

Reducing Power and Increasing Accuracy of On-body Sensing in Motion Capture Applications

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Abstract

Motion capture coupled with on-body sensing and biofeedback are key enabling technologies for assisted motor rehabilitation. However, wearability, power efficiency and measurement repeatability remain principle challenges that need to be addressed before widespread adoption of such systems becomes possible. The weight and size of the on-body sensing system needs to be kept small, and the system should not interfere with the user's movements or actions, but in general they are bulky due to their power consumption requirements. Furthermore, on-body sensors are very sensitive to positioning, which causes increased variability in the motion data. Isolating the characteristic patterns that represent the most important motion data affected by random positioning errors, while also reducing the power consumption, is our main concern. We consider an automated computational approach to address these two problems. We investigate the use of f-PCA for signal separation, whilst accounting for variability in sensor positioning. We use a robot arm to generate motion data which is analogous to the human joint flexion - extension motion. The data are captured by an active marker-based motion capture system. As both the motion capture system and the robot arm are very accurate in their operation, we are able to introduce deliberate placement errors in a precisely controlled manner to assess the efficacy of our approach. The results are independent of the technology used to measure motion because we consider joint angles as variables in our analysis. The proposed approach can thus be applied to other motion capture systems. The proposed post-processing technique can compensate for uncertainties due to sensor positional changes, whilst allowing greater energy efficiency of the sensors, thus enabling improved flexibility and usability of on-body sensing.

Keywords: Motion capture, on-body sensing, sensor power efficiency, sensor placement.

I. Introduction

Wearable computing devices are used to measure human body parameters via on-body sensors. These systems can capture different kinds of information such as motion and physiological activities [1]-[2]-[3]. Our work is motivated by the foreseen need for motion capture applications of home-based motor learning, for example, for assisted rehabilitation or ongoing motor training of disabled users, where wearable system design needs to consider the wearers' comfort and fitting requirements whilst targeting measurement performance. The weight and size of the system needs to be small, and the system should not interfere with the user's movements or actions, especially in motion capture applications [4]. Motion can be captured by placing sensors directly on the body, but they can be cumbersome, uncomfortable to wear and potentially easy to displace. These systems are sensitive to, and highly dependent on, changes in position of sensors, which affect measurement accuracy [2]. This could seriously undermine the effectiveness of self-administered motor training.

In order for motion capture system to be widely adopted as an assistive technology for home-based user-driven rehabilitation, they need to be robust to user placement errors, as well as portable and energy efficient [5]. In this paper we describe a signal processing approach to solve the combined problem of sensitivity to placement errors and power consumption. To our knowledge, this technique has hitherto not been employed in the context of reducing undesirable motion capture variability and improving power efficiency.

In motion capture, failure to place markers/sensors accurately is probably the single greatest contributor to measurement variability [6], which is a key impediment to the wider adoption of home-based assistive rehabilitation. In capturing of human motion via on-body sensors, the motion of a body is represented as a collection of time series streams describing the joint angles, called motion data. An articulated figure is often modeled as a set of rigid segments connected by joints which are constraints on the geometric relationship between two adjacent segments. This relationship is expressed with parameters called joint angles measured in three planes of three-dimensional space. With careful selection of joints so that, for example, segments are connected to form a tree structure, a collection of the joint angles of all the joints corresponds exactly to a configuration of a figure [23]-[24]. Placing markers accurately with respect to specific anatomical landmarks and determining the location of joint centers and other anatomical features in relation to these markers are very important in determining the anthropometry of an individual subject to derive motion data.

A number of marker placement protocols are in use in clinics and motion capture laboratories, but inter-session variability may still result, for example, if different motion capture sessions are run by different staff. Furthermore, particular care should be taken to ensure that sweating and rapid movements of the user do not affect the specific protocol's sensor/marker positioning. This problem of accurate placement is likely to be exacerbated if the sensors or markers are to be positioned by non-expert users.

Existing systems require tight fitting garments for precise sensor positioning [7]-[8]. Although close textile-body coupling is an advantage in sensor applications, it is uncomfortable and therefore not conducive to persistent motor training that is necessary

in long-term rehabilitation or motor function treatments. For looser garments, selecting appropriate sensor positions correctly is essential and is therefore carried out by experts. This prevents a wider adoption of such systems into user populations that would hugely benefit from them, such as rehabilitation patients requiring long-term treatment, or patients with disabilities needing ongoing motor training to maintain function [9].

