e.g. for catching a ball. But this solution is not suitable for a motor-impaired person, precisely because her motor-based communication channels are not functional. Haptic devices, e.g. joystick, are not well suited because they require grasping the device for a long period, a sustained effort which is not feasible. It is possible to use head-pose estimation and facial expressions as commands [5, 6], but these approaches imply to set up a context detection to automatically stop the command when the user is speaking or having some social interactions.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

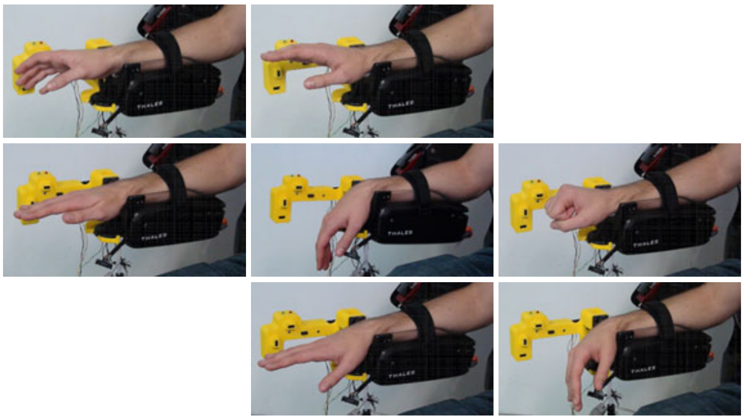

Fig. 1: The exoskeleton control rely on the recognition of seven hand positions. From left to right: right, up, forward, rest, backward, down and left.

The chosen solution of this paper is to rely on hand gestures for controlling the exoskeleton movements. Hand gesture recognition for Human Machine Interface [7] is an active research topic, but image-based approaches require computationally demanding algorithms and constraint environment, which are not compatible with the ESTA objectives. We propose to use a touchless interface based on IR-sensors, such as [8], but adapted to the motor capacities of persons affected by muscular dystrophy and neuro-degenerative disorders. Six hand positions are recognized to control the 4 degrees of freedom of ESTA exoskeleton, in a 3D euclidean space (see Fig. 1. A seventh hand position is used as resting state. There are 5 IR-sensors, 4 colinear placed on the right side and 1 orthogonal placed under the wrist.

2 Online calibration and adaptation algorithms

2.1 Learning schemes

Two calibration methods are proposed, using either a supervised scheme or an unsupervised one. The supervised and the unsupervised scheme rely on k-NN classifiers for associating hand positions with motor commands.

The supervised k-NN scheme uses an iterative approach, inspired from the edited k-NN [9]. Let $\Lambda = \{\Lambda_1, \ldots, \Lambda_C\}$ denotes the set of pre-selected exemplars used for the k-NN classifier with C classes and n exemplars in each class. Let $X = \{X_1, \ldots, X_M\}$ be a set of M examples. The X set is edited to remove the misclassified examples, which remove the ambiguous and outlier examples to separate the classification regions. This process is done iteratively on the examples X, i.e. X is partitioned in N equal subsets and each subset is classified, edited and added to the exemplar set Λ. The resulting exemplar set Λ is used for the evaluation.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence
and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0.
Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

The proposed unsupervised learning scheme is similar to the k-NN regression algorithm proposed by [10], rely on manifold embedding. Here, the unsupervised learning scheme is used for classification and needs only a few preselected exemplars Λ to classify the examples X. An example $x \in X$ is classified and then affected to its associated class, increasing the size of the training set Λ. Thus, only a small number of labeled exemplars is needed to classify the unlabeled examples. One can note that even if the examples label are available in our dataset, it is not used in the algorithm, except for its final evaluation.

