Task independent identification of sensor location on upper limb from orientation data

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***Abstract*— In this paper we describe a novel method for sensor placement identification, and demonstrate the effectiveness of this method on an upper limb neuroprothesis for tremor suppression under a variety of tasks. Our objective is to facilitate long-term tremor monitoring; tremor is the most prevalent movement disorder. Two assumptions are made: 1) movement and tremor demonstrate an additive effect further down the kinematic chain; 2) most applications have chained or fixed sensor locations. These assumptions justify obtaining absolute location through identifying relative location and thus to allow us to simplify the classification algorithm. Seventeen tasks were performed by patients suffering from essential tremor or Parkinson's disease. Ten features were found that resulted in 98.30% average accuracy (min: 92.31%; max: 100%) for the best configuration, irrespective of the task being performed. The method presented here is an important step towards more user-friendly and context-aware neuroprostheses for tremor suppression and monitoring, and facilitates the use of wearable sensors by non-trained personnel.**

I. INTRODUCTION

Pathological tremor is the most common movement disorder [1], and encompasses all types of tremors that impair motor performance (e.g., parkinsonian tremor and essential tremor [2]). Patients suffering from pathological tremor experience severe functional disability; 65 % [3] of tremor patients report serious difficulties performing activities of daily living (ADL) [1], [2], [4]. In this article we refer to pathological tremor as tremor. To enable the long-term monitoring of tremor patients, and to increase the adaptability of neuroprosthetics we need to be aware of the context and facilitate the donning and doffing. Context awareness would enable us to monitor both the evolution of the therapy, with or without the interaction with a neuroprosthetic, and the evolution of the tremor. Lately several researchers have demonstrated the ability to use wearable sensors for long-term data collection [5] and to quantify symptom severity in parkinsonian patients [6]–[10]. MIMUs (Magnetic and Inertial Measurement Units) have been proposed for use in tele-health and telerehabilitation solutions over the last decade, but have not yet been able to reach the end-consumer in great numbers. Weenk et al. argued that facilitating the donning and doffing could in part resolve this issue [11]. To our knowledge, little or no research has been done to automatically identify sensor locations on the body. We could only find one study [12] that looked at sensor placement identification in tasks other than walking. They reported 85 % accuracy in determining sensor location of 4 sensors, and needed a 6 minute data window to achieve this, in healthy subjects. The majority of ADLs however are shorter in duration, and it is unlikely that a patient will repeatedly endure such a lengthy calibration period. Other studies predominantly focused on sensor placement on the lower limbs and started from the hypothesis that the subject would be walking [11]–[14] . All this work has been based on accelerometer data. In an attempt to make their algorithm less dependent on sensor location and orientation, Weenk et al. were the first to complement accelerometers with gyroscopes [11]. They did so under the assumption that the body is a link of rigid body segments and that angular velocity is invariant of location on a rigid segment. Weenk et al. furthermore took advantage of the specific characteristics of walking and made assumptions related to the linearity of the direction of travel. The latter was subsequently used to transform from local to global sensor orientation. Unfortunately, no upper limb tasks exist that contain similar stable and repetitive characteristics, nor can it be expected of patient populations to always perform a certain motion in a standardized manner. Movement disorders can severely disrupt task execution to the extent that dominant direction is concealed by involuntary movement. Here we present a novel method to automatically identify relative sensor location on the upper limb. Because in many health and biomechanics applications sensors are used in chains or on fixed locations, we focus on relative sensor location. We start from the hypothesis that movement and tremor are more pronounced distally. We demonstrate that a basic classification method, that does not require training, can identify sensor location with high accuracy over a wide variety of tasks. Using orientation data we are thus able to identify sensor location, enabling us to later derive context information or biomechanical and physiological parameters with minimal bandwidth.

II. MATERIALS AND METHODS

A. Subjects

A group of 13 patients affected by essential tremor and Parkinson disease was recruited for this study. The patients were diagnosed by the neurological personnel of the Hospital 12 de Octubre and continued taking their regular medications at the time of the recordings. Informed consent was obtained

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from all patients prior to starting data collection. Approval for this study was obtained through the Ethics committee of the Hospital 12 de Octubre, granting its accordance to the Declaration of Helsinki.