Sensor misplacement adversely affects the reliable measurement of joint angles. Determining anatomical landmark positions to derive joints centers is influenced by sensor placement [10]. There are substantial differences between the ability of experts and self-marking operators to correctly determine anatomical landmark locations [11]. In [12] it has been shown that hip joint center mislocation of 30 mm in the anterior-posterior direction generates a mean error on the flexion/extension moment of about 22%. Physiological knee motions were observed in [13] such as the “screw-home” mechanism even when such motion did not occur, which was due to landmark position uncertainties. These uncertainties can lead to erroneous clinical interpretation of the estimation and thus misdiagnosis in rehabilitation. More importantly, within the context of assisted rehabilitation, they may result in incorrect interpretation of measurements by intelligent systems designed to provide user feedback that targets the user’s motor learning, in order to improve treatment outcomes.

Body sensing platforms for monitoring various biological and physiological signals face the challenge of achieving low-power consumption as well. The overall size of the electronic part of wearable systems is generally dominated by the size of the batteries. Hence to have less bulky systems, sensors need to operate with low power consumption. Changing the sampling rate has been used as a technique for reducing the power consumption. Adaptive sampling is established as a practical method for reducing the sample data volume and thus increasing the energy efficiency [14]. In [15] a low-power analogue system is proposed, which adjusts the converter clock rate. The system allows a low-power and small-sized implementation that can ultimately be integrated into a body-area network sensor. Reducing the sampling rate by compressive sampling approaches is a novel sensing/sampling paradigm asserting that one can recover certain signals from far fewer samples or measurements than traditional methods using the Nyquist rate [16].

Context-aware sensing, known as episodic sampling for wearable sensor technologies, has been introduced in [17]. The technique requires a trade-off between energy reduction and accuracy of the system. The effect of reducing the sampling rate of a wearable posture recognition system has been studied in [18]. It is shown that the performance of the posture classification is insensitive to reductions in the sampling rate from 100Hz down to 10 Hz for inertial sensors.

Our work shows how statistical signal processing techniques can be used to compensate for uncertainties in motion data due to random placement errors, while also reducing power consumption. We use functional data analysis techniques, including fitting functions on data sampled at a reduced rate, and principal component analysis to overcome undesirable signal variability.

The motivation for applying functional data analysis on human motion data is firstly, smoothness of motion data, which

implies that adjacent values in time are linked and it is unlikely that these values will differ greatly; and secondly, the principle that the best unit of information is the entire observed function rather than a string of numbers. It is assumed that human motion data have an underlying functional relationship governing them [19] - [20]. This is useful for analyzing human movement data where variability plays a key role and provides a means of identifying and examining the main sources of variability (e.g. pathology) in a set of motion signals [21].

We use PCA (Principal Component Analysis) and f-PCA (functional Principal Component Analysis) as signal separation techniques to derive the main pattern of variation in motion data, to compensate for the effect of random changes in the position of sensors, and to reduce power consumption. We explain how these techniques can be applied to separate the deterministic and stochastic components of movement patterns. In [23] we showed that the performance of these techniques is the same with respect to the separation of undesired source signals. Human subjects were recruited to capture their motion in a set of designed experiments. Applying the proposed approach on motion data showed its applicability on rehabilitation in motion capture applications [23].

In this paper, however, we show the superiority of f-PCA over PCA with respect to compensation of motion data variance, even when the sampling rate is reduced. The proposed signal processing approach is used as a post-processing technique. It can be used in motion capture laboratories for filtering the data and then returning the “cleaned” information, from which undesirable variations have been removed, to clinicians for assessment or to automated motion analysis and biofeedback subsystems of an assisted rehabilitation system. After applying the technique on captured data, marker placement errors can be ameliorated, before the results are sent to the clinicians for evaluation.

To enable a motion capture system to be tolerant to changes in the position of sensors and have a longer system lifetime, we propose signal processing techniques. Our method is described in Section II, where we explain the motion data acquisition process and experiment design. The signal processing techniques applied are introduced in Section III. The experimental results, which validate the applicability of the scheme, are given in Section IV. Section V concludes the paper.

II. Method

In our experiments we use a marker based motion capture system which is considered the “gold standard” in this field due to the measurement precision [24]. Robot arm motion, which is analogous to flexion and extension of human joint, is captured. The robot arm movement is repetitive with high accuracy which can simulate human joints motion in repetitive movements. We used this equipment because its high precision limits sources of variation except for the ones that we intentionally invoke. We consider joint angles as motion data in our analysis. This has the benefit of making the results independent from the technology used to measure motion allowing the proposed approach to be generalized for use with other motion capture technologies.

A. Motion Data Acquisition Process

The motion capture system used in the study has been described in detail in [18]. Here we outline it only briefly. We use a general-purpose 3D commercial optical motion capture system named *Codamotion*. The measurement unit contains three pre-aligned solid-state cameras which track the position of active infra-red LED markers, in real-time. The markers are powered from small battery boxes, which attach to the subject at specific landmarks via solid incompressible wands and plates designed for specific body segments. The wands and plates are secured by Velcro straps. In the case of the robot arm marker placement, since the arm itself is incompressible we did not use the wands but attached the marker boxes directly onto the arm.

