COMPARISON OF ACCELERATION AND EMG SIGNALS IN QUANTIFYING PHYSICAL ACTIVITY

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ABSTRACT

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A lack of proper physical activity is increasing problem in the world. According to WHO around 31% of people aged over 15 were insufficiently active in 2008. The lack of physical activity has been identified as a fourth leading risk factor for global mortality and it is responsible of a great deal of costs of the public health sector in the future. Therefore a new technology is developed to quantify physical activity.

The purpose of this study was to examine new kind of technology for measuring physical activity. Intelligent clothing (shorts with embedded EMG textile electrodes) is a new invention which measures EMG activity of right and left quadriceps femoris and hamstring muscles. EMG activity from the four muscles was compared to 3-D acceleration activity through the cross-correlation and integral analyses. Measurements were up to 12 hours long. 20 measurements of 12 study subjects were used in cross-correlation analyses. The influence of the number of recording channels on cross-correlation was also examined. In integral analyses group 1 (n=20) and group 2 (n=5) were analyzed separately because unfortunate baseline shift appeared in EMG signals in group 1 during the study, thus, results of group 1 are not completely reliable.

Cross-correlation analyses indicated fair correlation between acceleration and EMG signals r=0,62. The reduction of EMG recording channels from four to two had only slight influence on cross-correlation (0,58<r<0,60). Integral analyses pointed out strong match (90%) between the integrals of acceleration and EMG signals in group 2. According to this study, shorts with embedded textile electrodes could be used to quantify physical activity like accelerometers. However, a lot of research and technical development have to be made if long-term measurements will be executed.

Key words: electromyography, acceleration, physical activity, physical inactivity, technology, measurement.

TIIVISTELMÄ

Sakari, Mikkola 2012. Kiihtyvyys- ja EMG-signaalien vertailu fyysistä aktiivisuutta määritettäessä. Maisterin tutkinto. Liikuntabiologian laitos. Jyväskylän yliopisto. 60 sivua.

Fyysisen aktiivisuuden puute on muodostumassa kasvavaksi ongelmaksi maailmanlaajuisesti. WHO:n mukaan yli 15 vuotiaista noin 31% eivät liikkuneet terveytensä kannalta tarpeeksi vuonna 2008. Liikkumattomuus on luokiteltu neljänneksi suurimmaksi riskitekijäksi yleiseen kuolleisuuteen maailman laajuisesti. Näin ollen uudenlaista teknologiaa kehitetään fyysisen aktiivisuuden mittaamiseen, jotta ennaltaehkäisevää työtä voidaan tehdä.

Tutkimuksen tarkoituksena oli verrata älyvaatteella mitatun EMG signaalin piirteitä kolmiulotteiseen kiihtyvyyssignaaliin. Älyvaate mittaa quadriceps femoriksen ja hamstring lihasten EMG aktiivisuuta. 12 koehenkilön kahdestakymmenestä mittauksesta koostuva aineisto analysoitiin tutkimuksessa. Mittaukset olivat maksimissaan 12 tunnin mittaisia. Vertailu tehtiin ristikorrelaatio- ja integraalianalyysin avulla ja lisäksi ristikorrelaatioanalyyseissä tutkittiin älyvaatteen mitauskanavien määrän vaikutusta signaalin muodostumiseen ja korrelaatioihin. Integraali-analyysi perustui kokonaissignaalien pinta-alojen vertailuun joka tehtiin kahdelle ryhmälle: ryhmä 1 (n=20) ja ryhmä 2 (n=5). Ryhmä 2 analysoitiin erikseen, koska EMG signaalin nollataso heilahteli kohtuuttoman paljon useimmissa mittauksissa ja vain viidessä mittauksessa sitä ei ilmennyt.

Ristikorrelaatioanalyysit osoittivat että EMG- ja kiihtyvyyssignaalien välillä on merkittävä korrelaatio r=0,62. Kun enimmillään kaksi mittauskanavaa olivat poissa mittauksesta, ei merkittäviä eroja syntynyt tulosten välille (0,58<r<0,60). Integraalianalyysit osoittivat että pinta-alat täsmäämäävät melko hyvin ja ryhmä 2:n pinta-alat täsmäsivät noin 90%:sti. Tutkimuksen perusteella älyvaatteen avulla voisi olla mahdollista mitata pitkäkestoista fyysistä aktiivisuutta kuten kiihtyvyysmittareilla mutta se vaatisi teknologian kehitystä.

Avainsanat: elektromyografia, kiihtyvyys, fyysinen aktiivisuus, inaktiivisuus, teknologia, mittaus.

CONTENT

1 INTRODUCTION

There exists many methods for measuring physical activity. The most commonly known methods are: doubly labelled water, accelerometers, questionnaires, indirect measurement of energy expenditure, pedometers, and heart rate measurements (Ainslie et al. 2003). Accelerometers are a good way to gain objective and detailed information about physical activity behaviour. Accelerometers are generally more sensitive than self-reported measures (Copeland & Esliger 2009). A rarely used method for measuring physical activity is electromyography (EMG). It can be used for measuring the activity in a single muscle or in a group of muscles. With EMG measurement it is possible to determine and estimate the amount of time muscles are active and the patterns of daily muscle loadings. (Kern et al. 2001.)

According to the World Health Organisation the amount of overweight people will very likely be increased tremendously by 2015. The prevalence of obesity has already tripled in Europe since 1980 until 2011. It can be explained mainly with physical inactivity and unhealthy nutrition (WHO 2006). Physical inactivity and obesity are associated to type II diabetes and cardiovascular diseases (Sullivan et al. 2005). Daily muscle activity has positive effects on glucose uptake and insulin sensitivity and, thus, can protect from type II diabetes. (Mitchell & Kaminsky 1998.)

In this study muscle activity of quadriceps femoris and hamstring muscles is studied through EMG analyses and compared to acceleration of the body. The purpose of this study was to compare the triaxial accelerometer signals and EMG signals measured by intelligent clothing to find basis for activity calculations from EMG. Accelerometers are a commonly used method for measuring physical activity but the intelligent clothing with embedded EMG electrodes is a new invention. Analyses were made by using cross-correlation and integral analyses.

2 DEFINITION AND INFLUENCES OF PHYSICAL ACTIVITY AND INACTIVITY

2.1 Definition of physical activity and inactivity

Any bodily movement produced by skeletal muscle that requires energy expenditure is considered to be physical activity (Haskell 1994). Physical activity refers only to physical or physiological occurrences and can be categorized to several activities. Physical exercise is also sometimes mixed with physical activity. However, physical exercise is a part of the whole concept of physical activity and physical exercise is always structured, planned, and has final objective related to physical fitness. (Caspersen et al. 1985.)

An opposite concept for physical activity is physical inactivity. In sport medicine, physical inactivity does not mean total inactivity or steady state energy expenditure of the muscles, but a very low physical activity which is not enough to stimulate structures or actions of human body to maintain the action. Physical inactivity therefore means that when the muscle contractions occur too seldom or contractions are too weak, as a result the muscle cannot regenerate or maintain endurance or strength. (Vuori et al. 2005, 20.)

2.2 Health effects of physical activity and inactivity

Physical activity is considered to have versatile effects on health and it has preventive influence against many chronic diseases and it can also be used as a treatment for many diseases (Warburton et al. 2006). Physical inactivity, on the contrary, can lead to various diseases such as type II diabetes. It is a highly prevalent disease with enormous health impact. In 2007 7,8% of the population of the USA had diabetes and approximately 57 million people had so-called prediabetes, which means impaired fasting glucose or impaired glucose tolerance or both. Type II diabetes is characterized as a combination of insulin resistance and an inadequate compensatory secretory response and it is very often associated with obesity. Visceral fat accumulation and increased body fat are considered to be risk factors for development of diabetes and impaired glucose tolerance. (Bergman et al. 2009.)

Cardiovascular disease is nowadays the main cause of death in developed countries (Braunwald. 1997). Physical inactivity, obesity, and a number of inflammatory rheumatic diseases, including rheumatoid arthritis, have all been associated with a growing risk of cardiovascular disease. Endothelial dysfunction is considered to be an early step in the development of atherosclerosis and an independent predictor of cardiovascular mortality and morbidity (Halcox et al. 2002, Ross 1999). Makrilakis et al. (2000) studied association of physical activity and acute coronary event in diabetic patients. They discovered that moderate and vigorous activity is associated with a lower prevalence of acute coronary events in the investigated group. Lighter physical activity does not have any significant association with the development of acute coronary events.

Osteoporosis is a disorder wherein total bone mass has decreased and at the same time the structure of the bone has become thinner and weaker. Also, the shape of the bone has changed so that the chance of fracture has increased (Vuori et al. 2005, 297). Osteoporosis has become a large public health problem among the elderly population. Fractures of the hip are expected to double over the next 50 years (Cooper et al. 1992). Physical activity is considered to be a valuable method to prevent osteoporosis. The effects of physical activity are considered to prevent bone loss and increase muscle strength. In addition, the benefits of physical activity are not just limited to above mentioned influences of physical activity but it also has a reducing influence on bone fractures. Regular physical activity has a positive influence on the body. It stimulates bone growth and helps to preserve bone mass. Besides stimulating bone growth and preserving bone mass, physical activity decreases fallings by improving muscle strength, balance, and postural stability (Dalsky et al. 1992, Lau et al. 1992). Wolf et al. (1996) discovered 47,5% reduced risk of multiple falls among people who had regularly performed weight-bearing exercises.

According to WHO inactivity has become the fourth highest risk factor for global mortality and approximately 6% of all deaths are a consequence of it. Physical inactivity is assessed to be the main cause for approximately 21–25% of colon and breast cancers, 27% of diabetes and approximately 30% of ischemic heart disease burden. (WHO 2006.)

3 METHODS FOR MEASURING PHYSICAL ACTIVITY

Intensity levels of physical activity are commonly expressed by multiples of rest energy consumption of which a measure is the metabolic equivalent (MET). The MET-value indicates the energy consumption compared to the resting level energy consumption. MET-value can be stated using oxygen consumption; 1 MET equals to 3,6 ml/kg/min. (McArdle et al. 1991,166.) Table 1 shows some conservative estimations of MET values in normal activities.

TABLE 1. Normal activities and corresponding MET values (Modified from Ainsworth et al. 1998, 657-665)

METs	Activity	METs	Activity
0,9	Sleeping	4	Fishing
0,9	Watching TV	4	Massage
1,5	Typing on computer	4,5	Washing windows
2	Making bed	4,5	Washing and waxing a car
2,3	Washing dishes	5	Walking downstairs, with 10-20 kg
2,3	Ironing	6	Aerobics
2,5	Carpet sweeping	6	Walking uphill 5,6 km/h
2,5	Playing piano	7	Jogging
2,5	Police, directing traffic	7	Skating general
3	Child care (dressing, bathing)	8	Carrying bricks
3	Walking on job, moderate speed	8	Ice hockey
3	Volleyball, non competitive	8	Cross country skiing 7km/h
3	Walking downstairs	9	Running 8,4 km/h
3,5	Cleaning a house	10	Bicycling (vigorous)
3,5	Shopping (with trolley)	12	Firefighter job
4	Bicycling (leisure)	16	Running 16 km/h

Intensity of physical activity can be measured by several methods. Every method has its advantages and disadvantages and some of the methods are more accurate than others for quantifying energy expenditure. Physical activity can be measured by using direct or indirect methods. Direct methods are rare and unusable methods in field measurements and they are not discussed in study. The most well-known indirect methods are presented in the following chapters and the main focus is directed to accelerometers because they are used as reference devices in this study.

3.1 Doubly labelled water

The golden standard to measure energy expenditure in the field conditions is doubly labelled water. It is based on the use of sustainable isotopes. Normally a huge part of hydrogen of the human body is ^{1}H which means that the atom weight of hydrogen is 1. The biggest part of oxygen in the human body is in the format ^{16}O. Doubly labelled water measurements are based on the use of rare and heavier but non-radioactive isotopes like ^{2}H and ^{18}O. In the beginning of measurements a study subject takes an oral dose of water containing a known amount of hydrogen ^{2}H and oxygen ^{18}O isotopes. Both isotopes are mixed with normal oxygen and hydrogen in body water within a few hours. When energy is expended in the body, water (H_2O) and carbon dioxide (CO_2) are produced. Water is lost from the body in urine, breath, sweat and other evaporations while CO_2 is lost from the body in breath. Because both CO_2 and water contain ^{18}O, it is extracted faster than ^{2}H because CO_2 does not contain it. The difference between the rate of loss of ^{2}H and ^{18}O (figure 1) influences the rate of CO_2 production and that information can be used to assess energy expenditure. However, an evaluation of the ratio of CO_2 production to VO_2 production makes the calculation more accurate. This evaluation can be made in three different ways. First, a value for a respiratory quotient can be assumed to be something based on standard Western diet. Second, the study subject keeps some kind of diary of what kind of food one has eaten. This is used to estimate the ratio of CO_2 production to VO_2. If all this food is combusted, it can be assumed that the same ratio for the body will approximate the food quotient over a period of time. Third, the CO_2 production relative to

VO_2 can be assessed using methods which include indirect calorimetric techniques. (Westerterp 1999.)