B. Protocol

Patients were asked to perform 5 repetitions of a series of activities of daily living (ADL) at self-chosen speed, in the same manner as they would execute them at home. The tasks were identified from the literature of functional analysis in both healthy subjects [15] and tremor patients [16]. In addition to the ADLs patients were also requested to perform a set of functional movements that have been used in sensor-to-body calibration [17]–[19]. A 40 second resting trial was also recorded (task 13). An overview of the tasks is provided in Table 1.

C. Instrumentation

We used 4 MIMUs (Tech MCS, Technaid S.L., Madrid, Spain) incorporating tri-axial accelerometers, gyroscopes, and magnetometers to measure upper limb kinematics (11x26x36 mm; sampling rate: 100 Hz). Double sided hypo-allergenic tape was used to attach the sensors to the hand, distal forearm, proximal forearm (near the olecranon process), and distal humerus. An onboard extended Kalman fusion algorithm provided the orientation data. Proper alignment between sensor axes and anatomical axes was ensured upon placing the MIMUs. The four sensor configuration is based on the current design of the neuroprothestic presented in [20]. In addition to this configuration, we also tested two subsets more commonly used in biomechanics with only one sensor per segment (hand, forearm, and humerus). Two three sensor configurations were adopted: one where the distal forearm sensor is preserved; and one where the sensor is placed proximally on the forearm.

D. Data analysis

The orientation data from the MIMUs is decomposed using the Poisson equation to extract the angular velocity $[\dot{\theta}]$ [21]:

$$[\dot{\theta}] = [\dot{R}][R]^{-1} \tag{1}$$

where $[\dot{R}]$ represents the rate of change of the direction cosines and $[R]^{-1}$ corresponds to the body attitude. Based on pilot work on a mechanical mockup and healthy subjects [22] we selected 18 candidate features (Table 2). To ensure robustness against incorrect placement, the selected features are orientation invariant; we rectified the sensor data and combined information across all axes $(|x|, |y|, |z|)$. To enhance robustness across various intensities of tremor (from absent to severe) we used ranked values, at the cost of sacrificing the distance between the raw values. The basis of our approach is the assumption that the kinematic chain comprises an additive effect of movement on individual segments, i.e. movement of proximal segments is to an extent embodied in more distal segments. This pattern is also observed in tremor, often being more noticeable at distal than at proximal segments.

We use ranking as a classifier, instead of more complex structures that would require training. Ranking has a very low computational cost, making it ideal for integration in portable electronics. An additional advantage is that the chain of sensors can be modified without the need for retraining or changing between classifiers. The only requirement when using ranking is that the configuration (segments at which sensors will be attached) is known beforehand. Classification accuracy is expressed as the ratio of on-diagonal elements in the confusionmatrix to the total number of sensors. Values range between 1 and 0, with perfect classification corresponding to 1.

TABLE I

ADLs AND FUNCTIONAL TASKS PERFORMED BY ALL PATIENTS

1. Answering a phone	9. Elbow flexion
2. Buttoning a coat	10. Wrist circumduction
3. Brushing teeth	11. Opening and closing a food container
4. Combing hair	12. Pronation-supination
5. Cutting a steak	14. Drinking
6. Dialing a phone number	15. Signing a form
7. Wrist flexion	16. Reading a book
8. Eating with a fork	17. Opening and closing the door

TABLE II

CANDIDATE FEATURES FOR CLASSIFICATION OF SENSOR LOCATION

Feature	Feature base		
	Disp.	Vel.	Acc.
$\sum(Max(\|x\|, \|y\|, \|z\|))$	**1**	5	9
$\sum(RMS(\|x\|, \|y\|, \|z\|))$	**2**	**6**	10
$\sqrt{RMS(\|x\|, \|y\|, \|z\|)}$	**3**	**7**	11
$\sum(var(\|x\|, \|y\|, \|z\|))$	**4**	**8**	12
$\sum(Eigenvalues\ of\ covariance\ Matrix)$	**13**	**15**	17
$\sum(Principal\ component\ coefficients)$	**14**	16	18

