# Continuous Motion Decoding from EMG Using Independent Component Analysis and Adaptive Model Training

Qin Zhang, *Member, IEEE*, Caihua Xiong, *Member, IEEE* and Wenbin Chen, *Member, IEEE*

***Abstract*— Surface Electromyography (EMG) is popularly used to decode human motion intention for robot movement control. Traditional motion decoding method uses pattern recognition to provide binary control command which can only move the robot as predefined limited patterns. In this work, we proposed a motion decoding method which can accurately estimate 3-dimensional (3-D) continuous upper limb motion only from multi-channel EMG signals. In order to prevent the muscle activities from motion artifacts and muscle crosstalk which especially obviously exist in upper limb motion, the independent component analysis (ICA) was applied to extract the independent source EMG signals. The motion data was also transferred from 4-manifold to 2-manifold by the principle component analysis (PCA). A hidden Markov model (HMM) was proposed to decode the motion from the EMG signals after the model trained by an adaptive model identification process. Experimental data were used to train the decoding model and validate the motion decoding performance. By comparing the decoded motion with the measured motion, it is found that the proposed motion decoding strategy was feasible to decode 3-D continuous motion from EMG signals.**

## I. INTRODUCTION

Human-machine interface is important in human-centered robot operation, such as service robot and rehabilitation robot. In order to achieve accurate and natural robot movement, more and more research attempts to decode the user's movement intention to provide sufficient control command, and to guarantee the user's safety. In most conventional studies, binary command (on-off) were given to the robot, mainly through pattern recognition methods. Accordingly, the robot was triggered to move in a predefined manner. As described in [1], such decoding strategy is far from the intuitive control strategy in human motor control system, while continuous motion decoding is a viable solution generating intuitive motion control. Therefore, this work proposed a continuous joint motion estimation method from the muscle electric behaviors.

Upper limb movement is quite functional and important in human daily life, so this work focuses on the motion decoding of shoulder and elbow from multiple muscles eliciting such motions. Arm movement is a result of complex motion combination of multiple muscles. Muscle activities can be conveniently recorded using non-invasive electromyography (EMG) configuration, so called surface EMG (sEMG). The sEMG is a spatial and temporal summation of the action potentials generated by a number of motor units. It represents asynchronous properties with overlapping actions potentials generated in each muscle unit. We have attempted continuous motion decoding from a pair of agonist/antagonist muscles, but limited to decode single elbow flexion/extension [2]. Dario et al have deeply researched in proportional and continuous EMG decoding of 3-D wrist motions [3]. Artemiadis et al have done a series of work on EMG-based upper limb motion decoding for the tele-operation of robotic arm and achieved interesting performance [4][5]. Inspired by the concept of motion synergy and muscle synergy, they proposed to transfer both the joint motions and EMG signals from high-dimensional space into low-dimensional space through a dimension reduction technique, principle component analysis (PCA), and then decode joint motions from EMG in the low-dimension space. However, the non-stationarity, subject-specificity and crosstalk characteristics of EMG recordings are still unsolved problems [6].

As most of the muscles are combined into group or overlapped with each other even though they are structurally and/or functionally independent in anatomy, it is difficult in practice even to accurately locate recording electrodes on the muscles of our interest. As a result, the recorded multi-channel EMG signals are not only contaminated by kinds of internal and external noises but also mixed with adjacent muscle activities. Moreover, the problem of crosstalk is especially unavoidable when recording EMG signals from the bundles of muscles activating arm movement. Thereafter, we suppose it is possible to separate the EMG signals from various artifacts and this is helpful to improve the motion decoding accuracy. This technique is to resolve a blind source separation (BSS) problem. Independent component analysis (ICA) [7] is a typical BSS technique able to estimate the statistically independent source signals from their combinations. We proposed to combine the technique of ICA and adaptive model training method in order to make the EMG decoding more practically feasible in the presence of various artifacts in EMG recordings.

## II. METHODS

This work consists of three parts: data acquisition and processing, motion decoding modeling and motion decoding estimation. Experimental data were used for model training and estimation validation.

### A. Data acquisition and processing

As we focused on the shoulder and elbow motion in the 3-D space, the motion data and EMG data during performing drinking motion in seat situation were collected, as shown in

The authors are with the State Key Lab of Digital Manufacturing Equipment and Technology, Huazhong University of Science and Technology, Wuhan 430074, China qin.zhang@hust.edu.cn

978-1-4244-7929-0/14/$26.00 ©2014 IEEE

Fig. 1. Three rotational DoFs at shoulder joint and one rotational DoF at elbow were calculated by the marker position through a motion capture system (Vicon F20-MX3, Vicon Motion Systems Ltd, Oxford, UK) based on a kinematic model [8]. EMG signals were acquired from 6 muscles by an EMG acquisition system (Mega6000, Mega Electronics Ltd, Kuopio, Finland). The arm motion shown in Fig. 1 was repeated 10 times in order to have enough samples for model training and validation.