2.2 Adaptation mechanisms

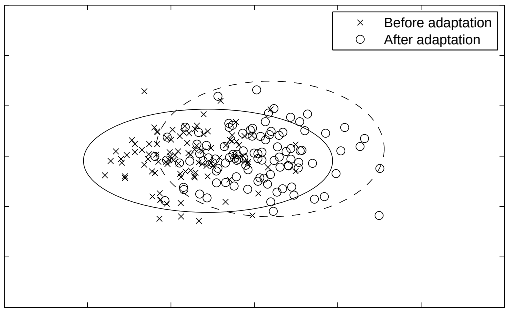

Fig. 2: Illustration of the adaptation mechanism. The "x" (and the plain ellipse) represent the exemplar set Λ after t iterations and the "o" (circled with a dotted ellipse) after $t' > t$ iterations.

The IR-sensor signal-to-noise ratio is greatly affected by (1) the ambient light and (2) the type and proximity of reflexive surface. This section describes the mechanisms handling these signal and noise variations.

The ambient light impacts the absolute value and the variance of the IR-sensors, thus an observed signal $x \in X$ could be expressed as $x = \mu(s + \sigma)$. The σ influence component is reduced with a low-pass filter and the μ component is removed by rescaling the IR-sensors values. The rescaling factor is evaluated online: it takes advantage of the fact that the left hand position leaves all the IR-sensors unobstructed, i.e. the hand does not affect the IR-sensors. The sensors thus send their maximum value, which depends on the current illumination, and it is possible to evaluate the rescaling factor.

The reflexive surface variations occurs when the user changes its arm and hand position, e.g. between two sessions or to find a more comfortable position. The hand movements could also change during a session as the user learns to improve its control of the system. To endow the system with an adaption mechanism to such variations, we implement an update of the exemplars used for the k-NN classifier. The adaptation mechanism updates regularly the set Λ,

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Method	Without rescaling	With rescaling
Supervised	77% ($\sigma = 8.9$)	90% ($\sigma = 2.7$)
Unsupervised	31% ($\sigma = 8.3$)	88% ($\sigma = 9.9$)

Table 1: Classification results of the supervised and the unsupervised learning schemes, with or without adaptation mechanisms.

e.g. every 100 iteration, by adding the current example x of class c to the set Λ_c and by removing the most distant (in the sense of x) exemplar $\lambda_i \in \Lambda_c$. To find the most distant exemplar λ_i, its index is determined with $\max_{i,\lambda_i \in \Lambda_c} d(x, \lambda_i)$. This adaptation mechanism endows the systems with the ability to evolve the Λ set, resulting in a slow adaptation of the training set, as illustrated on Fig. 2. This adaptation captures the variability of the user command.

3 Evaluation

The training dataset consist of labeled recorded from 12 subjects, in different illumination conditions and with different light sources, i.e. with natural and artificial lights. For each subject, several series of acquisitions (between 2 and 7) have been made for the 7 hand positions, resulting in 420 training examples. The algorithms are evaluated with ten-fold validation.

The Table 1 indicates the results obtained with the two learning scheme, standard deviation σ is also indicated. It appears clearly that the rescaling has a positive and important impact on the results. The supervised learning scheme gives very good results and could easily discriminate between the seven hand positions. The unsupervised learning scheme yields less accurate results but gives results largely above the chance level (14% for seven classes).

A sensitivity analysis is conducted on the k parameter, see Figure 3. This analysis showing clearly that for small k values ($k < 5$), the supervised scheme give its maximum accuracy. This is mainly due to the distribution of the sample in each class, some classes are very spread whereas others are very dense (particularly left and right movement classes). When increasing k, the dense classes could have a destructive effect, concentrating all the neighbors of a given test point.

The two learning schemes have also been evaluated on the ESTA system. The supervised classifier gives very good accuracy and is really reactive. This classifier is sensitive enough to generate micro-movements when the subject, going from one hand position to another, activate intermediate position.

The unsupervised learning scheme is very convenient to use, because it does not require a user-specific calibration. The initial exemplar set Λ have an important impact on the accuracy performance. After chosing carefully this Λ, the exoskeleton could be controlled very easily.

