Recognition of Upper Limb Movements for Remote Health Monitoring

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***Abstract*—In this paper we present two methodologies based on a systematic exploration to recognize three fundamental movements of the human forearm (extension, flexion and rotation) performed during an archetypal activity of daily-living (ADL) - 'making-a-cup-of-tea' by four healthy subjects and stroke survivors. The recognition methodologies have been further implemented in hardware (ASIC/FPGA) which can be embedded on a resource constrained WSN node for real-time detection of arm movements. We propose that these techniques could be used as a clinical tool to assess rehabilitation progress in neurodegenerative pathologies such as stroke or cerebral palsy by tracking the number of times a patient performs specific arm movements (e.g. prescribed exercises) with the paretic arm throughout the day.**

***Index Terms* — Clustering, WSN, CORDIC, ASIC, FPGA, movement recognition.**

I. Introduction

With a large number of stroke survivors in the world suffering from physical and cognitive disabilities, there is a strong requirement to improve the ambulatory care model within the home settings for achieving enhanced rehabilitation at reduced costs [1]. In this research work, we look into the domain of upper limb rehabilitation by detecting specific upper limb movements during activities of daily living (ADL). The three movements investigated, along with examples of their daily occurrence, were: extension/flexion of the forearm (reach and retrieve object); rotation of the forearm about the elbow (drinking action); and rotation of the arm about the median axis (opening a door, using a key or pouring action). These movements were chosen since they comprise a significant proportion of the activities performed with our upper limb in daily life [2]. The development of wireless low-cost miniaturized, wearable sensors has enabled recording of kinematic movement in natural environments over long durations thereby aiding in unobtrusive patient monitoring using a minimal number of sensors. In view of its long term operability it is imperative to choose low complexity data processing techniques that are executed on the sensor nodes itself, to yield energy efficient solutions [3]. We implement two approaches to recognize the arm movements – (1) clustering and minimum distance classifier and (2) tracking the orientation of the inertial sensor and mapping the transition in the orientations to the investigated movements. We further implement the two arm recognition methodologies on an ASIC and FPGA, which can be embedded on a resource constrained wireless sensor node (WSN) for real-time operations. These are discussed briefly in the following section.

For this study, movements are performed by four healthy subjects and four stroke survivors, in two phases – the subjects perform multiple trials of the three enlisted movements in a controlled environment representative of a '*training*' or '*exercise*' phase. The subjects then perform repeated trials of an archetypal activity of '*making-a-cup-of-tea*', which includes multiple occurrences of extension, flexion and rotation of the forearm, representative of the '*testing*' or *ADL* phase. Data was collected from a wireless tri-axial accelerometer and gyroscope, placed on the dominant wrist during the experiments.

II. Methodology And Results

A. Clustering & Minimum Distance Classifier

The *training* data are represented by a ranked set of 30 time-domain features. Using the sequential forward selection technique, for each set of feature combinations three clusters are formed using *k*-means clustering (*k*=3) followed by 10 runs of 10-fold cross validation on the *training* data to determine the best feature combinations. The movements from the *ADL* phase are associated with each cluster label using a minimum distance classifier in a multi-dimensional feature space, comprised of the best ranked features, using the Euclidean or Mahalonobis distance as the metric [2]. The process is further illustrated in Fig. 1.

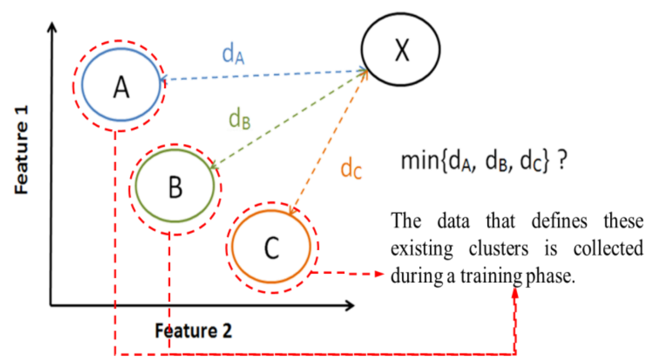

Fig. 1. Illustration of the minimum distance classifier. A, B and C represent the three movements performed in the training phase and X represents the test dataset in the respective feature space.

The three movements were detected with an overall average accuracy of 88% using the accelerometer data and 83% using the gyroscope data across all healthy subjects and arm movement types. The average accuracy across all stroke survivors was 70% using accelerometer data and 66% using gyroscope data.