The reflective markers of motion capture system were placed according to the definition of a joint coordinate system [9]. The motion recording was sampled at 50 Hz. Six channel of EMG electrodes were respectively placed on the six predominant muscles which activate the above four DoFs, that is, Biceps, Triceps, Trapezius, Deltoid posterior, Deltoid anterior and teres major muscles. The EMG signals were amplified (gain 305) and sampled at 1KHz. EMG recordings were synchronized with the motions by the Vicon motion capture system.

Fig. 1. Illustration of the experiment setup. A round trip of one motion sequence was shown.

Both the EMG and motion data were saved in a computer and treated off-line in Matlab (The MathWorks, Version 7.10.0.499, 64-bit, 2010). The EMG signals were first low-pass filtered (Butterworth, 6th order, cutoff frequency 300 Hz). And then a Fast independent component analysis (FastICA) [10] was applied for separating the muscle activities of our interest from various artifacts and noises. FastICA is also called fixed-point ICA which is one of the ICA algorithm families and can be obtained by different ways. A FastICA algorithm based on negative entropy maximization was adopted in this study due to its advantages such as fast convergency and robustness [7]. As we know, ICA works under the hypothesis that the original signals are linearly mixed and have non-Gaussian distribution. In this study, although EMG signals usually have super-Gaussian or Gaussian distributions in different activation levels [11], the artifacts like crosstalks and motion artifacts, have non-Gaussian distribution [12]. Moreover, we preprocessed the EMG signals via PCA before performing ICA in order to discard irrelevant structures and satisfy the hypothesis of ICA algorithm.

After performing the PCA, the dimension of the EMG signals was reduced from six to three representing more than 92% of the total variance. Independent information was subsequently obtained via FastICA from the three principle components. The recorded multi-channel EMG signals (shown in Fig. 2) have some motion artifacts and noises especially in Biceps, Triceps and Deltoid posterior when arm returned to the initial position. In comparison, the components after FastICA shown in Fig 3 are more clean and represent close relation with the intuitive repeated motion.

In the next step, EMG features were extracted from the three independent components. Several time-domain and frequency-domain features were calculated and used to validate the performance of motion decoding. We found that mean absolute value (MAV) was able to provide good decoding results, and multiple features did not significantly improve the decoding accuracy. Thus, only MAV of the three components (shown in Fig. 3) was calculated every 10 ms within 15 ms-analysis window and applied to decode the arm motion in this work.

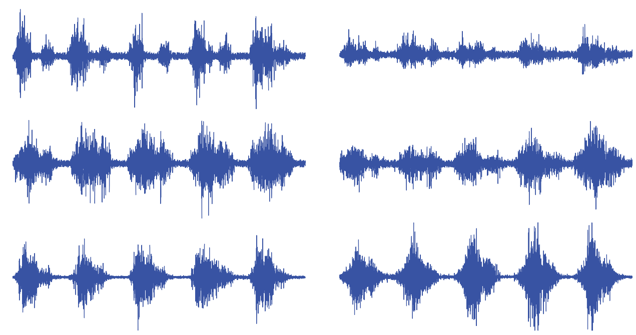

Fig. 2. EMG signals recorded from six dominant muscles activating shoulder and elbow motions in drinking movement. Five repeated motion sequences were shown here. The vertical horizon was unified within [-0.03, 0.03] mV. The muscles are respectively Biceps, Triceps, Trapezius, Deltoid anterior, Deltoid posterior and Teres major (listed from left to right and then from top to bottom).

For the motion data, the four joint angles were firstly calculated by the recorded marker positions based on the upper limb kinematic model [8]. And then the joint motion dimension was reduced from four manifold to two by PCA technique, with the two principle components describing 98.6% of the total variance. Until now, we obtained the EMG features and joint angles in lower-dimension to be the input and output respectively of the motion decoding model.

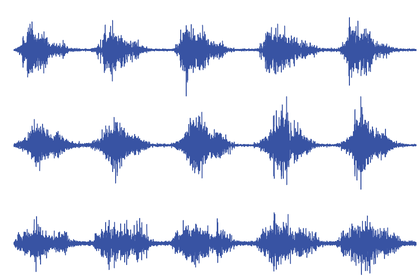

Fig. 3. The independent components were obtained by the FastICA following a PCA preprocessing. They were applied for motion decoding in a lower-dimensional space.

