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The Potential of Electromyography to Aid Personal Navigation

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ABSTRACT

This paper reports on research to explore the potential for using electromyography (EMG) measurements in pedestrian navigation. The aim is to investigate whether the relationship between human motion and the activity of skeletal muscles in the leg might be used to aid other positioning sensors, or even to determine independently the path taken by a pedestrian. The paper describes an exercise to collect sample EMG data alongside leg motion data, and the subsequent analysis of this data set using machine learning techniques to infer motion from a set of EMG sensors.

The sample data set included measurements from multiple EMG sensors, a camera-based motion tracking system and a foot mounted inertial sensor. The camera based motion tracking system at MMU allowed many targets on the subjects lower body to be tracked in a small (3m x 3m x 3m) volume to millimetre accuracy.

Processing the data revealed a strong, but not trivial, relationship between leg muscle activity and motion. Each type of motion involves many different muscles, and it is not possible to conclude merely from the triggering of any single muscle that a particular type of motion has occurred. For instance, a similar set of leg muscles is involved in both forward and backward steps. It is the precise sequencing, duration and magnitude of multiple muscle activity that allows us to determine what type of motion has occurred. Preliminary analyses of the data suggest that subsets of the EMG sensors can be used to distinguish, for instance, forward motion from backward motion, and it is expected that further analysis will

reveal additional correlations that will be useful in inferring the subjects motion in more detail.

This paper will introduce the EMG personal navigation concept, describe the data collected, explore the machine learning techniques applied to the dataset, and present the results of the analysis.

***Index Terms*—EMG, Physiology, Indoor Location**

I. Introduction

Pedestrian navigation, particularly in situations where GNSS signals are sparse, is the focus of much research. A common approach is to obtain an integrated solution thought the combination of information from several sources, such as WiFi fingerprinting, inertial sensors, vision sensors or sparse GNSS measurements.

Electromyography (EMG) measures the electrical activity generated by skeletal muscles. Since skeletal muscles are responsible for a pedestrians movement, EMG observations may offer a complimentary source of information to a dead reckoning system or even provide an entirely independent dead reckoning solution. The relationship between the activity of a large number of skeletal muscles and the movement of a pedestrians limbs is a complex one. However the premise behind this study is that limb, especially leg, movement is predictable from EMG measurements. Our objective is to explore this premise using EMG and position data collected in laboratory trials.

One objective of this study was to determine whether EMG measurements could provide a more reliable means of either detecting, or eliminating false detections of static periods in a foot mounted inertial navigation system (INS). Various studies have shown that foot-mounted inertial sensors can be used to determine a pedestrians motion to a useful accuracy (e.g. [10], [14], [16], [1]), but this concept works best when the pedestrians steps are distinct and when external constraints can be used. For example external information may be used to limit the accumulated errors in heading estimation which is a common feature of inertial-based navigation. This is especially true the case of the low cost inertial sensors that are usually used in this context. The foot-mounted INS technique relies strongly on being able to detect the period in each step when the foot is stationary on the floor, so that so-called zero velocity updates (ZUPTs) can be applied to constrain the growth of errors caused by the accelerometer and gyro sensor errors. During periods of distinct, regular walking paces these static periods are usually easy to identify, but if the pedestrian undertakes more complex movements, for example, shuffling on the spot then it may not be possible to identify a suitable ZUPT occurrence for several seconds, or false ZUPTs may be selected, leading to rapid growth in the integrated trajectory errors.

A more ambitious objective of the study is to attempt to recreate a pedestrians trajectory entirely from EMG measurements. If a person step length and direction can be estimated from lower limb EMG measurements then a full trajectory can potentially be recreated. In the past EMG signals have been used to count steps taken by a pedestrian and a neural network used to estimate step length when a GPS trajectory is available [5] [6]. In this work we aim to move beyond the simple regular stride case. Our method is designed to learn the mapping between the sequence and magnitude of EMG signals and the resulting movement in order to have the potential to determine the type and scale of both regular and irregular movements.