B. Sensor Orientation

The three movements are recognized by accurately mapping six predefined standard orientations of a tri-axial accelerometer located near the wrist, to the corresponding arm movements investigated. The arm movements are inferred by detecting transitions between the sensor orientations incurred during an activity. A sample transition between two pre-defined orientations, as shown in Fig. 2, demonstrates a drinking activity. Our experimental results show that the proposed methodology can independently recognize the three investigated movements with accuracies in the range of 91-99% for healthy subjects and 70%-85% for stroke patients [4].

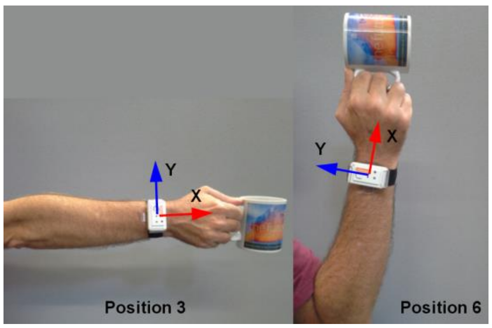

Fig. 2. Transition from Position 3 to Position 6, corresponding to a drinking type of activity, with the sensor worn on the right arm.

C. Hardware design

The clustering based approach has been implemented as an ASIC chip which can be embedded on a wireless sensor node (WSN) platform for long-time continuous detection of arm movements in real-time. The feature computation, cluster formation on the *training* data (being relatively time and memory intensive) were done in an offline mode (in software). The computation of the selected features on the *testing* data and the minimum distance computation (Euclidean) of the features from the pre-computed cluster centroids was done in hardware for real-time implementation. The arithmetic operations involved in computing the features on the *testing* data were realized using the different transcendental functions of the CoOrdinate Rotation Digital Computer (CORDIC) algorithm [5]. The design was synthesized using ST130 nm technology library at 20 MHz clock frequency to test its functionality at high speed. The synthesized design occupied an area of 347K (2-input NAND gate equivalent) with a dynamic power consumption of 25.9 mW.

The approach based on sensor orientation was coded in HDL and synthesized on the Altera DE2-115 FPGA board. For real-time operation as shown in Fig. 3, interfacing between the streaming sensor unit, host PC and the FPGA was achieved through a combination of Bluetooth, RS232 and an application software developed in C# using the .NET framework to facilitate serial port controls. The synthesized design used 1804 logic elements and recognised the performed arm movement in 41.2 µs, @50 MHz clock on the FPGA. The detected movements were displayed on a seven segment display in real-time.

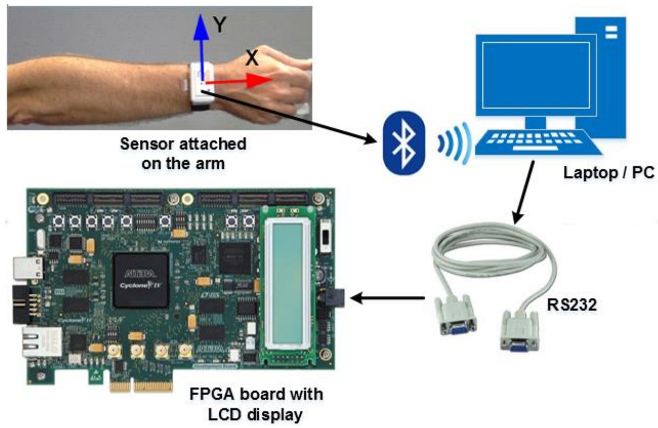

Fig. 3. Setup for the real-time recognition of arm movements using the sensor orientation approach.

III. Conclusion And Future Work

In view of the achieved results, the clustering based approach and the orientation based approach can be conveniently used for detecting arm movements in daily life. The clustering based approach can be conveniently used to include any other category of movements depending on the clinical requirements and hence has been developed as an ASIC. The implementation of the orientation approach does not use any memory element and avoids the overheads of complex data processing involved in any standard activity recognition system. Although implemented on FPGA, the salient features of the architecture makes it amenable for developing it as a low-power ASIC chip which can be embedded on a sensor platform along with other vital components such as A/D converter and a de-noising circuit to detect real-time arm movements for long-term continuous monitoring. Enumerating occurrences of these movements over time can indicate rehabilitation progress since the patient is more likely to repeat these movements as their motor functionality improves.

References

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