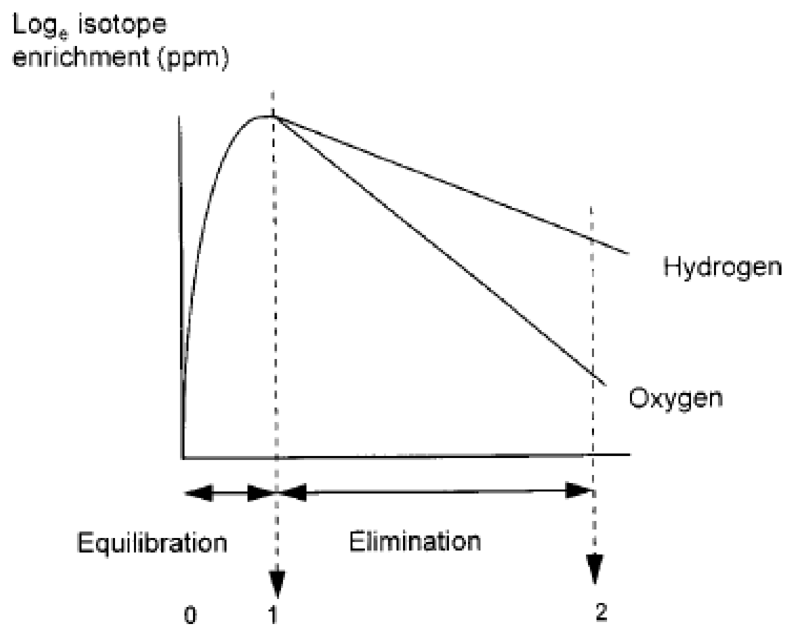

FIGURE 1. Elimination rates of hydrogen and oxygen (Speakman 1998).

Although the doubly labelled water technique does not specify the intensity or the frequency of the physical activity, it is an accurate method to measure total energy expenditure (Ainsworth & Lamonte 2001). Nevertheless, doubly labelled water has its own disadvantages despite its clear advantages. First of all, the cost of the ^{18}O is quite high and it requires high expertise for the analysis of the isotope concentrations in body fluids by mass spectrometry (Plasqui & Westerterp 2007). In field measurements errors occur if respiratory quotient is not known. However, the fact that the results provide the closest measure of energy expenditure makes the method valuable as a reference technique for validating estimations of energy requirements obtained by other methods. (Ainslie et al. 2003.)

3.2 Indirect calorimetry

There are two common indirect calorimetric systems for VO_2 measurement and energy expenditure. The first is based on so called ‘close-circuit’ method in which the study subject is isolated from outside air. Usually the respirometer contains pure oxygen and when the study subject breathes in this closed system the CO_2 is continuously removed as it passes through a soda lime. When the volume of gas decreases, the rate of the decrease is the measure of the rate of VO_2. Oxygen is not necessarily needed over a short duration for measuring VO_2. The study subject absorbs the produced H_2O and CO_2 with the change of volume that is corresponding to VO_2. The concerned method works quit well for measuring resting or basal metabolic rate, though absorption of a large volume of CO_2 produced during prolonged strenuous exercise might become a problem. (Ainslie et al. 2003.)

The ‘open-circuit’ method is generally suitable for measuring exercise metabolism. Two different procedures have been developed for ‘open-circuit’ method. In the first procedure, equivalent amount of gas to outside air passes through the study subject’s hood. The study subject inhales and exhales into the airstream flowing through the hood. Airflow and the percentages of carbon dioxide and oxygen are assessed with precision to calculate VO_2 and CO_2 consumption and hence respiratory exchange ratio. This method is useful for long term assessments when the study subject is performing only light exercise or if the study subject is at rest. The second procedure is the so-called time-honoured Douglas bag method which is considered to be accurate and theoretically valid. In this procedure the study subject wears a nose clip and mouthpiece or a facemask. Outside air or its equivalent is breath in through the mouthpiece or the mask containing a one-way valve and exhaled into the Douglas bag or a Tissot tank. The air volume in the bag or the tank is assessed to calculate minute ventilation. A sample of air is obtained to assess the oxygen and CO_2 concentrations. However, modern online electronic equipment nowadays generally replaces the Douglas bag method. (Ainslie et al. 2003.)

Humphrey & Wolf 1977 designed a system which was a battery operated and self-contained, portable instrument and it was engineered for measuring VO_2 online. CO_2 was not assessed and respiratory exchange ratio had to be assumed. Advances in technology have enabled the development of many new portable systems which are capable to measure CO_2 production and breath-by-breath pulmonary gas exchange. (Ainslie et al. 2003.)

3.3 Accelerometers

Accelerometers are commonly used equipment to measure body movements in terms of acceleration and they can be used to assess physical activity over long time periods. They have been used increasingly during past few decades and some researchers have found them to be a reliable method in measuring physical activity and thus energy expenditure. Accelerometers are traditionally used to measure pelvis movement and nowadays accelerometers are also used to measure hand movements. Accelerometers describe the intensity, duration and frequency of movement. The faster is the movement the bigger is the acceleration.

Acceleration (a) can be defined as a change of velocity (Δv) against a change of time (Δt) formula (1). Acceleration can also be defined as a time derivative of velocity or second derivative of a place (x) like in formula (2). Acceleration is commonly represented as gravitational acceleration in which 1g = 9,81 m/s^2. Acceleration is a vector quantity and it always has a magnitude and direction. (Enoka 2002, 6-11.)

$$a = (\Delta v)/(\Delta t) \tag{1}$$

$$dv/dt = dx^2/dt^2 \tag{2}$$

3.3.1 Functionality of accelerometers

Accelerometers are nowadays commonly used systems in biomechanical studies. They are practical and cheap solutions and the use of the accelerometers is not only limited to laboratory environments. The very basic idea of an acceleration sensor is based on a spring-mass system that in turn is based on Hooke's law (F=kx) and Newton's second law (F=ma). The functionality of the mass-spring system is not very complicated. When the system is forced to compress or stretch, caused by an outer accelerative movement, the spring generates restoring force that is equal to the amount of compression or stretch. The stretch or compression can be controlled with the mass and stiffness of the spring, as presented in formula (3). (Kavannagh & Menz 2007.)

$$F = kx = ma \Rightarrow a = (kx)/m \tag{3}$$

The sensitivity of accelerometer sensors is dependent on the cross-sectional area and the length of the sensor, material stiffness and the position of the seismic mass on its beam. When using multiple unidirectional sensors, they must be located rectangular to each other. (Chen & Bassett 2005.)

There are many kinds of accelerometers on the market but in clinical studies the most commonly used accelerometers are piezoresistive, piezoelectric, capacitive, and strain gauge types (Kavannagh & Menz 2007). The functionality of the piezoresistive accelerometers is based on change in resistance of solid silicon crystals compared with movement of the mass against the frame of an acceleration sensor. Functionality of capacitive sensors is based on change in capacitance. Piezoelectric sensors contain piezoelectric material which causes a charge when acceleration appears. Accelerometers can be uni-, bi-, or triaxial, which means that they measure acceleration one-, two-, or three-dimensionally (Mathie et al. 2004). Accelerometers can be used to measure static or dynamic acceleration. When human locomotion is measured, one should use dynamic accelerometers, and for static measurements static accelerometers (Kavannagh & Menz 2007). The most commonly used acceleration sensor type for measuring locomotion and physical activity is piezoelectric sensor because of its technical properties. However, when measuring physical activity, the piezoelectric sensors are not able to measure static movement in any way. (Chen & Bassett 2005.)

When using an accelerometer which is tied to a human body one should take into consideration certain facts which are related to the outcome signal. The signal is composed of four components: acceleration caused by a poor fastening, gravitation of acceleration, external vibration, and movement of the body (Mathie et al. 2004.). When measuring physical activity one should be concerned only about body movements. Usually the frequencies of daily activities are between 0,3-3,5 Hz (Bouten et al. 1997). Most commercial accelerometers have a measuring area between 0,1-10g and a frequency band between 0,25-7 Hz. (Chen & Bassett 2005.)

Technology of accelerometers is developing fast and nowadays most sensors are miniaturized micro electro mechanical sensors (Mathie et al. 2004.). These micro electro mechanical systems (figure 2) are based on compact solutions in which whole electronic system is integrated on the same silicon platform by using film capsulation technique. (Park et al. 2006.)

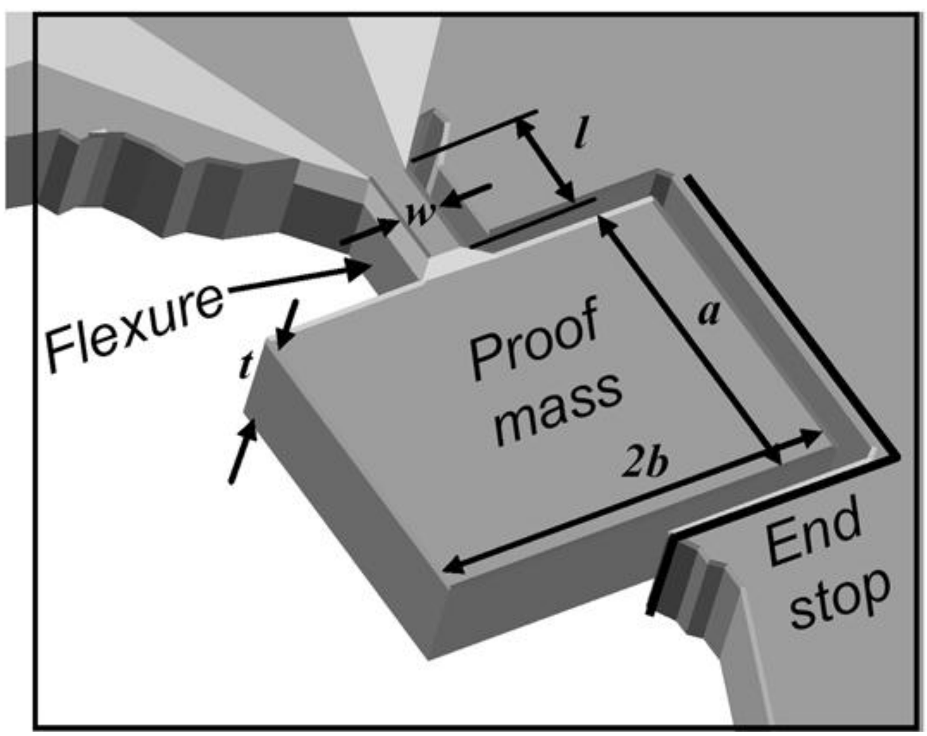

FIGURE 2. A Shape and dimensions of the piezoresistive micromechanical accelerometer (Park et al. 2006).

Park et al. (2006) introduced the smallest ever published fully packaged piezoresistive accelerometer. In the structure of a micro machined accelerometer, there are two different possible arrangements for sensing resistors. The first is a so-called quarter bridge configuration (figure 3) in which there is a lightly doped region on the opposite sidewall for the sensor and a heavily doped region on the opposite sidewall for conductive trace. There will be an equal amount of stress in opposite signs on each sidewall, upon a lateral acceleration. The sensitivity relies on the relatively high gauge factor of the lightly doped resistor compared to the heavily doped resistor because these two resistors are as series. The second arrangement is half bridge configuration (figure 3) and in this case there are lightly doped regions on both sides. The net resistance of this configuration is zero because there are two identical resistors with the same gauge factor under an equal stress with opposite signs. Because of this, an electrical trace on the top center of the flexure is needed to sense the signal between two resistors. The top electrical pathway requires wider flexure than “quarter bridge” in order to adjust the top center pathway. Due to stiffer and wider flexure, the resonant frequency is increased and sensitivity is decreased.

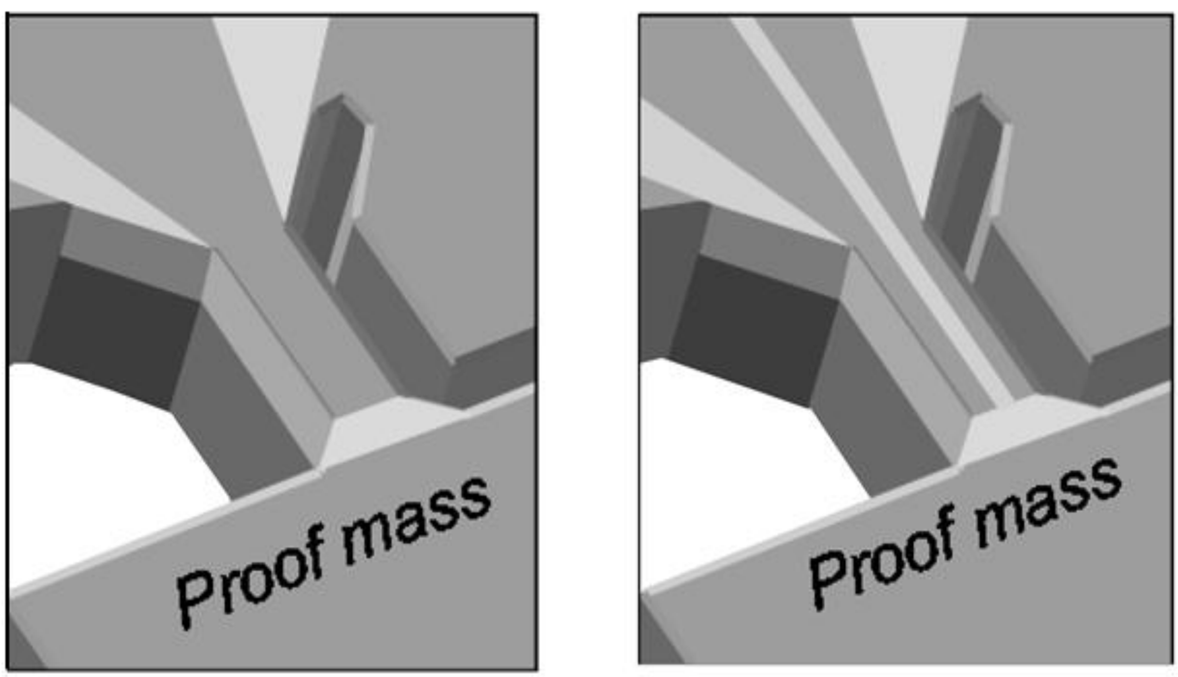

FIGURE 3. Left side “quarter bridge” and right side “half bridge” solution (Park et al. 2006).

3.3.2 Defining activity counts and energy expenditure with accelerometer

The raw outputs of accelerometers are considered to be so-called counts. However, the physiological meaning of these counts might be unclear in some cases. That is why the counts are changed to activity counts to assess the intensity of physical activity and the energy expenditure (Chen & Bassett 2005). Activity counts are commonly used to describe physical activity while using the accelerometer as a measuring system (Gorny & Allen 1999). Activity counts can be determined for different time periods and the most commonly used period is 60 seconds (Trost et al. 2005). Schwarz et al. (2000) introduced one model in which the activity counts are divided in three different categories to describe the intensity of physical activity according to MET values. Light activity is less than 3 MET and less than 573 counts, moderate activity is between 3 and 6 MET and between 574 and 4944 counts and vigorous activity is more than 6 MET and more than 4944 counts.