This study has made an initial investigation of the potential for this concept, by using machine learning techniques applied to a set of leg muscle measurements. We incorporate no knowledge of the location of each muscle within the skeleton so the encouraging results from the machine learning approach are expected to improve once a skeletal model is incorporated in future work.

In this paper we first describe the measurement of electric signals from skeletal muscles at the skin surface, so called 'surface EMG'. We then go on describe the machine learning regime implemented for this work and it's application to a dataset collected in a short data collection campaign.

II. Electromyography

Movement such as walking is generated by the active contraction and active force generation of skeletal muscles. Since active muscle forces cause movement, there is a rationale for the idea that measuring muscle activations can predict the subsequent movement. Muscle is electrically excitable tissue, and electromyography concerns the electrical measurement of muscle activity. EMG, the electrical activity of skeletal muscle, can be described mathematically as a random (stochastic) process which is amplitude modulated. When muscular effort is low, the amplitude of EMG is low; when muscular effort is high, the amplitude of EMG is high ([3], [7], [18]).

Skeletal muscles are composed of individual muscle fibers that contract when stimulated by a motor neuron. Motor neurons originate in the ventral horn of the spinal cord, they project to a muscle, and via multiple branches they form connections with many muscle fibers, typically one or more thousand for leg muscles. A motor unit is the smallest functional subdivision of a muscle. It consists of the motor neuron, its axon and all the muscle fibers that are innervated by its branches. When motor units are sufficiently stimulated, they transmit electrical impulses at rates ranging typically 5-20 impulses per second. The resulting motor unit wave train is a convolution of this sequence of impulses with the motor unit action potential which is an impulse response function with a polyphasic pattern characteristic of the motor unit. The motor unit action potential train transmits into and along the corresponding muscle fibers

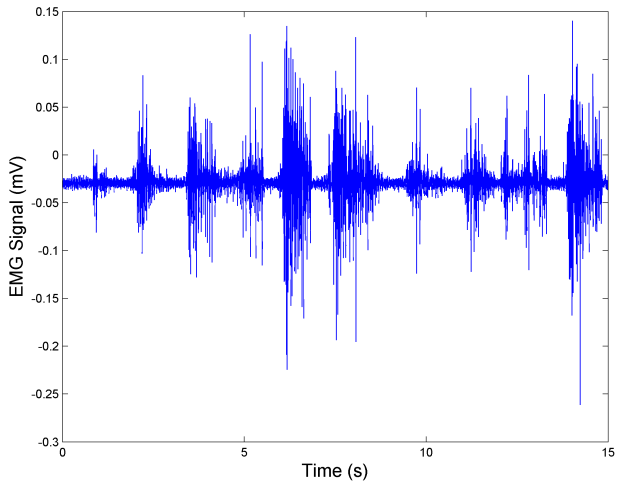

Fig. 1. Sample EMG signal recorded from the Left Vastus Medialis muscle during forward and reverse stepping

causing contraction of those fibers. Typically muscles in the leg contain hundreds of motor units and increasing muscle contraction is graduated by the progressive recruitment of small motor units with fewer muscle fibers to larger motor units containing more muscles fibers and which generate larger forces with faster twitch times. Thus muscles contain up to several hundred sources spatially distributed within the muscle and with a temporal distribution which is largely random and unsynchronized. The combined electrical activity of the muscle comprises the temporal and spatial summation of all sources. Combined, this signal is an interference pattern. When observed from the skin surface outside the muscle, the resultant signal has the characteristic of amplitude modulated random noise in which the time varying amplitude represents approximately the time varying level of active contraction and level of active force generation within the muscle ([3], [18]).

In figure 1 the signal recorded by an EMG electrode on the Left Vastus Medialis muscle is shown. Over this 15s period the participant repeatedly walked two paces forwards and two backwards.

