Chapter 20
ICA as Pattern Recognition Technique for Gesture Identification:
A Study Using Bio-Signal

Ganesh R Naik
RMIT University, Australia

Dinesh Kumar
RMIT University, Australia

Sridhar Arjunan
RMIT University, Australia

ABSTRACT

In recent times there is an urgent need for a simple yet robust system to identify natural hand actions and gestures for controlling prostheses and other computer assisted devices. Surface Electromyogram (sEMG) is a non-invasive measure of the muscle activities but is not reliable because there are multiple simultaneously active muscles. This research first establishes the conditions for the applicability of Independent Component Analysis (ICA) pattern recognition techniques for sEMG. Shortcomings related to order and magnitude ambiguity have been identified and a mitigation strategy has been developed by using a set of unmixing matrix and neural network weight matrix corresponding to the specific user. The experimental results demonstrate a marked improvement in the accuracy. The other advantages of this system are that it is suitable for real time operations and it is easy to train by a lay user.

INTRODUCTION

Hand actions and maintained gestures are a result of complex combination of contraction of multiple muscles in the forearm. There are numerous possible applications that are based on reliable identification of hand gestures including prosthesis control, human computer interface and games. There are three major modes of identification of the hand gestures;

1. mechanical sensors e.g. - sensor gloves. Pavlovic et al (1997) noted that, ideally, naturalness of the interface requires that

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any and every gesture performed by the user should be interpretable. The use of glove requires an external device and it also needs the user to noticeably move their limbs in a way that may not be convenient, especially in case of amputees. For amputees, the control commands should be based on the intent of the movement rather than the mechanical movement.

2. vision data with video analysis (Rehg & Kanade, 1993; Schlenzig, Hunter, & Jain, 1994). The state of the art in vision-based gesture recognition is far from providing a satisfactory solution to this problem. A major reason obviously is the complexity associated with the analysis and recognition of gestures. The video sensing is dependent on lighting conditions and unsuitable for very small gestures.
3. muscle electrical activity (Cheron, Draye, Bourgeios, & Libert, 1996; Koike & Kawato, 1996). Surface Electromyography (sEMG) is the electrical recording of the muscle activity from the surface. It is closely related to the strength of muscle contraction and an obvious choice for control of the prosthesis and other similar applications.

Many attempts have been made to use sEMG signal as the command to control the prosthesis (Doerschuk, Gustafon, & Willsky, 1983; Wheeler & Jorgensen, 2003), but to obtain a reliable command signal, the muscle needs to have high level of contraction and with only one primary muscle being active. These techniques are not suitable for gestures where the muscle activity is small and there are multiple muscles active simultaneously such as during maintained hand gestures. This is largely attributable to the high level of cross-talk and low signal to noise ratio, both of which are more significant when the muscle activation level is low. To reliably identify the small movements and gesture of the hand, there is a need to decompose sEMG into muscle activity originating from the different muscles. Spectral and temporal filtering is not suitable for this because of overlapping spectrum and simultaneously active muscles. Blind source separation (BSS) techniques have recently been developed and these provide a solution for such a situation.

BSS techniques such as Independent Component Analysis (ICA) have found numerous applications in audio and biosignal processing disciplines. ICA of sEMG has been proposed for cortical activation of arm, which is outer portion related to arm-movement combinations in 2000 (M. McKeown, 2000). Mckewon and Radtke (2001) demonstrated a method for Phasic and Tonic Coupling between Electroencephalogram (EEG) and sEMG using ICA. Decomposition of sEMG into motor unit action potentials (MUAP) originating from different muscles and motor units has been reported in 2004 (Nakamura, Yoshida, Kotani, Akazawa, & Moritani, 2004). The authors have demonstrated the separation of sEMG using ICA into individual muscle activity for the hand gesture identification (Naik, Kumar, & Palaniswami, 2008; Naik, Kumar, Singh, & Palaniswami, 2006; Naik, Kumar, Weghorn, & Palaniswami, 2007). Other researchers have also demonstrated the use of ICA for separation of other biosignals such as EEG (T.-P. Jung et al., 2000; T. P. Jung et al., 2000). The approaches of Jung et al (T.-P. Jung, et al., 2000; T. P. Jung, et al., 2000) and (Djuwari, Kumar, Naik, Arjunan, & Palaniswami, 2006) are based on using the mixing matrix as an indicator of the relative location of the active sources and these remain unchanged for an individual. This overcomes the magnitude and order ambiguity associated with ICA. One difficulty associated with ICA is that it is an iterative process and the initialisation is random in nature. Most of the ICA algorithms use machine learning based approach in estimating the sources. Because of this reason, the outcome of the separation has a randomness associated with it and the overall performance is not optimum. This results in reduced reliability when the separated signals are classified.

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