Before activity counts can be determined, there exist certain procedures concerning signal processing that have to be done. First, the raw analog signal should be amplified and filtered. Second, the analog signal should be digitally sampled with appropriate frequency incorporated with Nyquist theory. According to the Nyquist theory, the sampling frequency should be at least double compared to the highest frequency of the motion while measuring physical activity. Most frequencies of motion of a person's central mass are below 8 Hz. However, some specific movements of hands can be 25 Hz. The amplitude of the digitally sampled signal is determined by the hardware of the system, the amplification factor, and the A/D conversion factor. When using 8-bit conversion, like in most cases, the amplitude of the signal can vary between -128 and +128. The sampled signal is filtered using a band bass filter. By using the band bass filter, the measured acceleration is produced more linearly compared to body acceleration. The band pass filter also reduces artefacts caused by the aging of materials, temperature related drifts, and electrical noise. Used band width is usually 0,25-7,5 Hz. (Chen & Bassett 2005.)

To define activity counts, three different methods can be used. The first one is to measure the time that the signal is above some threshold level. The second is to count how many times the signal crosses some specified threshold point on the y-axis. The third, and the most commonly used method, is to measure the integral limited by the signal, x-axis, and y-axis. If the third method is used, the signal should be full-wave rectified before integration (Chen & Bassett 2005). In figure 4 the three methods are exemplified.

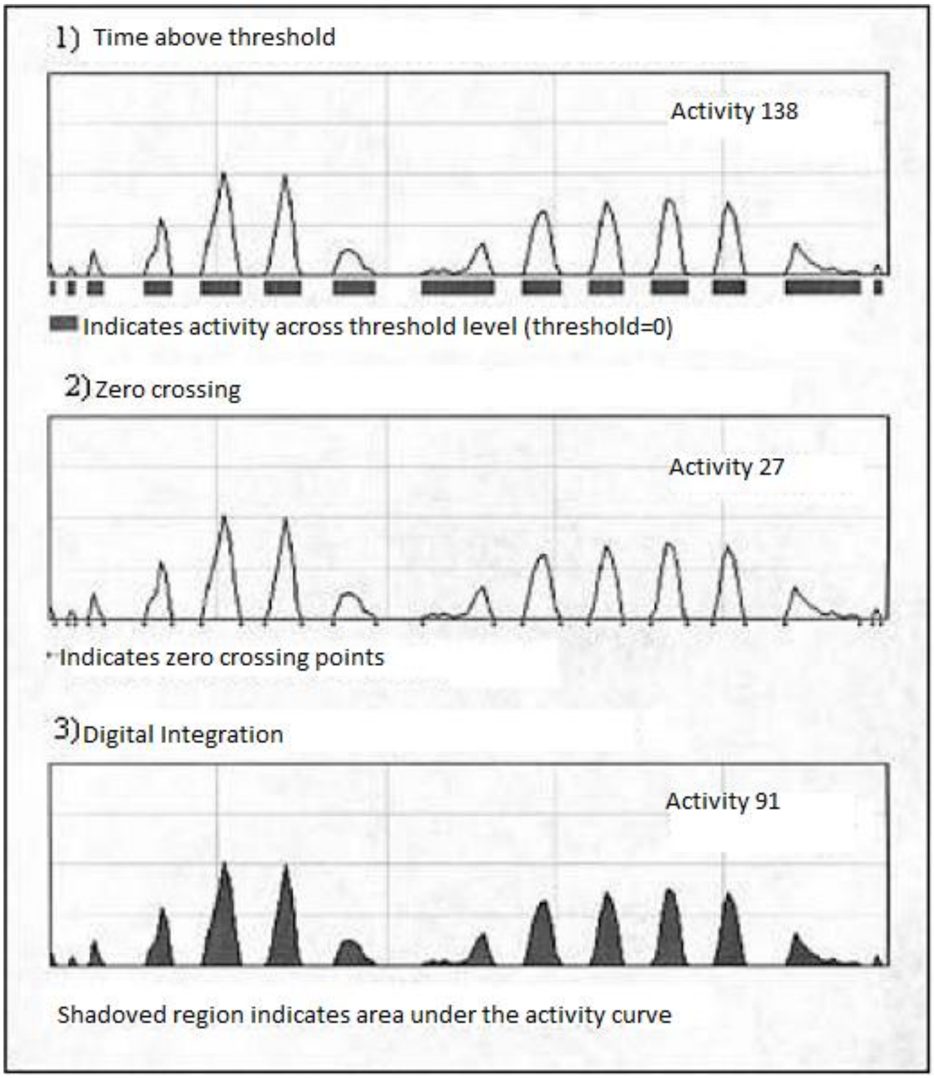

FIGURE 4. The three methods how to produce activity counts (modified Gorny & Spiro 2001).

When activity counts are calculated from time above some specific threshold level it simply means that activity counts are based on time above the threshold level (Leidy et al. 1997). Because the calculation is limited only to time, the amplitudes cannot be detected and intensity of physical activity cannot be detected. As mentioned before, in zero-crossing technique the threshold level is a low numeric value and calculation of activity counts is based on the amount how many times the signal crosses the set point within a determined epoch. Zero-crossing method has a similar shortcoming like the technique mentioned first; it does not take a stand for the intensity of the movement, because amplitudes are not detected. It can also give false information about the movement related to the acceleration caused by the noise in the signal (Van Someren et al. 1996). When using digital integration for calculation of activity counts, the area restricted by the signal and coordinate system is detected (Chen & Bassett 2005). Compared to the earlier methods this one can be considered to be a more advanced method because the intensity of the movements can be detected. (Redmond et al. 1985.)

Chen & Bassett 2005 suggested that the easiest way to produce activity counts from acceleration via integral analysis is to convert the integrals straight to activity counts simply by summing the integral values within some determined epoch which is normally one minute. Some problems are related to activity calculation based in basic integral analyses. The analyses delete signal characteristics which might be important for determining the type and intensity of physical activity. Also the epoch period is difficult to determine because too short epochs have little physiological meaning and long epochs can include many kinds of activities which might cause misclassification for activity levels and misinterpretations of the energy expenditure when results are averaged over the epoch. Figure 5 shows how different activities can have same activity counts at different activity level, and different standard deviations.

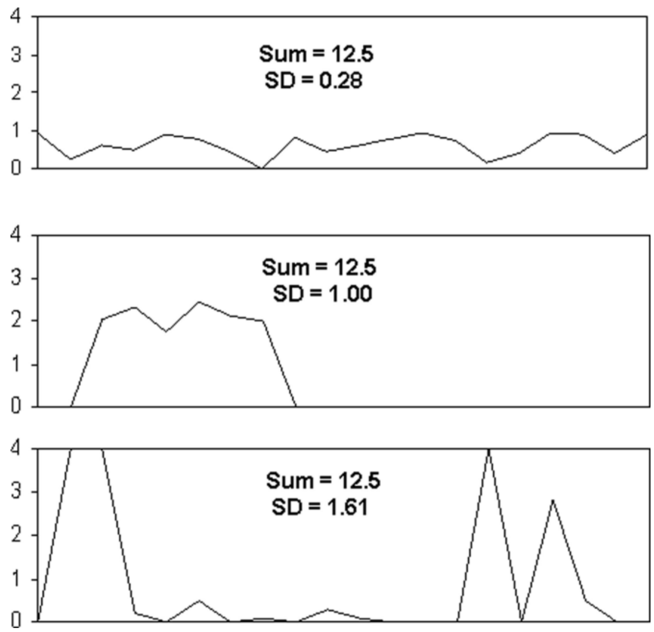

FIGURE 5. Three different activities performed at low, moderate, and sporadic levels over same time period with same output of activity counts (Chen & Basset 2005).

The four main characteristics of physical activity are intensity, duration, type, and frequency. The absolute intensity of physical activity is specified as its EE_{act} which refers to total energy expenditure of activity. That is the reason why many researchers use the minute-to-minute EE_{act} values gauged from accelerometers to categorize daily physical activity into intensity categories which are bordered by cut points. The former procedure enables the duration and the frequency of light, moderate, and vigorous physical activities to be recorded. Therefore the errors of EE_{act} prediction can lead to misclassification of duration and frequency of physical activity. (Chen & Bassett 2005.)

In most of the validation studies the correlation between activity counts and energy expenditure has been investigated using indirect calorimeter or doubly labelled water. In many studies the correlation between energy expenditure measured with indirect calorimetry and acceleration range between 0,58 and 0,92 during various activities. Bonomi et al. (2010) used doubly labelled water as the reference measure when they investigated properties of the $Tracmor_D$ accelerometer to measure free-living energy expenditure. Freedson et al. (1998) introduced a classical approach how to predict energy expenditure from activity counts using a linear regression equation. The study subjects performed physical activity on a treadmill at three different intensity levels and they were wearing an ActiGraph monitor at the hip. Calfas et al. (1998) executed a same kind of study by using individually developed regression equations and achieved 0,89 correlation with Tritrac-R3D accelerometer during walking trial. Despite advantages the linear approach has also its disadvantages. When approaching the physical activity measurements through linear point of view one should be aware that linear models do not take a stand for individual variation but rather give answers to the questions regarding validity as a group. (Chen & Bassett 2005.)

More complicated approaches for measuring energy expenditure with accelerometers are nonlinear models, which are mathematically more challenging. Chen et al. (1997) have developed a nonlinear power model that predicts energy expenditure from Tritrac-R3D counts. The model (formula 4) is based on a two-component power model which translates each individual's activity counts to minute-to-minute EE_{act} in a cross-sectional sample of heterogeneous women and men.

$$EE_{act} = a*(A_x^2 + A_y^2)^{p1/2} + b*A_z^{p2} \quad (4)$$

In the formula above A_z represents the vertical acceleration counts, and A_x and A_y are combined to represent horizontal acceleration. Variables a, b, p1, and p2 are determined by unconstrained nonlinear optimization algorithm for each study subjects. This model improved significantly prediction of EE_{act} in terms of correlation. (Chen & Bassett 2005.)

3.4 Heart rate measurements

During exercise there is quite a clear connection between heart rate and energy expenditure. However, the connection between these two variables is nonlinear during low activities and the heart rate changes more than oxygen consumption does. There is linear connection between heart rate and energy expenditure during the exercise. Thus, heart rate analysis can be used to estimate energy expenditure of a person moving at a moderate level. (Ceesay et al. 1989.)

Ainslie et al. (2003) suggest that heart rate and VO_2 measurements should be done for each individual so that it allows a variation in fitness between individuals based on calibration curve on simultaneous measurements of heart rate and VO_2. A typical human response curve (figure 6) shows how at low level of energy expenditure, heart rate does not increase as steeply as energy expenditure. It might be caused by the changes in stroke volume between lying, sitting and standing. This may be one of the reasons why 24-hour assessments of energy expenditure from heart rate can have errors up to 30% in individuals. However, the average error of the group is likely to be approximately 10% from true value. Heart rate measurements also provide information of the amount of time spent in high-intensity activity, which can be useful for assessment of physical activity rather than energy expenditure.

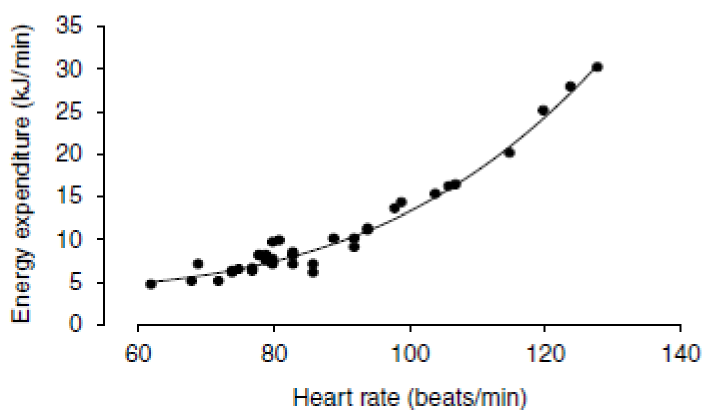

FIGURE 6. The relationship between energy expenditure and heart rate (Ainslie et al. 2003).

3.6 Questionnaires

Questionnaires are commonly used method for estimating energy expenditure and there exists several types of questionnaires. According to Ainslie et al. (2003) five different questionnaire methods have been reported to have been used in combination with doubly labeled water: Activity and recall questionnaires, the Baecke questionnaire, the Five-City questionnaire, the Tecumseh questionnaire and the Yale Physical Activity Survey (YPAS). The YPAS has been developed as an interviewer administered questionnaire for elderly people (Ainslie et al. 2003). It has been pointed out in validation studies of physical activity questionnaires with doubly labeled water that questionnaires assess different activity levels differently. Also other studies vary in their correlation coefficient with doubly labeled water depending on the used questionnaire or subject population. (Hertogh et al. 2008.)

Van Baak et al. (2007) studied physical activity comparing Short Questionnaire to Assess Health-enhancing physical activity (SQUASH) method and accelerometer data. SQUASH contains questions on commuting activities, leisure time activities, household activities, and activities at work. In commuting and leisure-time activities the reference period is typically one week during past few months. Each question consists of three main queries: days per week, average time per day and effort. Effort is considered to be the intensity of physical activity, whereby the study subjects indicate how hard the activity was: light, moderate or vigorous. In household and work activities intensity was pre-structured into two categories: light and vigorous. Completing SQUASH takes about 5 minutes.

International Physical Activity Questionnaire (IPAQ) is developed for international use to compare physical activity of different nationalities. There are two versions of IPAQ: the short version is suitable for regional and national use, and the long version suits better for research work which requires more detailed information. (IPAQ 2011.)