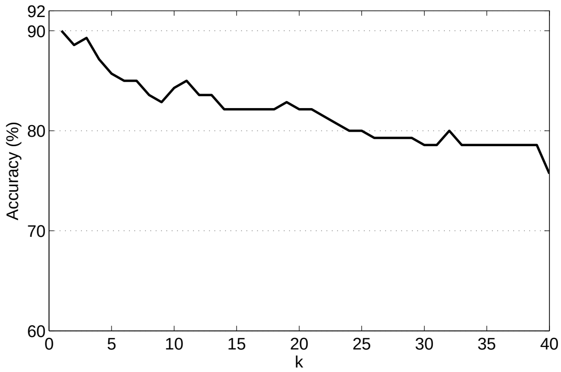

Fig. 3: Sensitivity analysis of the k value plotted against the accuracy for the supervised k-NN learning scheme.

4 Conclusion

This paper propose a touchless interface for the control of an arm exoskeleton in a assistive robotics context. The touchless interface rely on IR-based sensors to detect hand movement, and thus is affected by external factors (illumination) and user-specific factors (skin reflectance, characteristic hand movemenet). This contribution details the methods employed to reduce these two variabilities, using rescaling and adaptation.

As the calibration process could be tedious for the user, we propose an unsupervised training method, which does not require any calibration from the user. To obtain suitable results, the unsupervised calibration should be carefully initialized.

The perspective of this work are centered around the design of an hybrid interface. Such hybrid interface could be used to compensate the case where a user has a hand motor deficiency. We are thus investigating the coupling of the touchless interface with a brain machine interface.

Acknowlegdments

This work was support by the EADS Foundation and the Cerebraptic project.

References

[1] J. Rosen and J.C. Perry. Upper limb powered exoskeleton. *International Journal of Humanoid Robotics*, 4(3):529–548, 2007.

[2] E. Rocon and J. Pons. Introduction: Exoskeletons in rehabilitation robotics. volume 69 of *Springer Tracts in Advanced Robotics*, chapter 1, pages 1–20. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2011.

[3] B. Dellon and Y. Matsuoka. Prosthetics, exoskeletons, and rehabilitation [grand challenges of robotics]. *Robotics & Automation Magazine, IEEE*, 14(1):30–34, March 2007.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

[4] M. Baklouti, P. A. Guyot, E. Monacelli, and S. Couvet. Force controlled upper-limb powered exoskeleton for rehabilitation. In *Intelligent Robots and Systems (IROS)*, page 4202. IEEE, 2008.

[5] M. Baklouti, M. Bruin, V. Guitteny, and E. Monacelli. A Human-Machine Interface for assistive exoskeleton based on face analysis. In *Biomedical Robotics and Biomechatronics (BioRob)*, pages 913–918. IEEE, October 2008.

[6] S.A. Zerawa, C. Roesener, and A. Perner. Non-haptic interaction system. In *Industrial Electronics (ISIE), 2011 IEEE International Symposium on*, pages 1341–1346. IEEE, June 2011.

[7] A. Chaudhary, J.L. Raheja, K. Das, and S. Raheja. A survey on hand gesture recognition in context of soft computing advanced computing. In N. Meghanathan, B.K. Kaushik, and D. Nagamalai, editors, *Communications in Computer and Information Science*, volume 133, chapter 5, pages 46–55. Springer Berlin Heidelberg, Berlin, Heidelberg, 2011.

[8] D. Ryu, D. Um, P. Tanofsky, D.H. Koh, Y.S. Ryu, and S. Kang. T-less: A novel touchless human-machine interface based on infrared proximity sensing. In *Intelligent Robots and Systems (IROS)*, pages 5220–5225. IEEE, October 2010.

[9] D.L. Wilson. Asymptotic properties of nearest neighbor rules using edited data. *Systems, Man and Cybernetics, IEEE Transactions on*, 2(3):408–421, July 1972.

[10] O. Kramer. Unsupervised K-Nearest Neighbor regression. In *International Conference on Machine Learning and Applications*. IEEE, December 2011.