The sampling rate can be set between 1Hz and 200Hz, and depends on the number of markers in use. The volume within which the motion measurements can take place is defined by position and angles of four scanner units, each containing three cameras that detect infra-red pulses emitted by the markers. The cameras are rigidly mounted within scanner units so that the system can be pre-calibrated. The three-dimensional reference coordinate system of the measurement volume is fixed in relation to the scanner unit.

The active range of capture system is 1.5-5.2m from the scanners and follows a Gaussian distribution function so that optimal visibility occurs at a distance of approximately 3m from each scanner. All the experiments are carried out in this range in accordance with the motion capture setup protocol. The system is aligned with the assumed reference coordinate system before performing each experiment [23]. The maximum possible measurement time depends on a combination of the sampling rate and the total number of markers being tracked. As the number of markers decreases, the maximum measurement time can be increased proportionally for a given sampling rate. The angular resolution of each camera is about 0.002 degrees; this results in a lateral position resolution of about 0.05mm at 3 meters distance (horizontally and vertically), and a distance resolution of about 0.3mm.

For the purpose of the current investigation a robotic arm [25] was used to measure the effect of random marker placement errors during controlled rotations of one rigid body segment with respect to another. The robot has a movement positional repeatability of ± 0.02 mm. When defining rigid body segments for three dimensional kinematic analysis, a minimum of three markers are required per segment: two markers define the longitudinal axis of the segment (in our laboratory, we define the longitudinal axis as the Z axis; anterior-posterior axis is the X axis and the medio-lateral axis is the Y axis), and the third marker is placed off center from the Z axis to define the segment as a rigid body in motion capture model [26].

This arrangement of markers on rigid segments serves two functions. First, it enables us to define an Embedded Vector Basis (EVB) for the segment in which the axes are mutually orthogonal, therefore allowing us to measure rotations using Euler angles. Second, the embedded axes of the local segment co-ordinate system are anatomically meaningful. Euler angles are expressed through three sets of 3 by 3 matrices, with each matrix describing the rotation of a specific axis [27].

B. Experiment Design

In the designed experiments our concern is energy efficiency of the system while compensating for variability in the motion data due to random changes in the position of the sensors. We examine the extent to which power consumption is affected as the sampling rate increases. We expect that increasing the sampling rate decreases the sensors' battery lifetime. Conversely, by decreasing the sampling rate, we can increase the measurement interval and thus increase the system energy efficiency and lifetime, but also cause more variation and greater inaccuracy in the captured motion data. Our proposed technique can address both of these issues: improving power efficiency whilst compensating for the increased variation in the data.

We used a robot arm due to its ability to repeat actions with high precision. The robot arm was modeled as two rigid bodies; the upper segment defined as rigid body 1 (RB1), and the lower defined as rigid body 2 (RB2). On RB1, markers were placed at either end of the segment, 3 cm from the end and define the longitudinal Z axis of RB1. A marker was placed over the hinge joint between RB1 and RB2. This marker serves as the upper marker for the Z axis marker for RB2 as well as the third, off-center, marker required to define RB1 of the local coordinate system within the *Codamotion* software. As with RB1, RB2 was defined by two markers along the length of the segment and two further markers were used to define the RB2 segment local coordinate system. The same configuration of markers was used on both sides of each segment and the local coordinate axis system for each segment was defined using a set of orthogonal axes.

The robot arm motion of 130 degrees rotation was recorded during intervals of fifteen seconds. Each marker was moved in a random direction by a distance of 2 cm from the initial reference position in the plane of the body segment. We used a random number generator to derive the random position of sensors within a radius of 2 cm from the center of each joint. The random number generator generates a random angle between 0 and 360 degrees. It also provides a random radius between 0 and 2 cm. In order to control rotation data as much as possible, the movement was restricted to one degree of freedom; that is, the only movement was the rotation of RB1 with respect to RB2 in one fixed plane.



Fig. 1. The configuration of markers on the robot arm that was used on both sides of each segment. The large black boxes contain the batteries and electronics.

In the first step, we gradually reduced the sampling rate to see whether or not the energy efficiency of the on-body sensors will increase. We collected data from several motion capture sessions, each lasting 15 seconds. The voltage level of sensor batteries was measured before and after each session. The chosen sampling rates were 200, 100, 50, 25, 10, 5, 2, 1 Hz. The measured difference between the voltage-level of sensors before and after motion capture at different frequencies is due to the change in the sampling frequency.