Measuring the Electrical Muscle Signal

The electrical muscle signal is measured most easily from electrodes on the skin surface immediately outside the muscle. The alternative to surface recording is electrodes within the muscle. Measurement from the surface has the advantage of sampling a greater muscle volume which is more representative of contraction of the whole muscle. Electrode configurations vary including mono-polar, bipolar and multipolar. Bipolar and multipolar configurations usually provide differential measurement which allows better noise local noise rejection and local pre-amplification prior to further amplification and signal processing. The signal is typically high pass filtered at source to remove slowly varying skin-contact potentials and modern electrodes, such as the Delsys, Trigno sensors used in this work encode the signal digitally at source improving signal to noise ratios. The measured waveform is typically rectified and subsequently low pass filtered to extract the time varying amplitude. Adaptive, optimal pre-whitening is sometimes used as a preliminary post processing step to optimise the signal to noise ratio [7]. Electrodes are placed superficial to the muscle of interest where the belly of the muscle is substantial. Since the junction between nerve and muscle usually occurs centrally in the muscle belly in a region known as the motor point, and since action potentials spread to the ends of the muscle from the motor point, electrodes are usually placed slightly distal to the motor point [3].

Current Uses of EMG

The motor neuron originating from the spinal cord integrates all spinal and supraspinal neural input and provides the final common path for motor output from the nervous system. The motor unit provides the basic unit of actuation and, through connection of one motor neuron to thousands of muscle fibers, muscle provides an amplified version of that motor signal. Hence EMG provides the main, most direct measure of motor output from the nervous system and finds uses in scientific and clinical application.

In neurophysiology, investigation of the timing and extent of motor output in relation to well defined electrical, magnetic and mechanical stimuli identifies the contribution of individual neural pathways (spinal, trans-cortical, slow central loops) influencing motor output [18]. Movement is caused by a redundant, higher dimensional muscle system. In biomechanics, EMG allows investigation of how individual muscle forces and patterns of activation cause generation and impedance of movement. Sensori-motor control requires learning the mapping between motor command, force generation and movement. Training and storing internal neural models representing these mappings enables more accurate control and more accurate planning of control. These trained internal models also allow sensory analysis of muscle activation signals to estimate configuration of the body in a process known as proprioception [15]. EMG measurement contributes to investigation of these processes.

Clinically, EMG is used in diagnosis and rehabilitation. For example many myopathies including inflammatory and autoimmune myopathies are diagnosed in part by measurement and identification of abnormal motor unit and muscle activation patterns [8]. In neurological disorders, EMG contributes to diagnosis. For example in motoneurone disease, EMG identification of systemic fasciculation provides crucial diagnosis. In peripheral nerve and partial spinal cord injury, EMG measurement of spinal output, following transcranial magnetic, electrical or mechanical stimulation, allows diagnosis of the extent and level of lesion. In rehabilitation, measurement and real-time use of EMG provides feedback in sensori-motor

relearning [17] and provides myoelectric control of active prostheses [11].

III. Prediction of Movement Using EMG Signals

The prediction task was cast as a supervised learning problem, with the aim of predicting the change in distance of each foot over a small fixed time window. In general a short term causal relationship can be considered to exist between muscle activation (measured in proxy by the EMG sensors) and change in distance within short temporal windows. Therefore features were constructed as short multi-variate time series capturing the current, and a limited number of prior, EMG measurements across all recorded sensors. A (non-linear) mapping between these features and each variable to be predicted was then learnt using a training data set annotated with the feature of interest to be subsequently predicted. Such feature construction is based on the assumption that the limited temporal window is able to provide an accurate (potentially non-linear) mapping between the set of generated features and the position data, with each feature discriminative enough to map only to a single value in the domain of the variable of interest.