3.7 Pedometers

Pedometers are based on a simple principle. They simply count the number of steps, which are calculated by the vertical acceleration of the body. Pedometers are usually placed on pelvis and it reacts to every swing that is strong enough. People have different style of walking and that is why the sensitivity of pedometers should be adjusted according it. If the sensitivity is adjusted right, most pedometers should function accurately. There is usually a mode in pedometers where a user can set one's length of a step. Pedometers should be able to count the distance that had been walked by multiplying the amount of steps with the length of steps. One can always question the result because the ground is not always flat and the walking speed can also change. To some pedometers one can feed user's sex and weight and the pedometer estimates total energy expenditure (Crouter et al. 2003).

3.8 Electromyography

Electromyography (EMG) measures the electrical potentials (action potentials) which are delivered from the motor cortex or the spinal cord via motor neurons to the muscle fibers (Enoka 2002, 197). The EMG signal is affected by many factors such as the anatomical and physiological properties of the muscle, the nervous system and the measuring system used to measure the EMG (Basmajian 1978, 53). EMG can be measured using several methods depending on the context. Surface EMG is usually measured using bipolar configuration which is discussed later in this section. If smaller and deeper muscles are measured one can use Fine-Wire electrodes which are composed of two fine-diameter insulated wires and the wires are threaded through a hollow needle cannula. Activity of a single motor unit can be measured with a needle electrode. (Robertson et al. 2004, 168-169.)

Surface EMG is an algebraic sum of several signals of individual motor units and the signal of each motor unit is composed of signals of several muscle fibers. The total sum of the signals of one motor unit is called Motor Unit Action Potential. The amplitude of the Motor Unit Action Potential describes the intensity of muscle contraction and the harder the contraction is the bigger is the amplitude, also the size of muscle fibers of the motor unit influence on the amplitude. Figure 7 demonstrates how total surface EMG is composed. (Robertson et al. 2004, 165-166.)

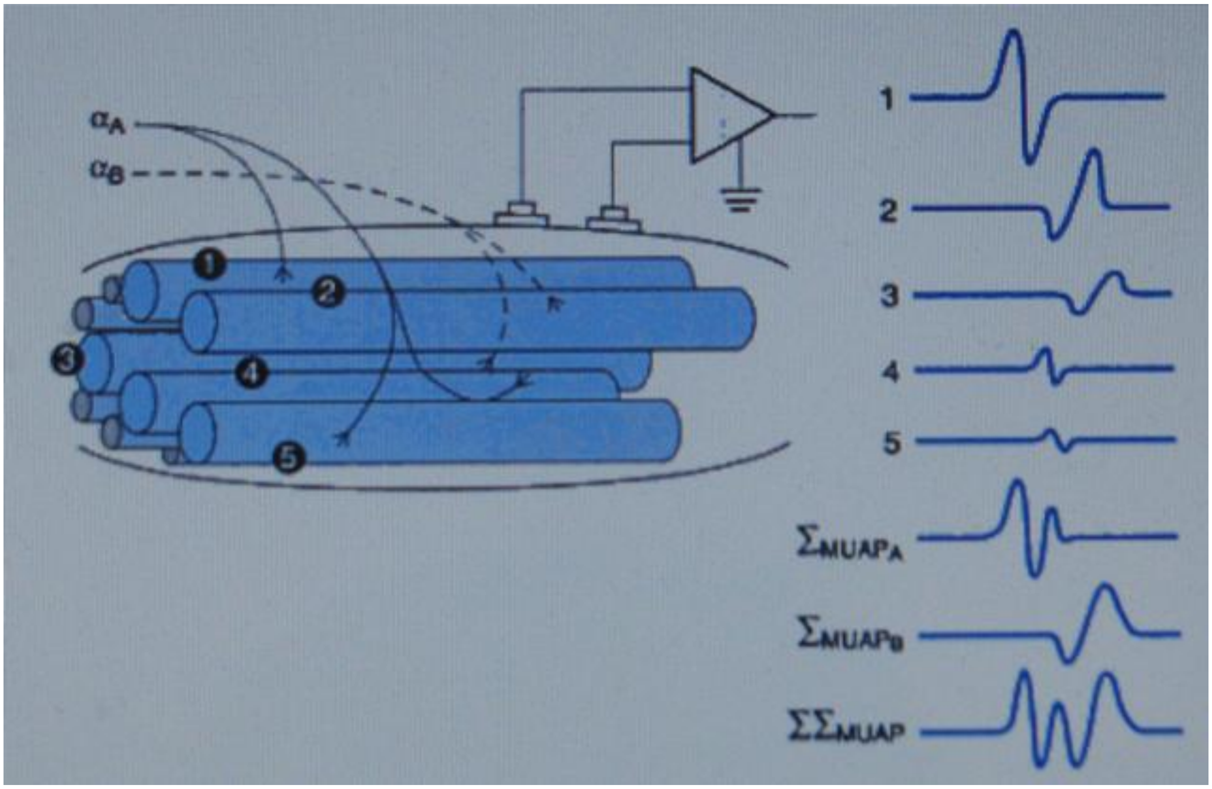

FIGURE 7. There are two different motor units α_A and α_B described in the figure. α_A is composed of single muscle fibers 1,4 and 5 and $\sum_{MUAPA}$ is a summed signal of those fibers. α_B is composed of muscle fibers 2 and 3 and $\sum_{MUAPB}$ is a summed signal of those fibers. The total EMG-signal ($\sum\sum_{MUAP}$) is composed of signals of both motor units. The figure also demonstrates that the distance between measurement electrodes and muscle fiber influence on the amplitude of the action potential of the muscle fiber. For example, the amplitude of the action potential of fiber-5 is lower than other amplitudes because fiber-5 is the furthest fiber from electrodes. (Robertson et al. 2004, 165.)

3.8.1 Generation and propagation of EMG signal

The electrical potential inside a muscle fiber is normally approximately -90 mV. This results from different concentrations of sodium (Na^+), potassium (K^+), and chloride (Cl^-) ions across the sarcolemma. However, there still exist differences in resting membrane potential between fast-twitch and slow-twitch fibers. In slow-twitch fibers the resting membrane potential is 9-15 mV more positive. The so-called neural messenger, which activates every segment of the muscle fiber, is an action potential (AP). The activation process begins when the muscle fiber membrane's permeability to Na^+ changes. Because these sodium ions are in relatively greater concentration outside of the muscle fiber, changes in permeability lead to an influx of sodium across the cell membrane. While sodium enters to the cell, the polarity of the membrane potential reverse, thus, the inside of the muscle fiber becomes positive in respect to the ambient extracellular medium. The positive potential is then approximately 30 mV. As the membrane's potential polarity reverses, the permeability of the membrane to potassium changes, causing potassium to exit the cell. Efflux of potassium is the main reason for repolarization of the cell and it leads to restoring of resting membrane potential. (Robertson et al. 2004, 163-164.)

By a passive process, the action potential propagates along each adjacent section of the muscle fiber and it propagates to both directions from the neuromuscular junction and makes the whole muscle electrically activated. When the action potential spreads to the muscle, it changes the membrane potential from negative to positive at each subsequent muscle fiber section. It changes back to negative when every adjacent muscle fiber area is successively activated. The deeper portions of the muscle fiber also become electrically activated as action potential propagates there through transverse tubule system. (Robertson et al. 2004, 164.)

3.8.2 Measuring surface EMG

Bipolar single differential system (figure 8) is a commonly used method for assessing surface-EMG. In this arrangement two electrodes are placed on the skin over the muscle and the ground electrode is placed on an electrically neutral side. It is characteristic for this method to include a differential amplifier which records the difference of electrical potentials between the electrodes. The distance between the electrodes is considered to be approximately 2 cm and the electrodes are placed between the distal joint and the motor point. When surface EMG is measured the impedance between skin and electrodes cannot be too high in order to get reliable results and that is why the skin needs preparation before the measurements. (Robertson et al. 2004, 164.)

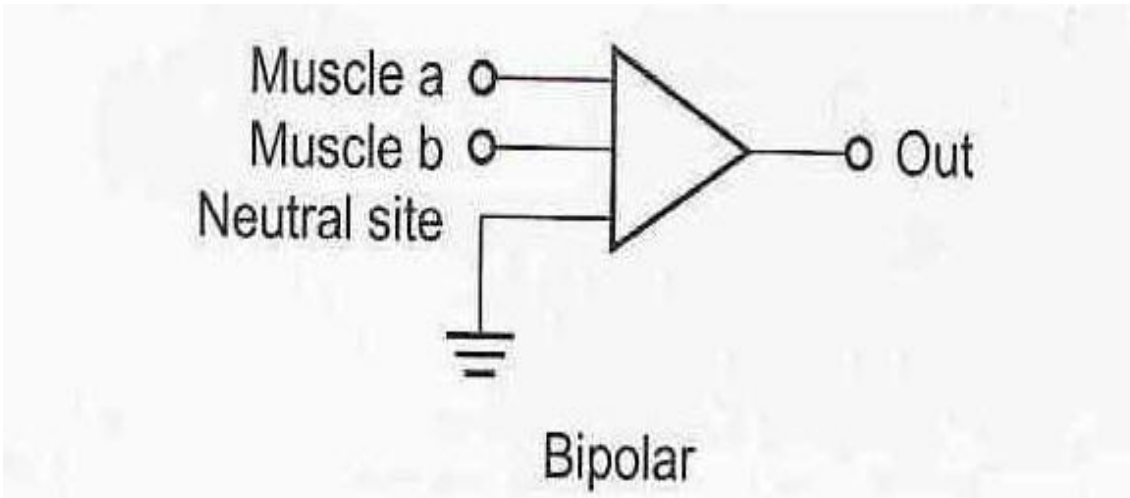

FIGURE 8. Bipolar single differential configuration (Robertson et al. 2004, 166).

Several factors affect the surface EMG signal measured from the skin surface. Some of the factors are physiological like thickness of the subcutaneal fat tissue layers. Other factors are non physiological caused by the quality of contact between skin and electrode, movement of the muscle in relation to the electrodes, inter electrode distance, shape of the electrode and their location. Also motor units have impact on EMG recordings. Firing frequency, motor unit discharge rate and synchronization might influence on the surface EMG. Carefully placed electrodes can help to reduce some of these distractions mentioned earlier. One of the non physiological factors that might also cause unwanted disturbance is crosstalk from nearby muscles. (Farina et al. 2004.)

Finni et al. (2007) introduced a new measuring system for EMG assessments. Shorts with embedded textile electrodes are composed of knitted fabric similar to elastic clothing, conductive electrodes, and into fabric integrated wires. EMG-signal is transferred to a removable electrical module which is attached on the waist area of the shorts during measurements. The textile bipolar electrodes are placed on the distal quadriceps and hamstring muscles and the grounding electrode is placed longitudinally on the lateral side. The electrodes are composed of conductive silver fiber yarns and non-conductive synthetic yarns which are woven together to form a fabric band. Electrical resistance of the silver fiber is 10Ω/10cm with dry electrodes. The wires that transfer the EMG-signal from electrodes to the module are made of steel fibres with short piece of silver coated fibre to make connection more reliable. There is a rubber sealing between the connector and the module to keep moisture outside of electronic contacts. Contact points in the shorts and module are gold-plated to keep the contact resistance low over time. The shorts with embedded textile electrodes are used to measure EMG in a different way than traditional measurement systems. EMG is traditionally measured from a single muscle but the shorts measure rather a group of muscles.

The shorts with embedded textile electrodes enable EMG measurements during daily life for long time periods (Lintu et al. 2005). Edgerton et al. (2001) recorded EMG for 24 hours using analog recording tape to quantify daily physical activity of four astronauts. They executed the measurements in two phases, each 12 hours long. Mean integrated EMG was used as a measure of physical activity and EMG was recorded from soleus, medial gastrocnemius, and tibialis anterior muscles. Klein et al. (2010) have also performed recordings of EMG for 24 hours and in those measurements physical activity was quantified by making threshold levels based on certain percentages of MVC.

4 PURPOSE OF THE STUDY AND HYPOTHESIS

This study is a part of a bigger research: "Muscle loading during physical activity and normal daily life: correlates with health and well being (EMG24)". The research is based on an idea that physical activity can be measured from EMG activity of quadriceps femoris and hamstring muscles. Earlier research related to this project is based on use of the intelligent clothing in EMG measurements and there are still some open questions how EMG activity could describe physical activity.

In this research intelligent clothing was compared to accelerometers as a measuring system. The main purpose was to investigate raw signals of intelligent clothing and accelerometers and to find similarities between them. Intelligent clothing with embedded EMG electrodes has been used to measure physical activity only in EMG24-project and there is not any established method for quantifying physical activity from EMG-signal. Accelerometers are commonly used devices to quantify physical activity and physical activity is measured via different kinds of activity counts depending on the purpose of the measurements. However, digital integration is considered to be the best way to approach activity calculation, although scientific literature is quite rare and every activity monitor manufacturer has its own unknown methods to produce activity counts.

Specific purposes of the study are:

1. To compare EMG-shorts in relation to accelerometers.
2. To find out how the cross-correlation between EMG and acceleration changes when the amount of muscles are reduced in EMG measurements.
3. To study how comparable the EMG and acceleration signals are through integral analyses.
4. To compare integrated signals and questionnaires to find suitable activities for activity calculations.

5 METHODS

The methods which have been used in this study are basic signal processing tools used commonly in studies when two signals are compared to each other. Cross-correlation is a commonly used method when the similarities of two different signals are examined. Because the cross-correlation analyses are based on comparison of the shapes of the signals, it was interesting to study how acceleration signal correlated with EMG. Digital integration was used to investigate if integrated EMG can be used for activity calculation in the same way like acceleration. The questionnaires were used to investigate quality and manner of physical activity.

5.1 Study subjects

Study subjects (n=12) were people from 20 to 76 years old and they had different physical activity background. All healthy persons who agreed on the terms of the research were able to participate on the study. In total 20 measurement days of 12 study subjects were included in the cross-correlation analyses. Integral analyses contained two groups because there appeared baseline shift in most of the signals and a second group was formed from signals without baseline shift, group 1 (n=20) and group 2 (n=5) measurements. The study was approved by the ethics committee of the University of Jyväskylä and the subjects signed an informed consent prior to any measurements.