III. RESULTS

Fig. 1 summarizes the results of the various features for the three configurations tested; results are grouped over all tasks, excluding the resting trial. A cutoff was made at 90 % accuracy, since lower levels of accuracy were deemed not useful in practice. Ten features remained (marked in bold in Table 2), which where subjected to a one-way anova to identify if there was a significant difference between them. No significant difference was observed between these ten features, when grouping the tasks for each configuration used ($p > 0.01$). Therefore, in what follows, we present average performance across the ten selected features.

Fig. 2 demonstrates the ability to identify the sensor location with respect to the task being performed. The various tasks are shown on the horizontal axis, the average accuracy of the features is depicted on the vertical axis. In rest (task 13) the accuracy is around 50 %, as can be expected. Other tasks with lesser performance (average

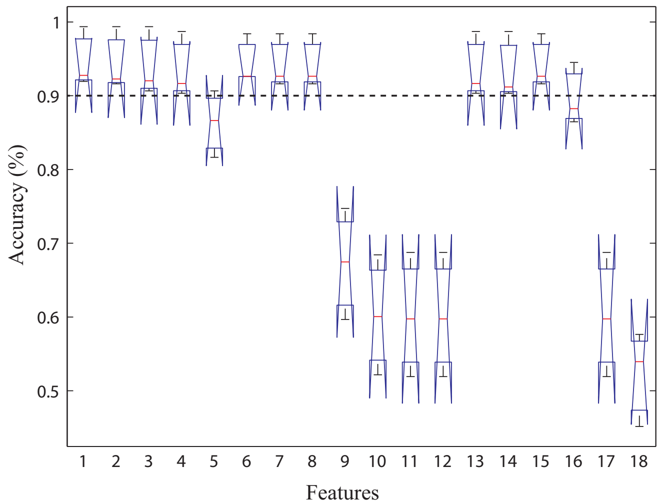

Fig. 1. Accuracy of each feature across all tasks and configurations.

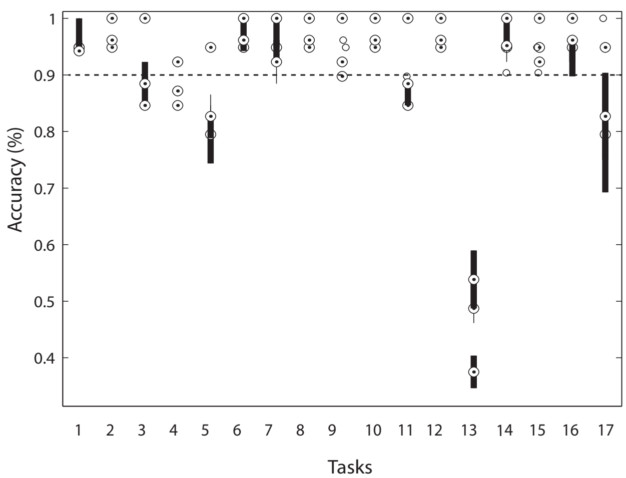

Fig. 2. Average performance of 10 selected features for each task.

accuracy of at least one configuration < 90 %) are turning a doorknob (task 17), opening and closing a Tupperware container (task 11), cutting a steak (task 5), combing hair (task 4) and buttoning a coat (task 3). Average accuracy of the ten features over all tasks, excluding the resting trial, are 91.77 % for the four MIMU configuration, 98.30 % for the three sensor configuration excluding the proximal forearm sensor, and 90.83 % with three sensors, where the forearm sensors was placed near the elbow. When the tasks with poorer performance (tasks 3,4,5,13,17) are all excluded, the average accuracy increases to respectively 94.13 %, 99.19 % and 93.55 %. The average maximal accuracies over the 12 remaining tasks are between 94.44 % and 100 % depending on the configuration.