In the next step we carried out ten sessions of marker wearing on the robot arm to explore the combined effect of lowered sampling rate and reduced accuracy of motion capture due to random changes in the position of sensors. We performed 10 motion capture sessions for each of 8 different sampling frequencies (200, 100, 50, 25, 10, 5, 2, 1 Hz), with sensors in randomly changed positions. That is, one randomization of sensor positions was captured for 8 different frequencies to enable comparisons and analysis of statistical significance. Therefore, we have the robot arm motion data for each frequency 10 times, each time with a different random change in sensors' positions.

The captured motion data of different marker wearing sessions differ in the number of samples per session, and in the variation due to random changes in position of sensors. We want to investigate whether or not decreasing sampling rate increases the variation in motion data. Increased variation would trade-off against the gain of a more energy efficient on-body sensor system.

III. The Signal Processing Technique

We use PCA and f-PCA as source separation techniques to see if the variations due to a reduction in sampling rate and random changes in position of sensors can be compensated for simultaneously. In this section we briefly introduce PCA and f-PCA as filtering techniques for separation of deterministic and stochastic components in the signal.

Before applying the techniques we need to separate movement cycles and ensure there is the same number of samples in each cycle. For that purpose we use time warping, a technique commonly used in action recognition, where identifying features during action sequences carried out at different speeds or captured using different numbers of samples in each cycle is an important problem to be solved. In such cases time normalization is necessary before or during the recognition process. Each cycle should be normalized so that it is represented by the same number of samples. Linear and nonlinear time normalization using dynamic time warping are the most common techniques that can be used for this purpose. Linear time normalization converts the trajectory's time axis from the experimentally-recorded time units to an axis representing cycle in a linear fashion [27].

A. Principal Component Analysis

Principal component analysis is a technique in statistical data analysis and feature extraction. Intuitively, PCA is a process to identify the directions in data, i.e., the principal components (PCs), where the variances of scores (orthogonal projections of data

points onto the directions) are maximized and the residual errors are minimized assuming the least square distance. These directions, in descending order, explain the variations in the underlying original data points; the first principal component describes the maximum variation, the second direction explains the next maximum variance and so on.

This technique can work as a tool for a separation of main and residual components within a data set. We can eliminate the consistent, dominant features by subtracting them from the data. For a brief mathematical description of our signal processing technique, we consider the multivariate motion data in the form of N different real-valued, time dependent motion vectors of each joint corresponding to N motion capture sessions [29]. Each motion vector consists of M time samples. So there would be N motion vectors, one for each session, each comprising M time samples. We combine these M -dimensional vectors into a single M -by- N motion matrix per joint angle as shown in (1). For L joint angle motion signals, we have L such matrices (in our case, $L=15$).

$$\mathbf{X} = \begin{bmatrix} x_1 [1] & \dots & x_N [1] \\ \vdots & \ddots & \vdots \\ x_1 [M] & \dots & x_N [M] \end{bmatrix} \quad (1)$$

Data need to be standardized, so they will have zero mean and unit variance, forming the matrix \mathbf{Y} as shown in (2). The standardization affects the PCA results; the covariance matrix of standardized data is equal to the correlation coefficient matrix and the eigenvectors are normalized to unity. The j th columns of \mathbf{Y} form M -dimensional vectors, which are the standardized time sequences of the j th column of \mathbf{X} .

$$\mathbf{Y} = \begin{bmatrix} y_1 [1] & \dots & y_N [1] \\ \vdots & \ddots & \vdots \\ y_1 [M] & \dots & y_N [M] \end{bmatrix} \quad (2)$$

Linear combinations of the original variables with maximum variance result in achieving principal components (PCs). The PCs are obtained from the N eigenvalues λ_i and eigenvectors \vec{e}_i of data covariance matrix, \mathbf{Cov}_{ij} , which is defined as $\mathbf{Cov}_{ij} = \langle [y_i(t) - \langle y_i(t) \rangle_T] [y_j(t) - \langle y_j(t) \rangle_T] \rangle_T$. Hence data can be represented as (3), where $\xi_n(t)$ are the corresponding time series called ‘‘scores’’. The number of principal components is equal to the number of original signal vectors, N . Principal components, also referred to modes, are shown by $\vec{e}_i^{(n)}$.

$$\vec{y}_i = \sum_{n=1}^N \xi_n(t) \vec{e}_i^{(n)} \quad (3)$$

Principal components correspond to the eigenvectors directly. Each eigenvalue represents a measure of the variance, deviation

or spread of the data along the corresponding mode or principal component. Usually, the eigenvalues are ordered from the highest to the lowest: $\lambda_1 > \lambda_2 > \dots > \lambda_{N-1} > \lambda_N$. The total population variance is given by the sum of all eigenvalues: *Total Variance* = $\lambda_1 + \lambda_2 + \dots + \lambda_{N-1} + \lambda_N$. The percentage of the total variance in the data explained by the i^{th} PC is given by:

$$\text{Explained variance } (i) = \quad (4)$$

$$\frac{\lambda_i}{\lambda_1 + \lambda_2 + \dots + \lambda_{N-1} + \lambda_N}$$

Thus, filtering of data that preserves the significant variance within the data but eliminates small variance contributions can be achieved by inverse transformation from the subset of PCs that contain most of the data variance, e.g. from the first P PCs, where $P < N$. This feature is used to remove the variance due to random placement errors, as these contribute a relatively smaller proportion of variance to the data when compared to the inherent variability of the motion data.