5.2 Measuring protocol

As mentioned before, the purpose of this study was to compare intelligent clothing and accelerometers in physical activity measurements. The study subjects wore the intelligent shorts with embedded textile electrodes and the accelerometer one to three days. Each study subject came to the laboratory in the morning and they put on the intelligent shorts and the accelerometer and in the next morning the data was downloaded before a new measurement was initiated. The subjects were instructed how to act with the equipment and they were given a questionnaire to fill. The subjects filled in a questionnaire (ATTACHMENT 1) by marking down the activities they were performing during a day.

5.3 Measuring equipment

Two technical devices were used to measure daily physical activity: triaxial (x,y,z) Alive Activity monitor (Alive Technologies Ltd, Australia), and intelligent shorts with embedded textile electrodes (Myontec Ltd, Kuopio and Suunto Ltd, Vantaa, Finland). The reason for using Alive Activity monitor for measuring accelerations was availability of raw acceleration data without any activity calculations.

The Alive Heart and Activity monitor contains a 3-dimensional dynamic acceleration sensor with dynamic range of +/- 2,7 g, (figure 9). The recording resolution of the monitor is 8 bits which refers to representation of the acceleration signal after A/D conversion. The recording frequency of the accelerometer is 75 Hz and frequency band 0-20 Hz. Dimensions of the meter are 90 mm(length)*40 mm(width)*16 mm(depth) and its weight with a battery is 55 grams.

FIGURE 9. Alive Accelerometer and orientation of x, y and z axis (Alive manual 2006).

The intelligent shorts (figure 10) are composed of four textile electrode units. The textile electrodes are located horizontally on quadriceps and hamstrings muscles. The electrodes are sewed into the hem of the shorts which is similar to sporting tricots with elastic material. The grounding electrode is located longitudinally on the lateral side of the shorts over tractus iliotibialis. The sizes of the electrodes are 2,5 x 9,5 – 14 cm for quadriceps muscles, 1,5 x 7,5 – 8 cm for hamstrings muscles and 2 x 29 – 33 cm for lateral grounding electrodes depending on the size of the shorts. The data from electrodes is transformed into an electrical module through the electrical wires which are integrated into the fabric under the lateral electrodes. The recording module includes signal amplifier, microprocessor, memory, and connection to the PC. The raw EMG signal is recorded with 1000 Hz sampling rate and band pass filtered with 50 – 200 Hz. Afterwards the raw data is rectified and averaged in 100 ms periods. Data is stored as ASCII files in electronic module and can be downloaded as an HDF file into the PC with HeiMo -program (Myontec Ltd, Kuopio, Finland).

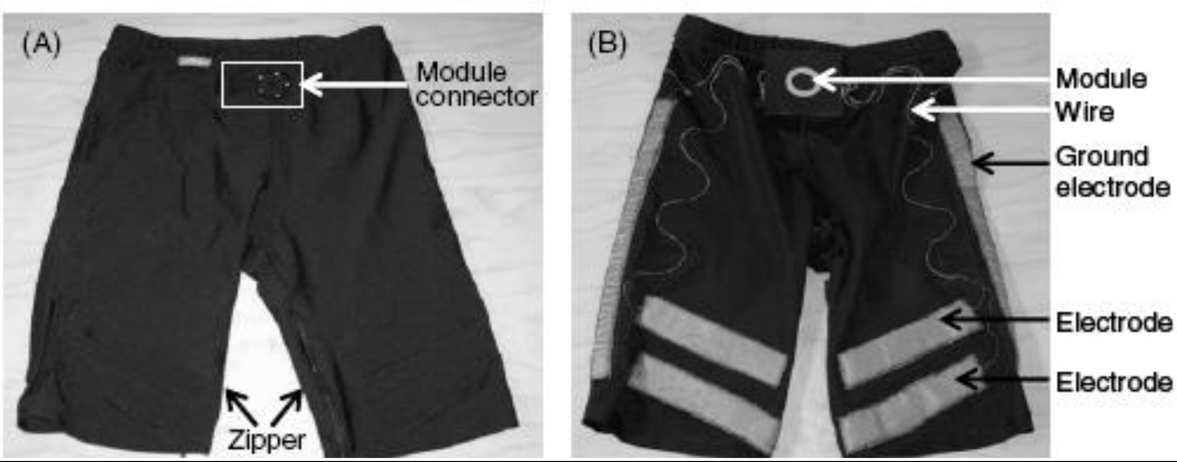

FIGURE 10. A) front outside view, B) inside view of the intelligent shorts (Finni et al. 2007).

5.4 Raw signal processing

Signal processing was one of the main areas of this study. Before the calculations, both raw signals had to be changed into the right format and filtered. The EMG signals had already been filtered before the calculations, so no filtering procedures were necessary to do. However, the EMG signals had to be changed to the same frequency with acceleration by using the same calculation as for the acceleration signals.

5.4.1 Acceleration signal

The acceleration signal was stored to a memory card of the accelerometer and after the measurement the data was loaded to a computer and saved as an ATS-file. The ATS-file was converted first into EDF format with ATS-to- EDF-converter and then into ASCII-format with EDF-to- ASCII-convertor. The reason why data was converted to ASCII format was related to later signal processing procedures; the ASCII formatted data was easier to process with Matlab. The first procedure was to filter the data with 2*n-1 band pass finite impulse response (FIR) filter. Before the data was run through the band pass filter, the frequencies were normalized to the Nyquist frequencies. After filtering, the data was sampled to 1 Hz because in earlier research related to the project 1 Hz was used in acceleration calculations. The last procedure before comparing acceleration to EMG-signal was to calculate a resultant vector $(x^2+y^2+z^2)^{0,5}$ composed of all three axes and then the signals were ready to be compared (ATTACHMENT 2).

5.4.2 EMG signal

EMG files had been transformed from HDF into ASCII files and then imported into MegaWin –program and the EMG data was visually assessed for the artifact removal. There had been four possibilities for cleaning procedures in earlier research when EMG had been processed. Remove some small artifact that is most likely caused by an electrical interference or loss of contact between the electrode and skin. The values would be replaced with interpolation technique from values prior to and after the removed value. In case of obvious bilateral movement (i.e. walking) the data from bilateral channel was copied. If artifact phase was long (longer than 30 minutes), the whole data was removed and not replaced with any other values, thus recording time varied between channels. Whole channel was removed if data was abnormal throughout the whole day. For this study only recordings with good quality were chosen and a maximum artifact of 5% of the length of a channel was accepted.

5.5 Cross-correlation analysis

The cross-correlation analyses were used to find similarity between the acceleration and the EMG signals. Cross-correlation analyses are commonly used to find out the similarity of two different waveforms which are in different phase. Cross-correlation is also known as a sliding dot product or inner-product. Cross-correlation can be expressed many ways depending on the purpose of a study. For continuous functions x and y, the cross-correlation (r) is defined in formula 5 as a function of delay (d), where mx and my are means of the corresponding series.

$$r(d)=\sum_i [(x(i) - mx)*(y(i-d)-my)] / [(\sum_i (x(i)-mx)^2)^{0,5} * (\sum_i (y(i-d)-my)^2)^{0,5}] \tag{5}$$

In this study the cross-correlations between acceleration and EMG signals were calculated using Matlab. Matlab has a function for determining cross-correlation and with small modification it was used in this study (ATTACHMENT 3). The results were scaled between -1 and 1 to get numeric values of correlations. The length of the both vectors had to be the same so that the cross-correlation analysis could have been executed with Matlab. The total EMG-signal was a sum of four different channels as it has been mentioned earlier. The analyses were done between one-(r_1), two-(r_2), three-(r_3), and four-(r_4) channel EMG-signals and acceleration signal. One-(r_1) channel EMG was from left quadriceps femoris. Two-(r_2) channel EMG was composed of left quadriceps femoris and right hamstring muscle. Three-(r_3) channel EMG was composed of left quadriceps femoris, left hamstring muscle and right hamstring muscle. It was also in interest to study if differences appear when muscles from anterior or posterior have been included in to the sum of EMG signal. Two-channel analyses were done three different ways: 1) left hamstring muscle and right quadriceps muscle (r_2) 2) quadriceps femoris ($r_{2.2}$) 3) hamstring muscles ($r_{2.3}$) were measured.

5.6 Integral analyses

The integral analyses were done to investigate if it is possible to find grounds for calculation of physical activity from EMG-signal through integral analyses like it is commonly done in acceleration analyses. The calculation was based on the comparison of the complete area of both signals. There is a function in Matlab that calculates the areas restricted by y- and x-axis (ATTACHMENT 3). The measurements were done for two different groups. In group 1 all 20 measurements of 12 study subjects were analyzed. In group 2 only 5 measurements of five study subjects were analyzed. The two groups were studied separately because there occurred baseline shift in EMG signals and a smaller group was studied afterwards just to prove that there is a strong match with the scaled areas of integrals. The smaller group is composed of measurements which do not include any known disturbances in the signal. A second criterion was the type of the physical activity the study subjects had reported performing during a day. Study subjects were not allowed to perform slow activity which requires strong lower limb muscle activity because, acceleration and EMG may not be comparable then.

One problematic issue related to comparison of the acceleration and EMG signals was different magnitudes of both signals (figure 11). Both signals were force to the same level by using idea of linear scaling. Linear scaling can be done two different ways and in this case the data was scaled in unit cube instead of unit variance. The unit cube forms a close scale for the data. After the scaling the signals were quite comparable although the zero-level of the EMG signals was unstable (figure 12).

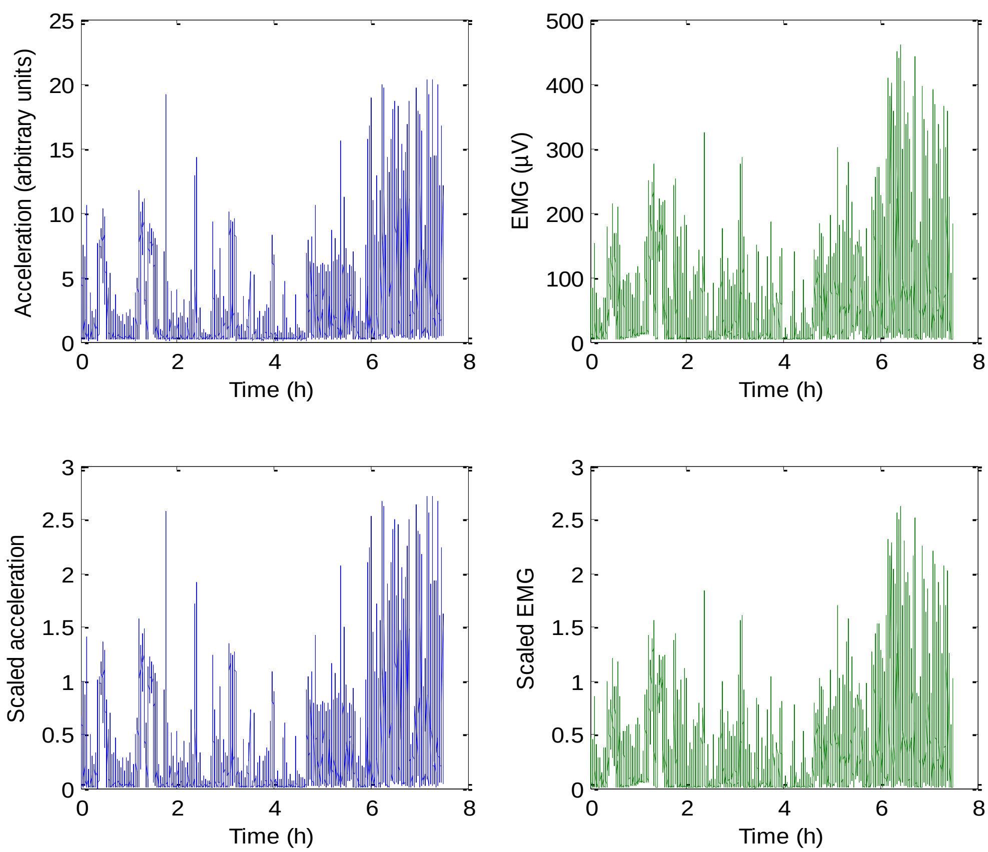

FIGURE 11. Example of one individual. Signals on top before scaling and on bottom after scaling. Activity levels are on y-axis.