A. Feature encoding

Specifically a feature was modelled as a temporally lagged multi-variate time series of fixed length, l. Under such an encoding one feature was constructed per time point using a lagged sliding window of length l over a set of m individual sensor readings. Formally:

$$F_t = T_{t-(l-1)}, \ldots, T_{t-1}, T_t \tag{1}$$

where t denotes the temporal instant at which the variable of interest is being measured and:

$$T_j = \begin{pmatrix} v1 \\ \vdots \\ v_m \end{pmatrix} \tag{2}$$

denotes the vector of measurements across all sensors for time instant j, with v_k denoting the scalar measurement for sensor k at time j. Under such an encoding a single feature can by represented as a $m \times l$ matrix:

$$F_t = \begin{pmatrix} v_{1,t-(l-1)}, \ldots, v_{1,t-1}, v_{1,t} \\ \vdots \\ v_{m,t-(l-1)}, \ldots, v_{m,t-1}, v_{m,t} \end{pmatrix} \tag{3}$$

In order to make all sensor measurements comparable univariate time series corresponding to individual sensors within each feature were each standardised to have zero mean and unit variance. Formally, let S_q denote a single row within F_t and let μ_{S_q} and σ_{S_q} denote the mean and standard deviation of S_q respectively, then:

$$S_q = \frac{S_q - \mu_{S_q}}{\sigma_{S_q}} \tag{4}$$

Given a training set of temporally aligned EMG measurements of length L for an individual, a set of such features was extracted using a sliding window: $\mathcal{F} = \{F_1, \ldots, F_n\}$ resulting in $|\mathcal{F}| = n = L - (l-1)$ features. In the training set feature labels were additionally extracted from a corresponding ground truth of the horizontal movement travelled, computed from a recording of absolute positional data. In the test set these labels we also extracted for use as the ground truth. A detailed description of the experimental setup and the acquisition of the EMG and ground truth positioning data is provided later in section IV.

B. Prediction model

A multi-variate time series aware k-NN regressor was implemented as the prediction model. A k-NN regressor is a (almost) non-parametric prediction algorithm which, given an input feature, predicts the outcome as a weighted result of the labels of the k closest features in a feature space populated by previously seen instances [12]. k-NN models are inherently able to learn non-linear relationships between the input features and the variable of interest. While almost completely non-parametric, k-NN regressors are defined by the choice of a distance measure. In standard k-NN models each feature is a vector and the distance measure used is one of the standard L_p measures, most commonly the Manhattan or Euclidean distance. In contrast, time series aware k-NN regressors enable the consideration of distance measure that acknowledge the presence of the temporal dimension such as dynamic time warping. Finally, a multi-variate time series aware k-NN regessors generalise these distance functions to multi-variate time series.

In this work we consider two different functions, the extension of the Manhattan distance to the temporal multi-variate case by assuming independence between temporal measurements and the mean dynamic time warping score across individual sensor (univariate) time series per feature. The former assumes strict temporal alignment is important and represents the computationally simplest approach. The latter is a variant of Dynamic Time Warping (DTW) [4], a measure of similarity between two time series with a relaxed alignment between time points, measuring the distance as the distance under which the time series are closest when allowing them to varying in time or speed with respect to one another. Such a measure has been shown to perform well across a number of domains [9].

Formally, let $F_{t,i,j}$ denote the ith row and jth column in the matrix representation of an arbitrary feature F_t. Then the two distance measures used were:

Manhattan:

$$\delta(F_p, F_q) = \sum_{i=1}^{m} \sum_{j=1}^{l} |F_{p,i,j} - F_{q,i,j}| \tag{5}$$

DTW:

$$\delta(F_p, F_q) = \frac{1}{m}\sum_{i=1}^{m}\frac{DTW(F_{p,i}, F_{q,i}) + DTW(F_{p,i}, F_{q,i})}{2} \tag{6}$$

where $DTW(\cdot,\cdot)$ is the standard DTW using the Manhattan distance the local cost measure as defined in [13][1].

The distance measures were used in a standard k-NN regressor, with $k = 3$ and a uniform weighting applied to the three resultant predictions.

IV. Data Collection & Signal Pre-processing

A. Experimental Setup

A 10-camera motion analysis system (VICON Nexus Oxford Metrics) was used to measure the body kinematics. Movements were tracked using 24 retro reflective markers placed bilaterally on the second metatarsal head, the lateral and medial malleoli, the navicular tuberosity, the tibial tuberosity, the medial and lateral tibial condyles, the medial and lateral femoral condyles, the anterior and posterior iliac spines. The position of the markers was tracked at 100 Hz in a locally defined reference frame.