B. Functional Principal Component Analysis

A useful technique to separate deterministic and stochastic components of movement patterns while preserving the time-dependence of the signals is f-PCA. It allows for separation of the main and residual components of a data set. Considering consistent features as coherent components implies the mechanisms generating these common structures follow deterministic rules, otherwise they would not be consistent. In contrast, the residual components often contain a degree of randomness or stochasticity.

This technique is an extension of the PCA statistical technique, where the principal components are represented by functions rather than vectors. The upper limiting number of principal components in the multivariate case is the number of variables, while in f-PCA the number of eigenfunctions is equal to the minimum of (K, N) , where K is the number of basis functions, and N is the number of variables [20]. The number of basis functions K should be less than or equal to the number of sampled data points, M .

An exact representation is achieved when $K=M$. The smaller K is and the better the basis functions reflect certain characteristics of the data, the less computation that is required. However, if we make K too small, we may miss some important aspects of the function that we are trying to estimate. A larger K provides a better fit to the data. By considering the mentioned challenges, we select the number of basis functions equal to the number of variables which is equal to 10.

In the first step, we should fit a function to the data for each motion vector. To fit a function to our data, we use a set of functional building blocks ϕ_k , $k = 1, 2, \dots, K$, called basis functions which are combined linearly (5). That is, a function $x(t)$ fitted to the measured data is expressed as a basis function expansion;

$$x(t) = \sum_{k=1}^K c_k \phi_k \quad (5)$$

Parameters c_k are the coefficients of the expansion. The matrix expression of N functions can be expressed as $\mathbf{X}(t) = \mathbf{C} \boldsymbol{\phi}(t)$, where $\mathbf{X}(t)$ is a vector of length N containing the functions $x_i(t)$, and the coefficient matrix \mathbf{C} has N rows and K columns. The functional eigenequation is

$$\int v(s, t) \xi(t) dt = \rho \xi(s), \quad (6)$$

where ρ is an eigenvalue and $\xi(s)$ is an eigenfunction of the variance-covariance function. The eigenfunction which is called principal component weight function, $\xi_1(s)$, can be found by (7):

$$\text{Maximize } \sum_i f_{i1}^2 \quad (7)$$

$$\text{Subject to } \int \xi_1^2(s) ds = \|\xi_1\|^2 = 1,$$

where the principal component score is defined as:

$$f_{i1} = \int \xi_1(s) x_i(s) ds. \quad (8)$$

Eigenvalues can be constructed stepwise by requiring each new eigenfunction computed in step l , to be orthogonal to those computed in the previous steps,

$$\int \xi_j(t) \xi_l(t) dt = 0, \quad j = 1, \dots, l-1 \quad (9)$$

$$\int \xi_l^2(t) dt = 1.$$

Deterministic and stochastic components of movement patterns can be separated by using f-PCA as a filtering technique, particularly when partitioning signals into deterministic and stochastic components. This is achieved by subtracting either one or other from the signal and can be regarded as filtering the noise or the common parts, respectively. Random changes in positions of sensors causes a random effect on the motion data, therefore to separate this effect from the main and coherent component of

movement, we partition the data into two elements, $\overset{\text{(global)}}{\mathbf{x}_i}$ and $\overset{\text{(filtered)}}{\mathbf{x}_i}$, as shown in (10):

$$\begin{aligned} \vec{x}_i &= \vec{x}_i^{(global)} + \vec{x}_i^{(filtered)} \\ &= \sum_{n=1}^{L < N} \xi_n(t) f_i^{(n)} + \sum_{n=L+1}^N \xi_n(t) f_i^{(n)} \end{aligned} \quad (10)$$

Here we assume the number of basis functions is greater than the number of variables. The sum of the dominant principal components weight functions is given by $\vec{x}_i^{(global)}$, so the filter characteristic depends on the data. The number of modes that define the global pattern influences the filtered pattern. We select the most relevant principal component weight function, the one with largest variation, and remove the rest from the f-PCA domain. We select the PCs that reflect at least 95 percentage of variance. The percentage of the total variance can be calculated by (4). The data are then returned to the original signal domain, but without the eigenfunctions containing smaller variations. This gives us filtered, cleaner data where random variation due to placement errors is removed.