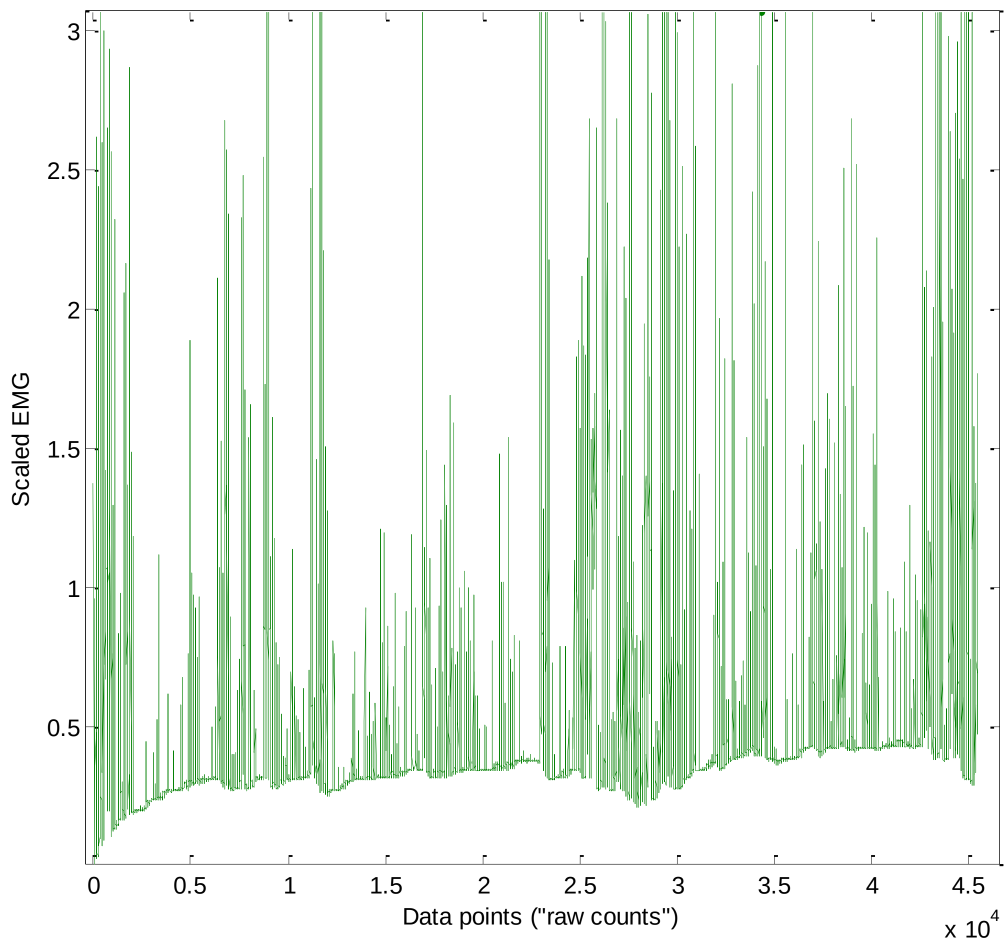

FIGURE 12. Baseline shift of EMG.

6 RESULTS

6.1 Cross-correlation analyses

All the cross-correlation values are means from 20 different assessments of 12 study subjects. The mean cross-correlation between acceleration and EMG composed of four channels was r_4=0,62. There existed only small differences with three-(r_3) and two-(r_2) channel EMG and acceleration r_3=0,61 and r_2=0,60 compared to four-channel EMG. When only one channel was available the cross-correlation was notably smaller r_1=0,56. Figure 13 visualizes the results between cross-correlations of the study subjects.

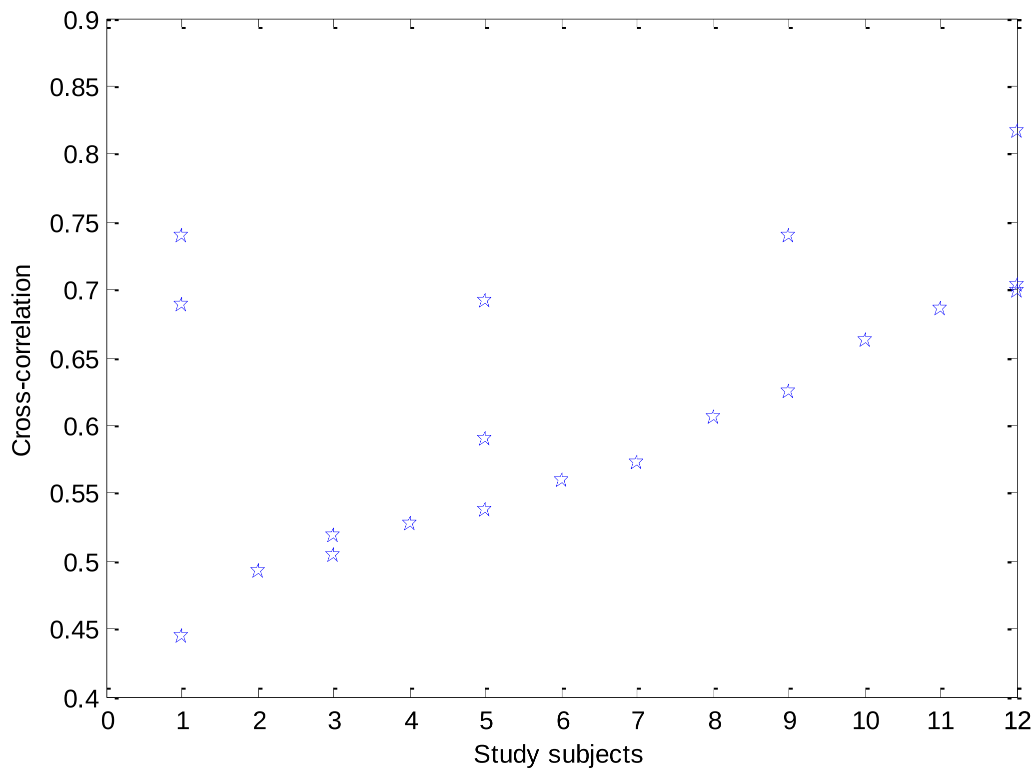

FIGURE 13. Cross-correlations of four-channel EMG and accelerations for each study subject. Two subjects had three measurement days and three subjects had two measurement days. Rest of the subjects had one measurement day.

The cross-correlations of the muscle combinations of r_4, r_3, r_2 and r_1 are shown in figure 14. It is clearly evident that only small differences can be observed between the cross-correlations. However, if only one channel (r_1) is available for recordings, the difference is notably bigger.

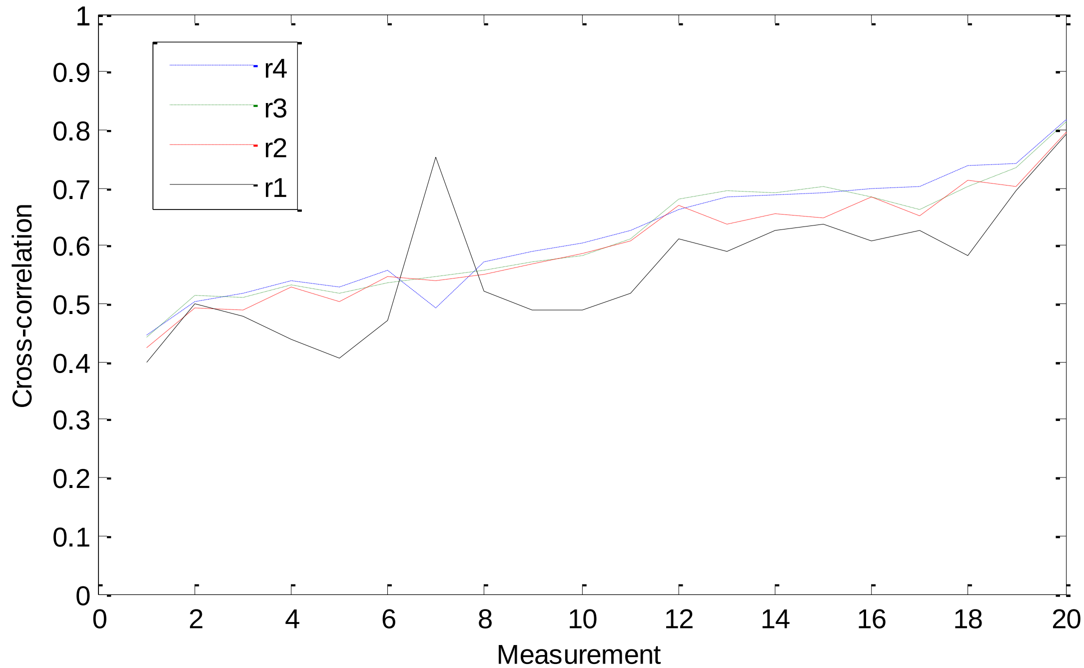

FIGURE 14. The figure illustrates how cross-correlation changes if the amount of recording channels and thus also the amount of muscles is reduced from measurements. r4 means that all recording channels and four muscle groups are involved in measurements and r1 means that only one channel and one muscle group is involved in measurements.

The differences between two-channel EMG signals were slight. The cross-correlation values were slightly smaller when only quadriceps femoris -r_{22} and hamstring muscles -r_{23} were studied separately r_{22}=0.59 and r_{23}=0.58. Slight differences can be seen in figure 15.

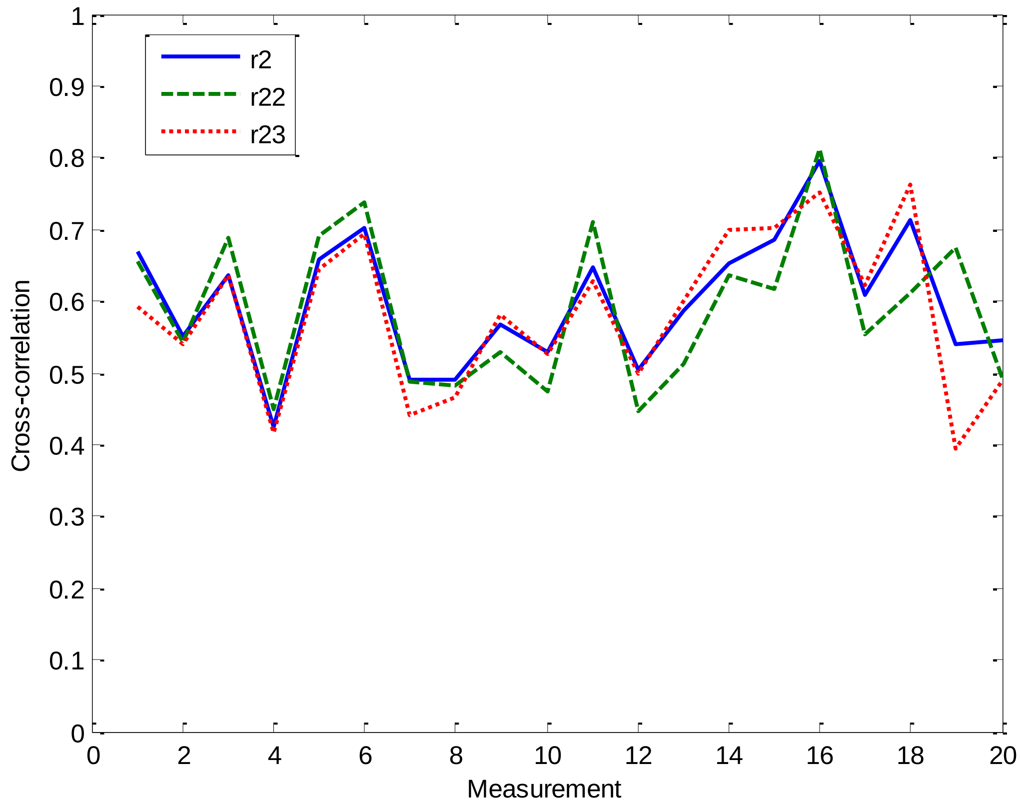

FIGURE 15.The figure illustrates that there does not exist any significant difference between cross-correlations when two muscle groups are measured and compared to acceleration. r22 refers to quadriceps muscles, r23 to hamstring muscles and r2 is combination of both.

6.2 Integral analyses

The mean match in group 1 (n=20) was 70% and the standard deviation of the results of group 1 was 0,163 and variance 0,027. The mean area match of the integrals of the signals in group 2 (n=5) was 90% and the standard deviation of group 2 was 0.061 and variance 0,004.

The results indicated that integral values of acceleration and EMG match quite well when the study subjects had reported performing normal daily physical activity and intensive physical activity which requires intensive movement. Figure 16 visualizes how well activities described by two signals of one study subject matched up when there does not exist any biased disturbances. The match between the signals was 95%.

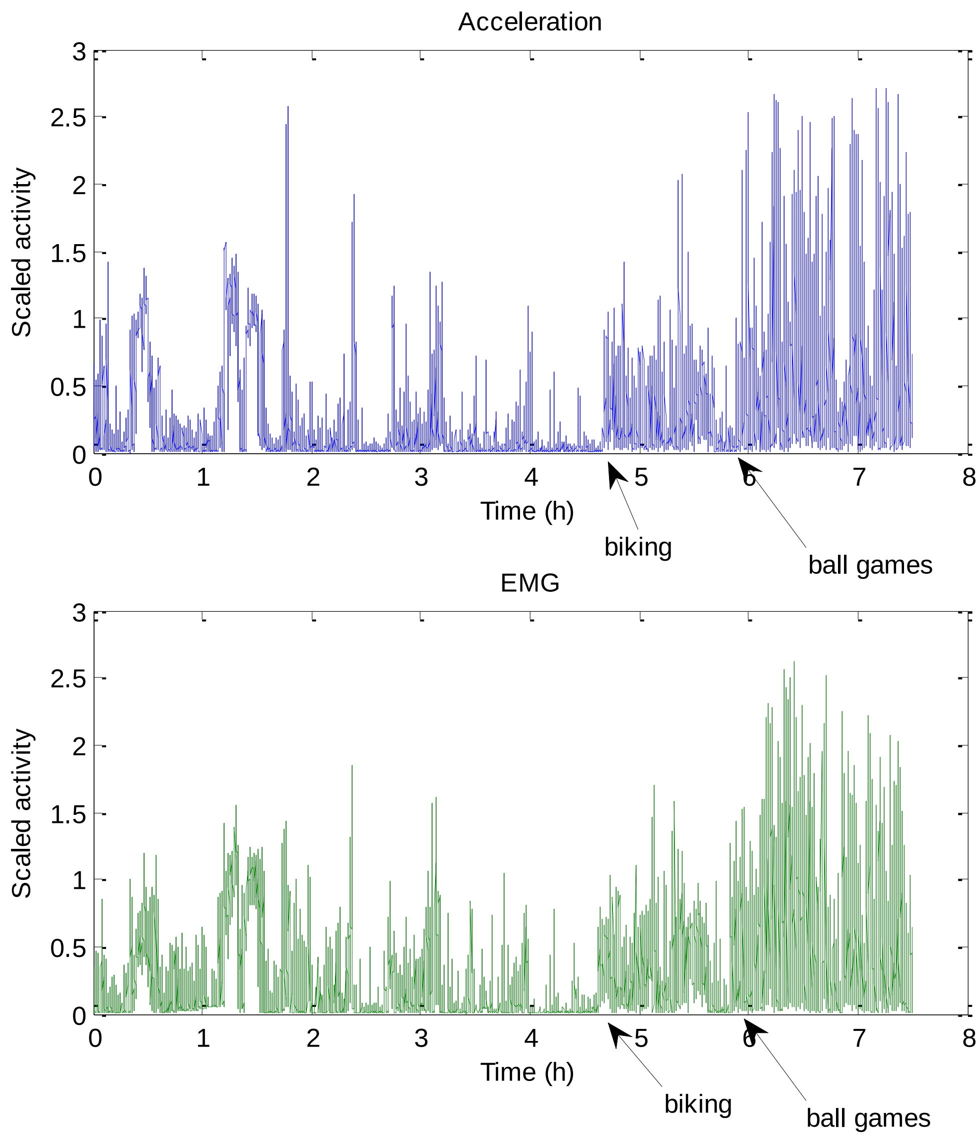

FIGURE 16. EMG is described on bottom and acceleration on top from a representative subject.