### B. Model structure

In order to to map the low-dimensional EMG features to the motion data, a Hidden Markov Model (HMM) was proposed as below:

$$\mathbf{x}(k) = \mathbf{A}(k)\mathbf{x}(k-1) + \mathbf{B}(k)\mathbf{u}(k-1) + \mathbf{w}(k) \quad (1)$$
$$y(k) = \mathbf{C}(k)\mathbf{x}(k) + \mathbf{v}(k) \quad (2)$$

where the previous state $\mathbf{x}(k-1)$ is transferred to the current state $\mathbf{x}(k)$ by a transfer matrix $\mathbf{A}(k) \in \mathbb{R}^{q\times q}$. Matrix $\mathbf{u}(k-1) \in \mathbb{R}^{n\times 1}$ contains the previous model inputs which are known at each current step. Matrix $\mathbf{B}(k) \in \mathbb{R}^{q\times n}$ relates the previous model input $\mathbf{u}(k-1)$ to the current state $\mathbf{x}(k)$. The measurement model relies on the state element $\mathbf{x}(k)$ as in (2). The $\mathbf{w}(k)$ in (1) and $\mathbf{v}(k)$ in (2) are respectively Gaussian white noise of the system model and the measurement sensor. All the states in $\mathbf{x}$ and the model coefficients contained in matrices $\mathbf{A}$ and $\mathbf{B}$ are combined into coefficient vector $\mathbf{\Theta}$ and will be determined during the next model training process.

### *C. Model training*

It is well known that the EMG signals have non-stationary property such that the motion decoding mapping can be considered as a time-variant system. In order to train the time-variant system, a Kalman filter (KF) with fading factor was previously proposed to adaptively identify joint torque from EMG during isometric muscle contraction [13][14] and decode single joint angle from EMG during dynamic muscle contraction [2]. This method was also applied in this study to estimate the joint angle from EMG which provided more accurate training results comparing with non-adaptive methods. The recursive algorithm of KF consists of two phases, prediction and correction.

In the prediction phase, the system is assumed to be stationary, the *a priori* state estimate at instant $k$, $\hat{\mathbf{\Theta}}^-(k)$, is calculated from the *a posteriori* state at previous instant k-1, $\hat{\mathbf{\Theta}}(k-1)$, according to (3). The estimate error covariance $\mathbf{P}(k)$ is propagated according to (4).

$$\hat{\mathbf{\Theta}}^-(k) = \mathbf{F}(\hat{\mathbf{\Theta}}(k-1), \mathbf{u}(k-1), 0) \quad (3)$$
$$\mathbf{P}^-(k) = \mathbf{D}(k)\mathbf{P}(k-1)\mathbf{D}^T(k)/\lambda \quad (4)$$

where $\mathbf{D}(k)$ is the Jacobian matrix of the partial derivations of the process transfer function $\mathbf{F}$ with respect to the variables involved in $\mathbf{\Theta}$.

In the correction phase, $\mathbf{K}(k)$ in (5) is called as KF gain that minimizes the *a posteriori* error covariance,

$$\mathbf{K}(k) = \mathbf{P}^-(k)\mathbf{H}^T(k)(\mathbf{H}(k)\mathbf{P}^-(k)\mathbf{H}^T(k) + \lambda)^{-1} \quad (5)$$

where $\lambda$ is a fading factor allowing to neglect some old measurements for enhancing the training performance. The choice of $\lambda$ must consider a tradeoff between tracking smoothness and accuracy, which is fixed at 0.997 as in our previous works [13][14]. $\mathbf{H}(k)$ is the Jacobian matrix of the partial derivations of the sensor transfer function $\mathbf{G}$ with respect to $\mathbf{\Theta}$.

$$\hat{\mathbf{\Theta}}(k) = \hat{\mathbf{\Theta}}^-(k) + \mathbf{K}(k)(y(k) - \mathbf{G}(\hat{\mathbf{\Theta}}^-(k), 0)) \quad (6)$$
$$\mathbf{P}(k) = (\mathbf{I} - \mathbf{K}(k)\mathbf{H}(k))\mathbf{P}^-(k) \quad (7)$$

When the actual measurement $y(k)$ is available, an *a posteriori* state estimate is generated by incorporating the measurement as in (6). An *a posteriori* error covariance estimate is obtained via equation (7).