Having shaved and cleaned the skin, ten surface wireless EMG electrodes (Trigno, Delsys, Boston, MA, USA) were placed on one participant. Data were recorded at 1000Hz bilaterally from the gastrocnemius medialis, tibialis anterior, vastus lateralis and medialis and semi-membranosus muscles.

Data collection was performed in 15s periods with the participant asked to perform a set of predefined movements in each session. Three types of motion are considered in this work, forward / backward steps, a "figure 8" path and a circular path. The type and extent of the motions was limited by the space in which the retro-reflective markers could be tracked by the VICON system.

B. Signal Pre-processing

Position measurements from the VICON tracking system were rotated to a local level reference frame before being differenced to give horizontal and vertical change in position for each measurement epoch.

The recorded EMG signals were downsampled via an absolute summation over discrete windows of 15 data points, with each resulting data point representing the magnitude of the muscle activation over a 0.05 second period. The horizontal distance travelled per foot was then computed from the data from the VICON system and downsampled to match the sampling rate of 0.05 second periods. This was again performed using discrete windows, this time of 5 data points using a standard summation function, with each resulting data point then representing the total movement over a 0.05 second period. Features were then constructed as described in section III from the EMG signals based on a lag of 10 points ($l = 10$) representing a time period of half a second.

[1]In this work we use the implementation from [2].

V. Results

The two predictive models were evaluated by dividing the EMG recordings from the data collection campaign into two groups, one for training and one for testing, such that one of each motion type existed in each set. Each set was duplicated and annotated with the positional data of either the right or left foot. Per foot models for each of the two model variants were then trained and predictions from the test set made and compared to the ground truth. The models were evaluated based on the Mean Absolute Error (MAE) and the Explained Variance (EV) and subsequently plotted for visual inspection. The results for all models are shown in Table I and plots for the models based on the Manhattan distance shown in figures V and V. Plots for the DTW version are omitted due to their similarity to the Manhattan distance based model. Given a predicted time series (in this case the values represent the distance moved) $\hat{D} = \hat{d_1}, \ldots, \hat{d_n}$ and the known ground truth time series $D = d_1, \ldots, d_n$ the MAE and EV are respectively defined as:

$$EV(d, \hat{d}) = 1 - \frac{Var(d - \hat{d})}{Var(d)} \tag{7}$$

$$MAE(d, \hat{d}) = \frac{1}{n}\sum_{i=1}^{n}|d_i - \hat{d}_i| \tag{8}$$

	Right		Left	
	MAE	EV	MAE	EV
k-NN (Manhattan)	0.0053	0.9494	0.0086	0.8716
k-NN (DTW)	0.0057	0.9168	0.0087	0.8716

TABLE I
Prediction results as measured by the Mean Absolute Error (MAE, 0 best) and Expected Variance (EV, 1 best) for predicting the distance travelled per foot.

The results depicted in figure V (based on the Manhatten distance) shows the result of comapring the predictied velocity to the measured velocity from the vicon tracking system. The prediction shows a cumulative distance travelled error of 3.32m (left foot) and 0.43m (right foot) after 45s of walking. The predicted velocity was seen to have errors which were normally distributed and the cumulative distance travelled error is the result of a random walk.

VI. Conclusion

In this work we have demonstrated the prediction of human movement from measurements of the signals generated by leg muscles (via electromyography measurements). We have used machine learning methods to determine a non-linear mapping

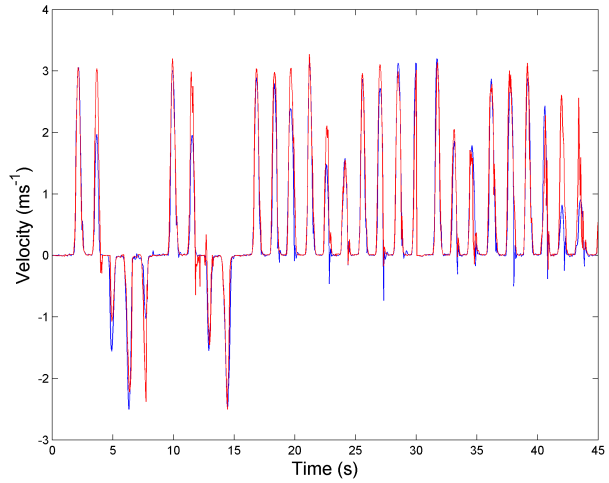

Fig. 2. Predicted (red) and observed (blue) velocity of the left toe using the model based on the Manhatten Distance.