In figure 16 the study subject has reported performing normal physical activity like walking, standing up from a chair, biking, or ball games during the measurement. The intensities of the signals increase systematically when physical activity is constant and the nature of activity changes to more intensive activity. According to the questionnaire, the subject has biked between 4,5 h and 5,5 h and the level of physical activity has been continuously high. After the biking the study subject has reported to have been playing ball games and the intensity level has increased and the both signals have been acting the same way during both activities.

In second example the study subject has reported to have been performing intensive activity in the beginning and in the end of the measurement (figure 17). Between 2,5 h and 6,5 h only occasional activities have been reported. The match between the signals was 93%.

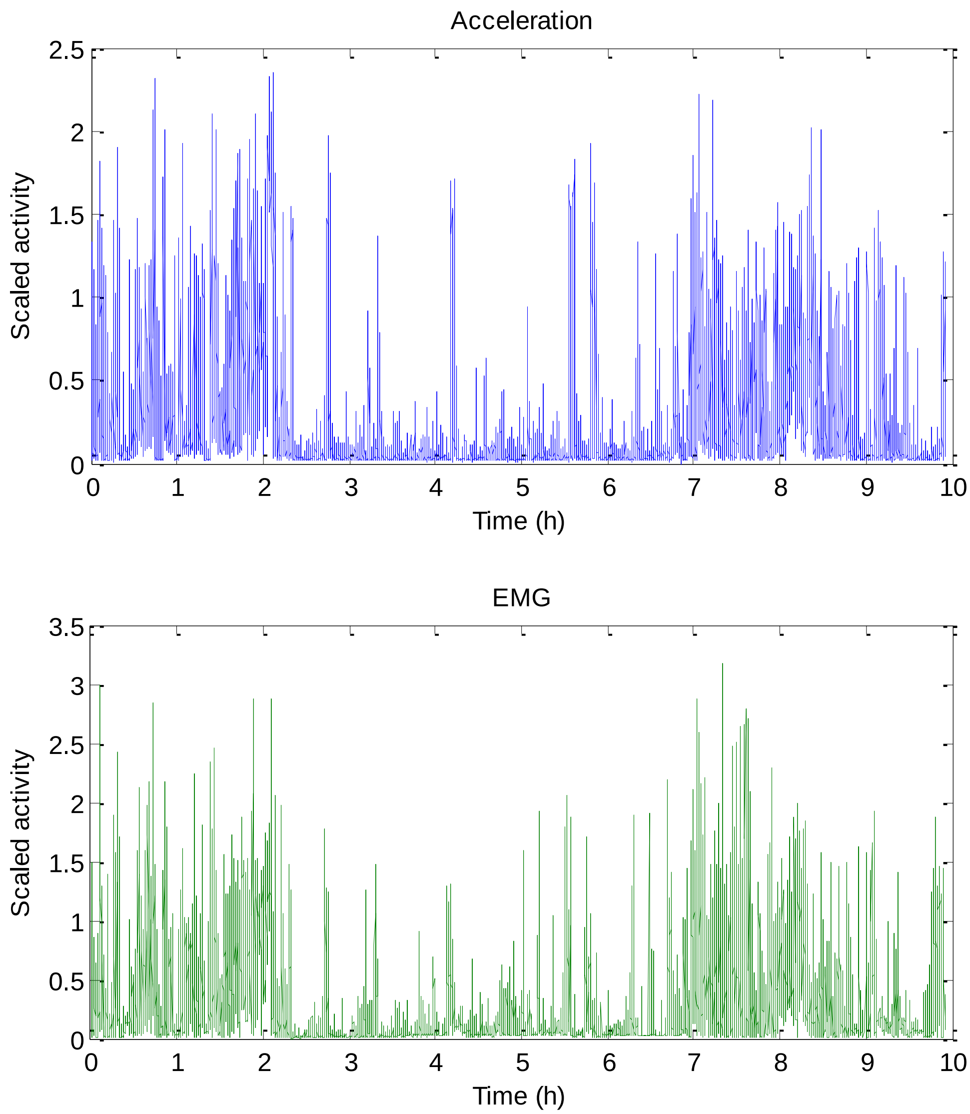

FIGURE 17. EMG and acceleration from a subject. Y-axis describes activity and x-axis time (h).

Another example of basic physical activity performed by one study subject can be seen from figure 18. In this case the study subject has reported to perform standing, standing up, walking, and biking. Most part of the day the study subject had been sitting, standing up, standing still, or walking. The match between the signals was 88%. In the two other measurements of group 2 the study subjects have reported to perform very similar activities like in this one.

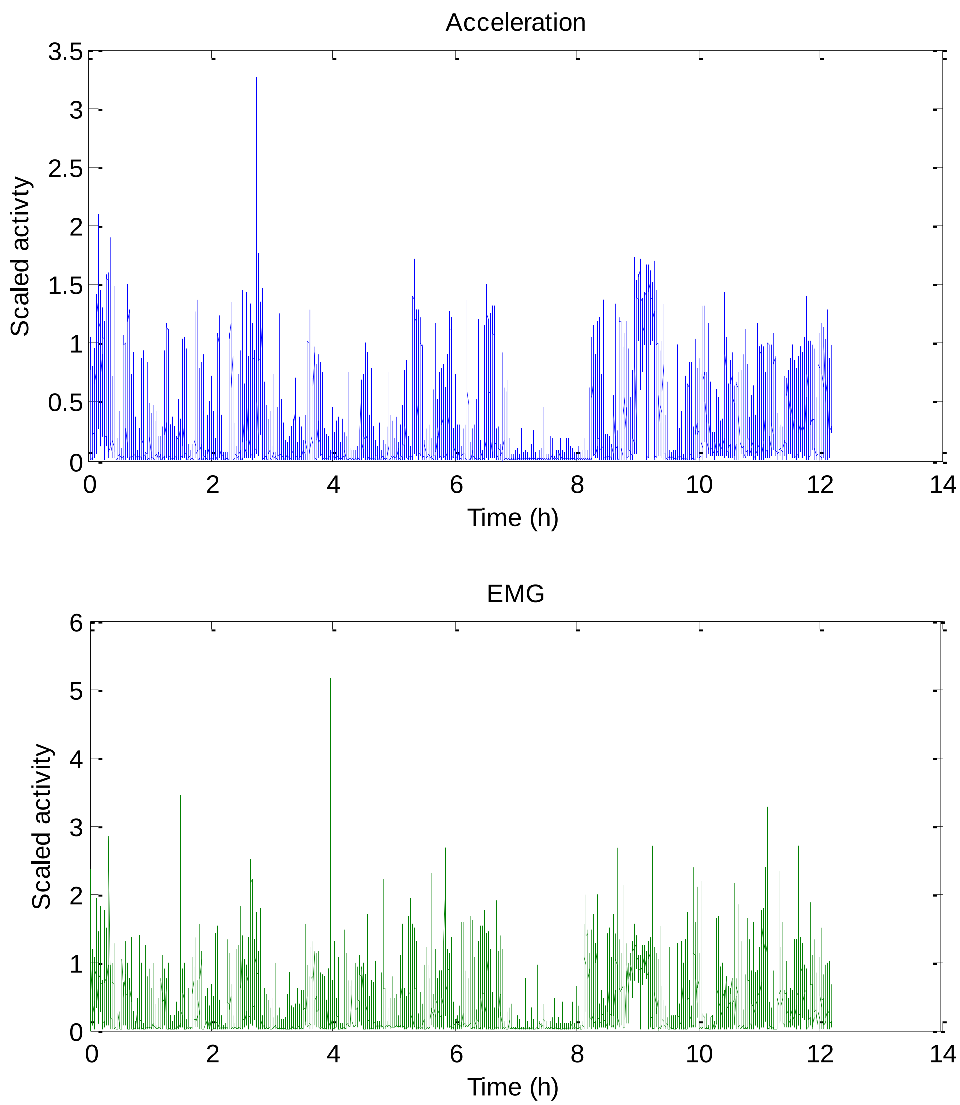

FIGURE 18. Comparison of EMG and acceleration on a day with low intensity activities.

When a study subjects had been carrying heavy loads during a day, EMG activity was much higher than acceleration (figure 19). In this particular measurement EMG activity was almost twice as high as acceleration based activity and the match between the signals was only 53 %. As it is reasonable to state, there are many activities that require strong muscle activity from quadriceps femoris and hamstring muscles when the rest of the body movement is slow and accelerometers indicate only activity of low intensity level.

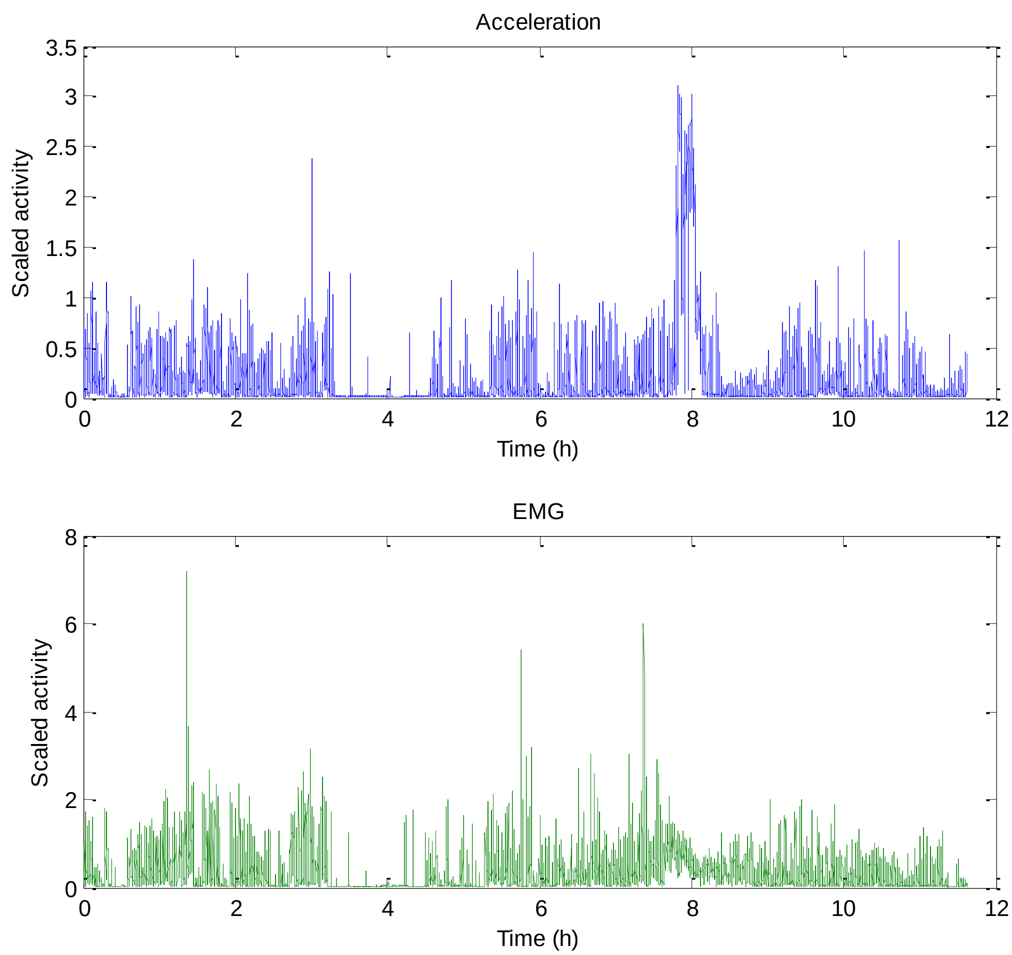

FIGURE 19. Comparison of EMG and acceleration on a day with strong EMG activity during slow movement.

7 DISCUSSION

The idea of this study was to compare intelligent clothing in relation to accelerometers by examining the cross-correlation between the EMG and acceleration signals and to study how comparable the EMG and acceleration signals are through integral analyses. The cross-correlation analyses were used to investigate the similarity between the shapes of the two signals. Integral analyses were done to find out if there exist grounds for quantifying physical activity from EMG signal through integral analyses, like it is commonly done with accelerometers. Cross-correlation between the two signals was on average r=0,62 and integrals matched in group 1, by 70% and in group 2, by 90%. In following sections the results are discussed and clarified in a wider extent.

7.1 Cross-correlation analysis

The results of the cross-correlation studies indicated that there exist some similarities between the shapes of acceleration signals and EMG signals after current signal processing. An important thing to remember is the different features of these two signals. Acceleration describes movement and its intensity and surface EMG summed muscle activity based on recruitment and firing rate of motor units. However, the cross-correlation analyses were also done to investigate if there turns out to be differences in results when smaller amount recording channels and thus smaller amount of muscles were involved in measurements. As the results indicated, only slight differences can be observed when at least two channels out of four were functional. When quadriceps femoris and hamstring muscles were studied separately there was a very small difference between the cross-correlations r_{22}=0.59 and r_{23}=0.58. The cross-correlations were between 0,58 and 0,62 when at least two channels were taken into account, and only slight changes can be stated. Even when only one channel was functional the cross-correlation was 0,56 between the signals. Thus, now it is evident that there exists a significant correlation between EMG and acceleration signals.