## III. Results

To evaluate the proposed 3-D continuous motion decoding method, the experimental data were used to train the decoding model and validate the decoding performance. Firstly, in the signal processing step, the recorded EMG signals were processed by a PCA and FastICA technique resulting in three independent components. The EMG features were extracted from the three components. The joint angles were calculated from the motion capture systems based on the upper limb kinematic model. The joint angles were also reduced by PCA resulting in two-manifold motion space. Next, in the model training step, the three EMG features and the two angle components were respectively treated as the input and output of the EMG-based motion decoding model. The model was then trained by an adaptive KF using a part of experimental data. Last, in the cross-validation step, the rest experimental data were used to validate the motion decoding performance of the proposed method. Now, we got 2-D joint angles from the EMG signals and the trained decoding model. It is easy to calculate the joint angles in original 4-D space from the 2-D joint angles using principle components as presented in [5].

Fig. 4 shows the model training performance with the adaptive Kalman filter. The blue lines are the ground truth of the 4-DoF joint angles and the red are the trained angles using the proposed decoding model and model training method. Although 3-D arm motions include multiple muscles and multiple joints coordinating the muscle contractions and joint movements, the decoding model and the model training can still work well to provide good model training performance. Especially, the training model was used to decode the joint angles only using EMG signals. The estimated 4-DoF joint angles from EMG are shown in Fig. 5. We can find that the decoded joint angles are quite close to the ground truth. Considering the difficulties and status of continuous motion decoding only from EMG signals, this results indicate the feasibilities and effectiveness of the proposed motion decoding approach in 3-D motion decoding from multiple EMG signals.

## IV. Conclusions and perspectives

EMG signals are popularly used to decode human motion intention for robot movement control. Traditional motion decoding method uses pattern recognition to provide binary control command which can only move the robot in a predefined pattern. Moreover, few works have achieved significant progress in upper limb motion decoding in 3-D space other than those in 2-D space. In this work, we proposed a motion decoding method which can accurately estimate 3-dimensional continuous upper limb motion only from multi-channel EMG signals. In order to prevent the muscle activities of interest from motion artifacts and muscle crosstalks which especially obviously exist in the upper limb

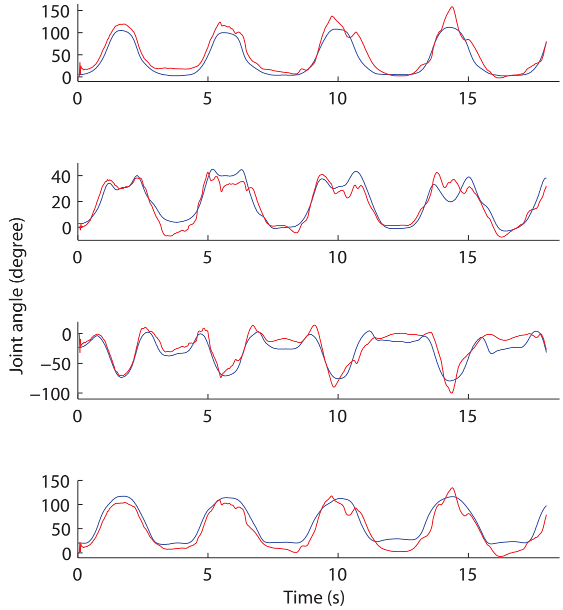


Fig. 4. Model training results. Blue: joint angle ground truth, red: estimated joint angle. From top to bottom: shoulder flexion/extension, shoulder abduction/adduction, shoulder rotation and elbow flexion/exension

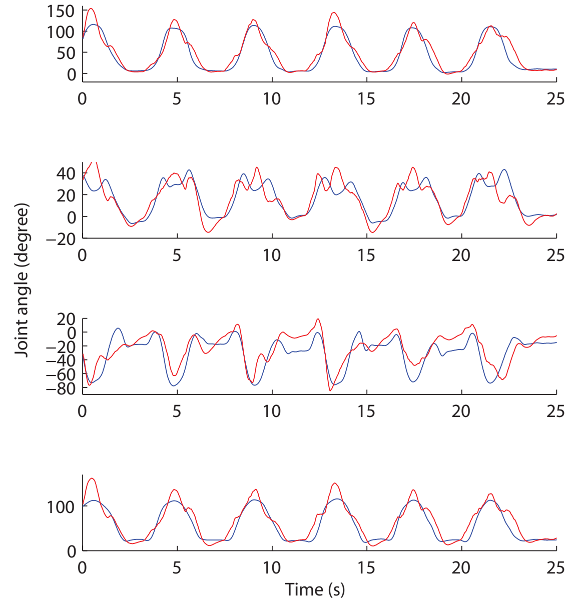


Fig. 5. Motion decoding only from EMG signals. Blue: joint angle ground truth, red: decoded joint angle. From top to bottom: shoulder flexion/extension, shoulder abduction/adduction, shoulder rotation and elbow flexion/exension.