IV. Results and Discussion

In our experiments the voltage before and after motion capture session in different frequencies was measured in 15 seconds intervals for the six sensor boxes. We measured all sensor voltages in the same, full condition of sensor battery. Fig. 2 shows that as sampling frequency rate increases, voltage drop within the fixed time of the measurement session, increases as well. It shows the impact of reduction in frequency on energy usage. There is a reduction in power consumption due to decreasing sampling rate.

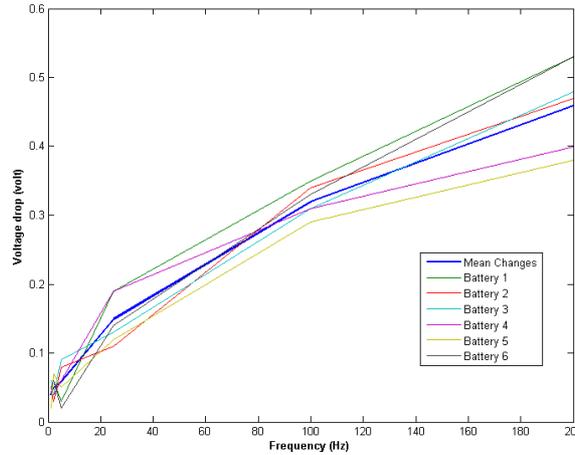


Fig. 2. Voltage drops in sensors batteries versus frequency of sampling.

In the next step we performed ten marker wearing sessions on the robot arm. In each of the sessions, the positions of sensors were randomly changed within a 2 cm radius from the landmarks. Motion data were captured using different frequencies for each marker wearing session. The variances of unprocessed and processed captured motion data sampled at different frequency rates are shown in Table 1.

The data variance of ten marker wearing sessions for each sampling frequency was calculated as the square of the standard deviation of each joint angle motion signal. As expected, the reduction in sampling rate increases the variance. Results show that down to the Nyquist frequency the variance is of the same order of magnitude. Although there is an increase in magnitude of variance from 100 Hz to 200 Hz, this is an insignificant amount that can be due to high frequency noise. The residual high frequency noise in the position measurement arises mainly from photo-detector current noise in the cameras and the effects caused by room lighting [24]. In motion capture, these kinds of noise are usually compensated for by using a low pass filter. A further reduction in sampling rate below the Nyquist frequency causes a significant increase in the variance. However, applying the filtering technique compensates for the increase in the variance. The results show that f-PCA outperforms PCA in terms of data variance, as illustrated in Fig. 3. Clearly, by applying the f-PCA and PCA techniques we can compensate for the effect of random sensor positioning errors within measured motion data, while achieving greater power efficiency, thus enabling a potentially more reliable and more comfortable on-body sensing system for wearers.

Table 1
Variance change before and after applying PCA and f-PCA

Frequency (Hz)	Before	After		Percentage of change (%)	
		PCA	f-PCA	PCA	f-PCA
200	7.6601	6.9826	4.8996	8.84	36.04
100	6.7113	6.1446	4.1501	8.44	38.16
50	6.1156	5.5804	3.6543	8.75	40.25
25	6.0807	5.0608	3.2224	16.77	47.01
10	10.8290	4.1176	2.6794	61.98	75.26
5	16.1705	7.8966	5.8977	51.17	63.53
2	41.5028	6.6151	4.7679	84.06	88.51
1	273.5735	25.4157	17.7664	90.71	93.51

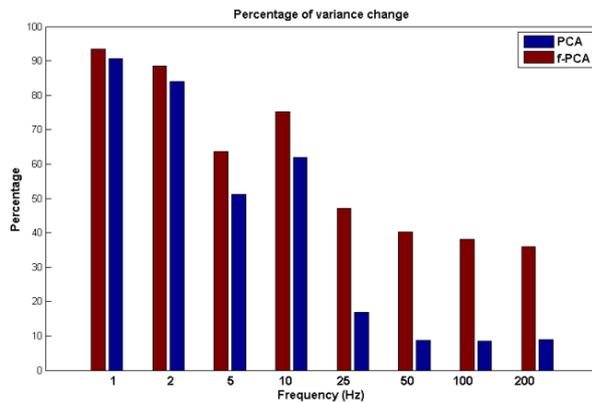


Fig. 3. Percentage of variance change for different frequencies before and after applying PCA and F-PCA based signal separation techniques.