IV. Discussion

We have proposed a method to identify sensor location that constitutes a first step towards a more intelligent neuroprosthesis, and facilitates the use of wearable sensors for long-term monitoring. We estimated relative sensor location in a population of both tremor and Parkinson patients over a variety of tasks. Using three different configurations we further demonstrate the strength and flexibility of the presented method. Average accuracies of up to 99.19 % are reported for the configuration with three MIMUs, with the forearm sensor placed distally. Using four MIMUs and thus multiple sensors per segment we were still able to attain an average accuracy 91.77 % over all motion trials. Using orientation data we can thus determine sensor location and in the future extract context information with minimal bandwidth requirements.

The literature on identifying sensor location focuses on absolute location on the body. However, many applications require that sensors are placed in a chain or on a specific segment(s). Using this information enables us to deduce absolute position of each sensor from their relative position in the chain. Relative sensor location assumes that the segments on which sensors are going to be placed, the configuration, are known beforehand.The benefit of relative versus absolute sensor location is that it drastically simplifies the classification and classifier. We demonstrated that using ranking we can achieve a comparable [11] or higher [12] accuracy than reported in the literature, with the advantage of flexibility to alterations in or between configurations.

We have focused on a unilateral setup, starting with the neuroprosthesis presented in [20] in mind. Previous work has used as many [13] [12], or more sensors [11]. Our work is the first considering the use of various sensors on the same segment, and the first to focus on the upper limb. Our results indicate that it is possible to distinguish between sensors placed on the same segment using orientation data.The method presented here can easily be modified to have less/more sensors or segments, as shown in the different configurations adopted in the present work. This is also supported by our previous work on healthy subjects; where the trunk was added as a fourth segment [22].

Kunze et al. were the first to attempt to identify sensor location based on arbitrary data. They used a four sensor setup and reported an 82 % accuracy when 6 minute periods were used [12]. Under the hypothesis that movement can be considered additive further down the kinematic chain, and using relative rather than absolute location, we achieved considerably better results. Our task set consisted of both gross motor and fine motor tasks. We achieved average accuracies ranging from 91.77 % to 98.30 % over all tasks, with a maximal accuracy of 100 % being reached in several tasks as shown in Fig. 2. We hypothesize that the lesser performance of some tasks (3,4,5,13,17) is due to the excessive movement of soft-tissue they provoked.

In recent work by Weenk [11] an attempt has been made to investigate the sensitivity of location of the sensor on the segment. Previous work has exclusively relied on accelerometer data but Weenk et al. were the first to use gyroscopes as an additional sensor. A slight drop in performance was reported but they still achieved 97.2 % accuracy. In our work we rely exclusively on orientation data. Our algorithm thus only uses gyroscope and accelerometer data indirectly. To further assess the influence of sensor location we included two configurations with 3 MIMUs (i.e. one MIMU per body segment), where the sensor of the forearm was placed distal or proximal. Under the 4 sensor configuration we achieved an average accuracy of 91.77 %, with an increase up to 98.30 % when the only forearm sensor was placed distally. Using the proximal forearm sensor we achieved a slightly worse result. We assume that the decrease in performance between the latter configurations is due to impacts with the elbow (and sensor) on the table. Considering this limitation and given the nature of our features, and the results obtained over the various configurations, we conclude that our method is location and orientation invariant. We did however place the sensors on ideal locations, attempting to limit soft tissue artefacts, to enable extraction of tremor characteristics.

V. CONCLUSION

We foresee that the work presented in this paper will enable the long-term monitoring of (tremor) patients and will facilitate the use of wearable sensors, in particular in telemedicine applications. We have introduced a method to automatically identify relative sensor location and validated it on a mixed patient population and over a variety of ADLs. This is the first task independent location detection algorithm based on orientation data that only requires upper limb movement and does not need any training, and only the second location detection algorithm to be tested on a patient population. In the future we will apply this algorithm to further our understanding on tremor, and to assist in task identification.

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