motion, the FastICA was applied to extract the independent source EMG signals following a PCA-based signal preprocessing. The motion data was also changed from 4-manifold into 2-manifold by a PCA technique. A HMM was applied to decode the motion from the EMG signals after the model being trained by an adaptive model identification process. Experimental data were used to train the decoding model and validate the motion decoding performance. By comparing the decoded motion with the calculated motion from motion capture system, it is feasible to use our method to continuously decode the 3-D motions from EMG signals. Just as the EMG decoding was able to be used to control the robotic leg after a targeted muscle reinnervation (TMR) surgery [15], the accurate arm motion decoding from EMG is promising to be used for the prosthetic arm control combining with TMR technique in the future.

## ACKNOWLEDGMENT

This work was partly supported by the National Natural Science Foundation of China (Grant No. 51305148 and No. 51335004), National Basic Research Program of China (973 Program, Grant No. 2011CB013301), and National Science Fund for Distinguished Young Scholars of China (Grant No. 51025518).

## REFERENCES


[1] D. Farina, N. Jiang et al., The Extraction of neural information from the surface EMG for the control of upper-Limb prostheses: Emerging avenues and challenges, IEEE Transactions on Neural Systems and Rehabilitation Engineering, DOI 10.1109/TNSRE.2014.2305111, 2014.

[2] Q. Zhang, R. Hosoda, G. Venture, Human Joint Motion Estimation for Electromyography (EMG)-Based Dynamic Motion Control, in the proceedings of the 35th International Conference of the IEEE Engineering in Medcine and Biology Society, Osaka, Japan, July 3 - 7, 2013, pp. 21-24.

[3] N. Jiang, J. L. G. Vest-Nielsen et al., EMG-based simultaneous and proportional estimation of wrist/hand kinematics in uni-lateral trans-radial amputees, Journal of NeuroEngineering and Rehabilitation, 9:42, 2012.

[4] P. K. Artemiadis and K.J. Kyriakopoulos, EMG-Based Control Of a Robot Arm Using Low-Dimensional Embeddings, IEEE Transactions On Robotics, 26(2): 393-398, 2010.

[5] P. K. Artemiadis and K.J. Kyriakopoulos, A Switching Regime Model for the EMG-Based Control of a Robot Arm, IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics, 41(1):53-63, 2011.

[6] P. K. Artemiadis, EMG-based Robot Control Interfaces: Past, Present and Future, Advances in Robotics and Automation, 1:e107, 2012.

[7] A. Hyvarinen, J. Karhunen and E. Oja, Independent component analysis, John wiley and sons, INC., 2001.

[8] W. B. Chen, Human upper limb kinematics and anthropomorphic robot kinematic design and motion planning [D], Wuhan: Huazhong University of Science and Technology, 2012.

[9] G. Wu, F. C. T. van der Helm et al., ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motionłPart II: shoulder, elbow, wrist and hand, 38: 981-992, 2005.

[10] D. Staudenmann, A. Daffertshofer et al., Independent component analysis of high-density electromyography in muscle force estimation, IEEE Transactions on Biomedical Engineering, 54(4): 751-754, 2007.

[11] K. Nazarpour, A. H. Al-Timemy et al., A note on the probability distribution function of the surface electromyogram, Brain research bulletin, 2012.

[12] G. R. Naik , D. K. Kumar and M.Palaniswami, Hand gestures for hci using ICA of EMG, in Proceedings of the HCSNet workshop on Use of vision in human-computer interaction, Australian Computer Society, Inc., Sydney, Australia, pp. 67C72, 2006.

[13] Q. Zhang, M. Hayashibe and C. Azevedo-Coste, Evoked Electromyography-Based Closed-Loop Torque Control in Functional Electrical Stimulation, IEEE Transactions on Biomedical Engineering, 60(8): 2299 - 2307, 2013.

[14] Q. Zhang, M. Hayashibe et al., FES-induced torque prediction with evoked EMG sensing for muscle fatigue tracking, IEEE/ASME Transactions on Mechatronics, 16(5), pp. 816-826, 2011.

[15] L. J. Hargrove, A. M. Simon et al., Robotic leg control with EMG decoding in amputee with nerve transfers, The New England Journal of Medcine, 369:13, 2013.