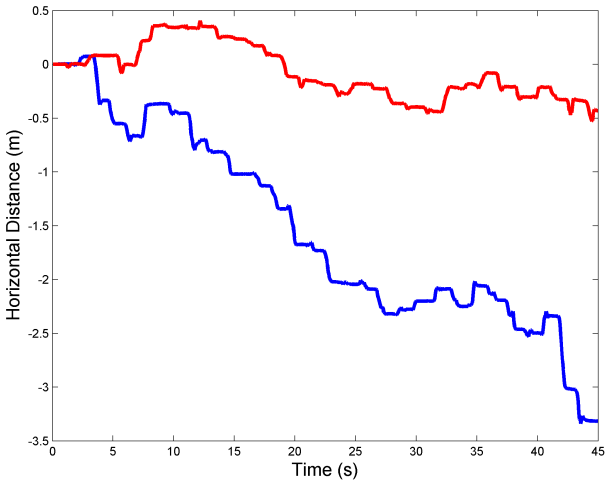

Fig. 3. Cumulative difference between predicted and observed horizontal distance travelled for the left foot (blue) and right foot (red)

between EMG signals and foot velocity. We have used this mapping to predict distance travelled for both feet over a bref 45 second dataset. At the end of the trajectory the cumulative distance travelled error was 3.32m (left foot) and 0.43m (right foot). the predicted velocity was seen to have errors which were normally distributed when compared to the output from a camera based tracking system.

Navigation based on EMG techniques has the potential to provide standalone pedestrian dead reckoning system or offer data complimentary to other navigation systems. For example in future work the velocity predicted from EMG measurements may be used to aid a foot mounted inertial navigation system in situations where zero velocity periods are sparse or difficult to identify. The ability to map EMG signals to movement also has application in other disciplines. In this paper we propose the application of this form of study to research in neurophysiology, biomechanics and sensori-motor control and it's use in clinical and rehabilitation settings.

This work presents initial findings from this potentially fruitful area of research. Further analysis is needed to explore this potential.

VII. Future Work

The analysis presented in this work shows much potential for further development and application in systems of personal navigation, scientific investigation of neurophysiology, biomechanics and sensori-motor control and in clinical and rehabilitation settings. A current and topical question in neurophysiology is the extent to which proprioception uses central neural signals of motor effort and peripheral signals of muscle activity in the neural process of estimating configuration and movements. Using machine learning approaches, investigation of the predictive, information content of EMG provides an exemplary model of what might be possible for the human nervous system. Combined with neurophysiological measurement this approach can progress understanding of neural function. Equally, combined with experimental investigation this approach can advance understanding of the neural modelling that occurs during sensori-motor learning in which the nervous system learns the mapping between motor output and movement control.

Analysis of the explanatory power of subsets of the muscle predictors can advance biomechanical understanding of force and movement generation from the redundant muscle system and can advanced individualised diagnosis of normal and disordered function in musculoskeletal and neurological conditions. Ability to relate subsets of muscle predictors to movement can help develop diagnosis of partial muscle dropout following peripheral and spinal cord nerve damage. These techniques have likely application in myoelectric control of active prostheses, and also in clinical analysis of gait and postural disorders in conditions ranging from decline with ageing and decreasing balance control, to neurological deficits such as cerebral palsy, Parkinsons disease, dystonia, to deficits following stroke and spinal cord injury. Applications also include monitoring of safe, efficient movement patterns in specialist occupations precluding remote line of sight navigational systems such as mining and firefighting and in monitoring of vulnerable elderly citizens in residential care homes.

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