According to the results, the type of the physical activity can be identified with both signals up to a certain point. Probably the best way to identify the action would be combined analyses of cross-correlation and intensity of both signals. Chen & Basset (2005) suggests that detailed signal characteristics might be crucial if physical activity types and intensities are wanted to be detected. However, they do not give any specific models for analyses and they do not report the characteristics that should be studied.

7.2 Integral analyses

Integral analyses were done to investigate if activity calculation for EMG could be done like it is commonly done for acceleration. Although most of the physical activity studies have been done using commercial accelerometers, it is known that calculations of activity counts are in most of the models based on some kind of integral analyses. Thus, this study was made to find sufficient grounds for activity calculation for EMG signal similar to acceleration. According to these analyses, the integrals of the two signals matched quite well; in group 1 there is a 70% match and group 2 there was a 90% match between the areas. How the activity counts should be calculated through integral analyses and what would be the best way to do it are good questions to ask. What kind of signal characteristics are needed to involve the calculations and what kind of epochs should be used to derive the physiological message from the signal and at the same time identify the performed activity are complicated questions related to these analyses.

7.3 Evaluation of the research

The study was interesting and challenging because intelligent clothing is quite a new invention and it has not been used much for physical activity assessments earlier. While physical activity measurements were ongoing, there were still open questions about how the analysis should be done and what kind of methods should be used. Because only a small amount of data of good quality was available, it took a while to find an appropriate amount of measurements for this study. The EMG data collection was one of the most time consuming processes in this research. In retrospect, if different data would have been selected for integral analysis, the EMG-signal could have been composed of up to three channels and at least one recording channel could have been omitted from calculations. Would it after all have had significant influence on total EMG if one or two channels would have been left out of integral calculations is difficult to say. The results provide a lot of information about advantages and challenges there are if intelligent clothing is used to measure physical activity based on activity counts similar to accelerometers.

The questionnaires provided basic information about daily activity and this information was valuable in integral analyses. Naturally, it would have been better if reports had been more specific, but on the other hand, the day long measurements enable only rough estimations of daily physical activity. For detailed analysis there should be controlled measurements in which study subjects would perform given tasks in supervised circumstances. One important thing the questionnaires pointed out is the manner of physical activity that cannot be measured with accelerometers like it can be done with intelligent clothing.

As mentioned before the main characteristics of physical activity are intensity, duration, type, and frequency. When using the intelligent clothing to measure physical activity the intensity of physical activity has a double meaning because muscle activity can be intensive without fast movement of the body. If the intensity of muscle activity and contents in which people perform physical activity in daily life is observed, it is clearly evident that the muscle loads and intensities are totally forgotten in activities like stairs climbing when accelerometers are used as measuring equipment. One essential idea, why intelligent clothing was studied, is its capability to describe intensity of physical activity whenever the legs are used in a movement that requires strong muscle activity but only moderate movement. If intelligent clothing could be used to measure physical activity like accelerometers, it might be a more advanced method for clinical use.

Shorts with embedded textile electrodes measure only muscle activity of quadriceps and hamstring muscles and rest of the muscles are not involved in activity measurements. Therefore the shorts are suitable for activity measurements when people use their legs to move but even then the total activity of the body cannot be detected. Accelerometers have the same problem. If the accelerometer is located on pelvis the measured activity is just estimation from total activity because hand movements cannot be detected. For more accurate activity measurements one should use more devices to measure all parts of the body. However, it is not very meaningful to use several devices at the same time to measure physical activity in daily life because the data analyses get more and more complicated and measurements become too complicated to carry out if several electrodes are used. If EMG is measured for a long period, the risk to get noisy data increases because the electrodes are not invented for long-lasting measurements. The impedance between skin and electrode can increase if the contact is bad and it is a common problem in long-lasting measurements.

8 CONCLUSIONS

Cross-correlation analyses indicated that there are similarities between acceleration and EMG in daily activity. Since the mean correlation between the acceleration and EMG was 0,62, only some kind of activity can be found similar through the signal analyses. Next step would be detailed analyses of different kind of activity patterns to get specific information about how the shapes of EMG and acceleration signals match and find out how much the cross-correlation analyses can be used to identify action. There were only four assessments out of twenty in which the correlation was greater than 0,7, and only one assessment in which the correlation was greater than 0,8. The cross-correlation analyses alone do not give enough information about performed physical activity if EMG and acceleration are compared, thus, further research should contain some kind of intensity analysis combined with cross-correlation analysis.

Integral analyses pointed out that a strong match in total daily activity between measured acceleration and EMG can be detected when normal daily activities are being performed. In group 2 integral areas matched on average by 90%. Integral analyses also pointed out that intelligent clothing could describe extents of intensity of the movement better than the accelerometer when large thigh muscles are involved in action and specific action is performed. As mentioned before, acceleration was only 53% from EMG signal when the study subject had carried heavy loads during the day. What would be the best way how integral analyses should be used for activity counts calculations is a good question. Most of the physical activity research done with accelerometers is based on use of commercial devices, thus, the signal processing tools besides digital integration are unknown. This study points out that digital integration could be used to convert EMG signal into activity counts.

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9 APPENDIX

9.1 The questionnaire

Aktiviteetti	7.00-7.30	7.30-8.00	8.00-8.30	8.30-9.00	9.00-9.30	9.30-10.00	10.00-10.30	10.30-11.00	11.00-11.30	11.30-12.00	12.00-12.30	12.30-13.00	13.00-13.30	13.30-14.00	14.00-14.30	14.30-15.00
Töissä																
Makaaminen																
Istuminen																
Seisominen																
Hidas kävely																
Kävely																
Kävely alamäkeen																
Kävely ylämäkeen																
Portaiden laskeutuminen																
Portaiden nouseminen																
Hidas hölkkä																
Nopea hölkkä																
Juokseminen																
Nopea juokseminen																
Pyöräily																
Pyöräily ylämäkeen																
Tuolilta nouseminen																
Lattialta nouseminen																
Raskaan esineen nostaminen																
Raskaan esineen kantaminen																
Raskaan esineen kannattelu																
Portaat tai ylämäki ja raskas esine																
Portaat tai alamäki ja raskas esine																
Kyykistyminen																
Esineen poimiminen lattialta																
Oleskelu koukistetuilla polvilla																
URHEILU/LIIKUNTA																
Voimaharjoittelu																
Pallopelit																
Pyöräily																
Hiihtäminen																
Luistelu																
Muu aktiviteetti, mikä?																

9.2 Matlab codes for handling acceleration signal

```
function filter_dir(sd)
% FILTER_DIR filters data files in a directory
% FILTER_DIR(SD) filters all the ascii data files in the directory given
by SD.

% Find the files and the directories in the starting directory
d = dir(sd)

% Iterate through the names to find valid data files
for i = 1:length(d);
    it = d(i);
    if length(it.name) < 7
        continue
    end
% If found a valid file, then filter all the files in the directory
```

```
    if (strcmp(it.name(end-6:end),'x.ascii') == 1) | (strcmp(it.name(end-
6:end),'y.ascii') == 1) | (strcmp(it.name(end-6:end),'z.ascii') == 1)
        it.name
        filter_and_average_10hz([sd filesep
it.name],75,128,64,0,1,1000,0.5,11,0,3);
        % vika luku 3-> ottaa joka kolmannen pisteen (aik. 1 = joka
piste)
        % -> 25Hz)
%         break;
    end
end


function g = fir_bandpass(n,fl,fh)
% FIR_BANDBASS type fir bandpass filter
% FIR_BANDBASS(n,fl,fh) designs an order 2*n-1 bandpass finite impulse
response (FIR) filter.
% The filter is based on a rectangular window, and the passband is fl < f
< fh,
% where the frequencies are normalized to the Nyquist frequency (half the
sample frequency).

c1 = (fh-fl)/2;
g(n) = 2*c1;
for i = [2:n]
    xn = i-1;
    c = 3.14159*xn;
    c3 = c*c1;
    g(n+1-i) = sin(c3)/c*2*cos(c*(fl+fh)/2);
    g(n+i-1) = g(n+1-i);
end




function y = moving_average(x,n)
% MOVING_AVERAGE calculate the moving average
% MOVING_AVERAGE(x,n) calculates the moving average of the input vector x
% with the window half-width n, i.e. each value is averaged with the
neighbours
% wihtin the distance n

y = conv(ones(1,2*n+1)/(2*n+1),x);
y = y(n+1:end-n);




function
filter_and_average(name,fs,offset,scale,n0,skip0,n,fl,fh,n1,skip1)
% FILTER_AND_AVERAGE filter data with bandpass filter and calculate
moving average
% FILTER_AND_AVERAGE(NAME,FS,OFFSET,SCALE,N0,SKIP0,N,FL,FH,N1,SKIP1)
filters the data in the file named NAME.
% The original data has the sampling frequency FS. First data is scaled
to values (x-OFFSET)/SCALE.
% Do the following steps:
```

```
% 1. Calculate moving average of the data with a window half-width N0
% 2. Reduce the data by a factor SKIP0, i.e. SKIP0=1 gives the original
data, SKIP0=2 skips every second point etc.
%    This will also reduce the sampling frequency by the same factor.
% 3. Filter the data with a bandpass filter of an order N, with passband
frequency limits FL < f < FH given in Hz.
% 4. Calculate moving average of the data with a window half-width N1
% 5. Reduce the data by a factor SKIP1.
% 6. Save the filtered data in the file that has the name of the original
file with '_filtered' appended,
%    i.e. 'M1_AccelX.ascii' -> 'M1_AccelX_filtered.ascii'

% Exit from this function, if the file does not exist
if exist(name,'file') == 0
    return
end
x = load(name);

% Scale data
x = (x - offset)/scale;

% Step 1
x = moving_average(x,n0);

% Step 2
% Reduce data
x = x(1:skip0:end);
% Reduce sampling frequency
fs = fs/skip0;

% Step 3
% Normalize the pass band frequencies to the Nyquist frequncy fs/2
if (fl > fs/2) | (fh > fs/2) | (fl > fh)
    disp( 'ERROR: Passband frequencies must be 0 < FL < FH < FS/2.');
    disp(['       Now FL = ' num2str(fl) ', FH = ' num2str(fh) ', and
FS/2 = ' num2str(fs/2) '.']);
    return;
end
fl = fl/fs*2;
fh = fh/fs*2;
% Design filter
b = fir_bandpass(n,fl,fh);
% Filter
x = filter(b,1,x);
% Remove the filter delay
x = x(n:end);

% Step 4
x = moving_average(abs(x),n1);

% Step 5
% Reduce data
x = x(1:skip1:end);
% Reduce sampling frequency
fs = fs/skip1;
```

```
% Step 6
% Extract the parts of the filename
[directory,base,extension] = fileparts(name);
% Save filtered data
save([directory '/' base '_filtered' extension],'x','-ascii');

% activity calculated in 1hz non-overlapping windows; NOT 10hz!!
%
activity = [];
window_size = floor(fs);
steps = [1:window_size:length(x)];
for i = 1:length(steps)-1
    activity = [activity; sum(x(steps(i):steps(i+1)-1))];
end
save([directory '/' base '_act' extension],'activity','-ascii');


function calc_tot_act(sd)

% Find the files and the directories in the starting directory
d = dir(sd);

% Iterate through the names to find valid data files
for i = 1:length(d);
    it = d(i);
    if length(it.name) < 11
        continue
    end
    if (strcmp(it.name(end-10:end),'x_act.ascii') == 1)
        x_data = load(it.name);
        yname = strrep(it.name,'x_act.ascii','y_act.ascii');
        if exist(yname,'file')
            y_data = load(yname);
        else
            continue
        end
        zname = strrep(it.name,'x_act.ascii','z_act.ascii');
        if exist(zname,'file')
            z_data = load(zname);
        else
            continue
        end
        tot_data = sqrt(x_data.^2 + y_data.^2 + z_data.^2);
        tot_name = strrep(it.name,'x_act.ascii','tot_act.ascii');
        save(tot_name,'tot_data','-ascii');
    end
end
```

9.3 Matlab codes for cross-correlation and integral analyses

```
importdata('name');
a1=[];
a1 = importdata('name'); % kiihtyvyysdata
data2=xlsread('name');
p=data2(:,1);p2=data2(:,2);p3=data2(:,3);p4=data2(:,4); %lukee taulukosta
kyseisen rivin.
x=[];x=p;
y=[];y=p2;
z=[];z=p3;
k=[];k=p4;
r1=[];
%r1=x+y+z+k;
%r1 = sqrt(x.^2 + y.^2 + z.^2 + k.^2);

fs=10; % muunnetaan emg data samantaajuiseksi kiihtyvyyden kanssa.
emg1 = [];
window_size = floor(fs);
steps = [1:window_size:length(r1)];
for i = 1:length(steps)-1,
    emg1 = [emg1; sum(r1(steps(i):steps(i+1)-1))/10];
end;

ac=[];% muodostetaan vektorit samanpituisiksi
i=1;
for i = 1:length(emg1),
    if a1(i) < length(emg1),
    ac = [ac ; a1(i)];
end;
end;

a=[]; %skaalausmetodit
acmax=mean(ac)+3*std(ac);
acmin=mean(ac)-3*std(ac);
scale=0.5*(acmax-acmin);
offset=acmin+scale;
a=(ac-offset)/scale;

emg=[];
emg1max=mean(emg1)+3*std(emg1);
emg1min=mean(emg1)-3*std(emg1);
scale=0.5*(emg1max-emg1min);
offset=emg1min+scale;
emg=(emg1-offset)/scale;

m=abs(min(a));
n=abs(min(emg));

acc=[];
for i=1:length(a),
    acc=[acc;a(i)+m];
end;
```

```
emg9=[];
for i=1:length(emg),
    emg9=[emg9;emg(i)+n];
end;

%ristikorrelaatioiden laskenta
[r,lags]=xcorr(emg9,acc,'coeff');
max(r)

%integraalit trapetzoidaaliseen numeeriseen integrointiin perustuen.
d=trapz(acc);
g=trapz(emg9);
q=d/g
```