It is shown in Fig. 3 that as the sampling rate reduces, the improvement will increase. However, by comparing PCA and f-PCA filtering results we see that f-PCA can better compensate for variations due to random changes in the position of sensors than PCA. The advantage of f-PCA over PCA is more obvious at higher frequency sampling rates. Figure 3 shows that f-PCA works better than PCA at all frequencies, although we see a change in the trend of relative improvement below 25 Hz, which is due to sampling below the Nyquist frequency. We know that the sampling rate must be at least twice the maximum frequency present in the signal, which is called the Nyquist rate. In the motion data that we captured the Nyquist rate is 20 Hz, which explains the reduction in the relative improvement below 25 Hz.

The proposed signal processing approach adds processing complexity to the motion capture procedure of the order of $2(O(n \log n) + O(\log(nm^2)) + O(m^2))$ [30]. In this formula n is number of samples and m is the dimensionality which is equal to the number of variables. However, since on-body sensing systems usually have a central system for analyzing the data that is located far from the body and connected to a powerful processing unit with a connection to an abundant electricity supply, processing complexity is not a challenge in this case.

To test for statistical significance of our results, we carried out a multiple comparison test on the data. In this test we considered variance in the data as the dependent variable, and the sampling frequency and applied techniques as independent variables. We used a two-way ANOVA (Analysis of Variance) test on the results produced at different sampling frequencies. For each test, data were grouped into 4 categories. The first group is the baseline where there is no frequency change (i.e. the sampling rate is the standard 200 Hz), and the filtering techniques are not applied on the data. The rest of the results were grouped into three treatment groups, depending on whether either or both of the two independent treatments, that is, reducing the sampling rate and/or application of the f-PCA technique, were applied. The hypothesis is that there is significant difference in variance after applying the proposed approach from the baseline where the filtering technique was not applied on the data sampled at the 200 Hz standard sampling rate. The test results show that there is a sufficiently small p value (less than 0.05) for the hypothesis. It means there is a significant difference from the baseline and the marginal means of the 3 groups' populations in the test. This implies that there is a substantial effect due to the application of the proposed technique.

The multiple comparison test confirms that reducing the frequency increases the variance in the data significantly and applying the f-PCA technique compensates for this increase in the variance. Taking all these results together, it is clear that PCA-based signal separation techniques can be useful in removing unwanted variation in motion data and enable a more flexible assisted rehabilitation system for sensor-based motion capture.

V. Conclusion

In this paper we studied technical challenges related to portability of on-body sensing systems specifically with regard to motion capture applications. We considered power consumption and positional uncertainties as two main issues in these systems. By proposing a post-processing approach we show how these challenges can be overcome. The motion of a robot arm was captured whilst “random” changes were made to the positions of sensors for different sampling frequencies. The movement of robot arm was analogous to flexion and extension of a human body joint. Ten marker-wearing sessions of the robot arm were captured for each different sampling frequency whilst introducing random changes in the positions of the sensors. Results show that despite the inherent accuracy of both the motion capture system and the repetitive robot arm movements, significant variation in the motion data exists due to these random changes in the positions of sensors as well as variation in the sampling frequency. Reducing the sampling rate has the benefit of lowering the power consumption and therefore permits the use of smaller batteries leading to improved comfort for the wearer. However, as the sampling frequency decreases, the variation in patterns of motion increases. Nevertheless, we have shown that after applying f-PCA and PCA signal processing techniques the increased variation due to sampling frequency reduction, as well as the variations due to errors in marker positioning can be substantially reduced, thus providing a step towards a robust and flexible assisted rehabilitation. Furthermore, we considered joint angles as motion data in our analysis. This has the benefit of making the results independent from the technology used to measure motion, and allows the proposed approach to be generalized for use with other motion capture technologies.

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References

- [1] Pantelopoulos, A., and Bourbakis, N.: 'A survey on wearable sensor-based systems for health monitoring and prognosis', *IEEE Transactions on Systems, Man, and Cybernetics*, 2010, 40, (1), pp 1-12
- [2] Bonato, P.: 'Wearable sensors/systems and their impact on biomedical engineering', *IEEE Engineering in Medicine and Biology Magazine*, 2003, pp 18-20
- [3] Hanson, M. A., Powell Jr, H., Barth, A. T.: 'Body area sensor networks: challenges and opportunities', *Computer*, January 2009, pp 58-65
- [4] Tang, S.: 'Recent developments in flexible wearable electronics for monitoring applications', *Transactions of the Institute of Measurement and Control*, 2007, 29, pp 283-300
- [5] Jovanov, E., Yang, C., Zhang, Y.: 'Body sensor networks: from theory to emerging applications,' *IEEE Transactions on Information Technology in Biomedicine*, 2009, 13, (6), pp 859-863
- [6] Baker, R.: 'Gait analysis methods in rehabilitation,' *Journal of NeuroEngineering and Rehabilitation*, 2006
- [7] Wade, D., Jong, B.: 'Recent advances in rehabilitation,' *BMJ*, 2000, 320, pp 1385-1388
- [8] Knight, J., Deen-Williams, D., Arvanitis, T., Baber, C., Sotiriou, S., Anastopoulou, S. Gargalagos, M.: 'Assessing the wearability of wearable computers,' in *10th IEEE International Symposium on Wearable Computers*, Montreux, Switzerland, 2006
- [9] Harms, H., Amft, O., Troster, G.: 'Influence of a loose-fitting sensing garment on posture recognition in rehabilitation,' in *IEEE Biomedical Circuits and Systems Conference*, 2008, Baltimore, MD
- [10] Harms, H., Amft, O., Tröster, G.: 'Does loose fitting matter? Predicting sensor performance in smart garments', *7th International Conference on Body Area Networks*, 2012, Oslo, Norway
- [11] Croce, U., Leardini, A., Chiari, L., Cappozzo, A.: 'Human movement analysis using stereophotogrammetry part 4: assessment of anatomical landmark mislocation and its effect on joint kinematics,' *Gait and Posture*, 2005, 21, pp 226-237
- [12] Groce, U., Cappozzo, A., Kerrigan, D.: 'Pelvis and lower limb anatomical landmark calibration precision and its propagation to bone geometry and joint angles,' *Med Biol Eng Comp*, 1999, 37, pp 1029-1034
- [13] Stagni, R., Leardini, A., Cappozzo, A., Bendetti, M., Cappello, A.: 'Effect of hip joint centre mislocation on gait analysis results,' *Journal of Biomechanics*, 2000, 33, pp 1479-1487
- [14] Piazza, S., Cavanagh, P.: 'Measurement of the screw-home motion of the knee is sensitive to errors in axis alignment,' *Journal of Biomechanics*, 2000, 33, pp 1029-1034
- [15] Hamouda, Y., Phillips, C.: 'Adaptive sampling for energy-efficient collaborative multi-target tracking in wireless sensor networks,' *IET Wireless Sensor Systems*, 2010, 1, (1), pp 15-25
- [16] Candes, E., Wakin, M.: "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, 2008, pp. 21-33.
- [17] Reger, R. and Taylor, J. T.: 'An adaptive sampling system for sensor nodes in body area networks,' *IEEE Transactions on Neural Systems and Rehabilitation*, April 2009, pp 183-189

- [18] Au, L., Batalin, M., Stathopoulos, T., Bui, A., Kiase, W.: 'Episodic sampling: towards energy efficient patient monitoring with wearable sensors,' in 31st IEEE International Conference of the EMBS, 2009, Miniapolis-USA
- [19] Rendic, R., Gaura, L., Brusey, J., Kemp, J.: 'Wearable posture recognition systems: factors affecting performance,' in International Conference on Biomedical and Health Informatics, 2012, Hong Kong-China,
- [20] Ormoneit, D., Black, M. J., Hastie, T., Kjellstrom, H.: 'Representing cyclic human motion using functional analysis,' Image and Vision Computing, 2005, pp 1264-1276,
- [21] Ramsy, J., Hooker, G., Graves, S.: Functional data analysis, (2005, New York: Springer)
- [22] Coffey, N., Harrison, A., Donoghue, O., Hayes, K.: 'Common functional principal components analysis: a new approach to analyzing human movement,' Human Movement Science, 2011, 30, pp. 1144-1166
- [23] Haratian, R., Twycross-Lewis, R., Timotijevic, T., Phillips, C.: 'Towards flexibility in sensor placement for motion capture systems: a signal processing approach,' IEEE Sensors Journal, 2013
- [24] Codamotion user guide, Charnwood Dynamics Ltd, 2005
- [25] Denso robot, setting-up manual, Denso wave incorporated, 2011
- [26] Hamill, J., Selby, W.: Three dimensional kinematics in Research Methods in Biomechanics, Human Kinetics, Champaign: IL, 2004
- [27] Trefethen, L., Bau, D., Numerical Linear Algebra, Philadelphia, PA.: Society of Industrial and Applied Mathematics, 1997
- [28] Sakoe, H., Chiba, S.: 'Dynamic programming algorithm optimization for spoken word recognition,' IEEE Transactions on Acoustic, Speech, and Signal Proc., 1978, 26, (1), pp 43-49
- [29] Haratian, R., Timotijevic, T., Phillips, C.: 'A PCA-based technique for compensating the effect of sensor position changes in motion data,' in 6th IEEE International Intelligent Systems (IS) Conference, 2012, Sofia
- [30] Haratian, R. 'Towards flexibility in on-body sensing systems: a signal processing approach' PhD Thesis, Queen Mary University of London: UK 2014.