Detecting and Interpreting Muscle Activity with Wearable Force Sensors

Paul Lukowicz[1], Friedrich Hanser[1], Christoph Szubski[1,2], and Wolfgang Schobersberger[2]

[1] Institute for Computer Systems and Networks, UMIT, A-6060 Hall, Austria
csn.umit.at
[2] Research Department for Leisure, Travel and Alpine Medicine, UMIT, A-6060 Hall, Austria
http://www.umit.at

Abstract. In this paper we present a system for assessing muscle activity by using wearable force sensors placed on the muscle surface. Such sensors are very thin, power efficient and have also been demonstrated as pure textile devices, so that they can be easily integrated in such garments as elastic underwear or tight shorts/shirt. On the example upper-leg muscle we show how good signal quality can be reliably acquired under realistic conditions. We then show how information about general user context can be derived from the muscle activity signal. We first look at the modes of locomotion problem which is a well studied, benchmark-like problem in the community. We then demonstrate the correlation between the signals from our system and user fatigue. We conclude with a discussion of other types of information that can be derived from the muscle activity based on physiological considerations and example data form our experiments.

1 Introduction

Motion monitoring is an important aspect of many pervasive computing applications. For one, user motion is indicative of the general user activity. The most obvious case are the modes of locomotion (sitting, standing, walking, running etc.). In other applications hands motions were analyzed to recognize steps of an assembly procedure [1], interaction with objects, or general gestures. Beyond activity recognition motion analysis plays an important role in a variety of pervasive computing applications related to rehabilitation, nursing, lifestyle monitoring, sports and wellness [2]. As an example, our group is involved in a project devoted to a wearable nordic walking trainer. The aim of the project is to monitor user motions and ensure that the user gets the maximum benefit of the exercise while minimizing risk factors such as joint damage or overextension. In another project we look at assistive system for the elderly where motion patterns are important to understand the users general condition including, for example, assessing the risk of serious falls.

Today the main approaches to motion analysis are visual tracking and body-worn inertial sensors (acceleration, gyroscopes). In the paper we propose a novel

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method for unobtrusive motion monitoring: the use of wearable force sensors to assess muscle activity. This approach is based on the following ideas:

– Muscle activity is associated with changes of muscle shape. In particular in the limbs, these changes are noticeable on the surface as certain parts of the muscle 'inflate' or 'deflate'.
– Force sensors that react to surface pressure can be manufactured as ultra thin foils or even in textiles using capacitance change between two conductive layers. If integrated in tight garment or elastic bands such sensors can be used to detect muscle shape changes.
– The relationship between muscle activity and different limb motions is well understood. Thus, general activity information can be inferred from muscle shape changes.
– Muscle activity contains information that goes beyond mere motion type. This includes physical effort and fatigue as well as subtle motion characteristics that are of interest to many medical, nursing and sports applications.

1.1 Related Work

Monitoring muscle activity is widely practiced in medicine and sports. The scientific standard technique is called electromyography (EMG, e.g. [3]). It relies on a pair of electrodes placed at specific locations on the surface of the muscle belly (International standards written by Merletti [4]). EMG is a rich and reliable source of information about muscle activity by detecting the electromechanical properties of muscle fibres. However, since the electrical potentials that it measures are very faint, it requires careful electrode placement and excellent contact with the skin. In general, EMG electrodes require glue in order to attach to the skin. In some cases even small needles are used. In addition, complex signal processing is needed to make sense of the signals, so that EMG devices are bulky and expensive. In summary they are not suitable for typical pervasive applications.

The second tool for monitoring muscle activity is the mechanomyographic (MMG) technique. While EMG comprises the sum of the electrical contributions, the MMG signals (using vibration transducer, such as accelerometer or piezoelectric crystal contact sensors) present the mechanical oscillation that is detectable over a contracting muscle by attaching electrodes on the skin overlying the target muscle [5].

Force sensors have been used in pervasive computing for event detection. Examples include force sensors placed in shoes to detect heel strikes [6, 7] and in furniture components to automatically verify the correctness of assembly procedures [8].

Motion monitoring using body-worn sensors is a vast research field. The main two directions are activity recognition oriented work (e.g. [9, 10, 11, 12, 13] and many more) in the classical pervasive computing field and motion characterisation oriented work (e.g. [14, 15, 16, 17, 18] and many more). The latter has its roots in the biomechanics/sports community, however, is increasingly gaining importance in pervasive computing with the advance of applications related to sports, wellness and health.

The approach presented in this paper can benefit activity recognition as well as motion characterisation. In both areas it will do so by enhancing existing systems in two ways:

1. It will provide an additional *source* of information about user motion. Such additional information can be combined with existing approaches to improve system accuracy through sensor fusion. It can also be used as an alternative, wherever existing approaches are inappropriate. Thus, for example, accelerometers and gyroscopes mounted on the leg will register not only leg motion, but also the overall motion of the user system of reference. By contrast, our muscle-activity-based method will only provide information about leg motion.
2. It will provide an additional *type* of information about user motion. This includes such things as physical effort associated with the motion, user fatigue or subtle motion characteristics related to the way the motion is generated by the musculo-skeletal system of the user.

1.2 Paper Contributions

In this paper we focus on showing that

1. under realistic assumptions it is possible to acquire good muscle activity signal with our approach, and
2. information relevant for a range of pervasive applications can be extracted from this signal.

To this end we begin in section 2 by describing the general idea of muscle activity measurement using force sensors. Section 2 also contains the characterisation of our sensors and a description of our system. We then proceed in section 3 to a quantitative experimental evaluation of the influence of sensor attachment and position on signal quality. In doing so we prove that reasonable signal quality can be reliably achieved with a simple, practical attachment scheme such as an adjustable elastic band. In section 4 we give two specific examples how activity information can be derived from such signals. The first example is the well known modes of locomotion problem (walking, fast walking, going downstairs, going upstairs). It demonstrates that our system provides an additional source of information for standard context recognition tasks. In the second example we show the correlation between the signals from our sensors and user leg muscle fatigue. This demonstrates how our sensors can provide information that goes beyond what can be derived from inertial motion sensors. For both examples we provide a physiological explanation of how the information is extracted and quantitative experimental data. We conclude in section 5 with a qualitative discussion of further examples of information that can be derived from muscles signals.

2 The Idea

2.1 Muscles and Muscle Inflation

It is a well known phenomenon that the muscle tends to 'inflate' when put under strain. This phenomenon is used by body builders when 'showing off'. When using inertial sensors to monitor limbs motion it is often a source of errors as sensor mounted on the limbs register muscle shape changes instead or together with the actual limbs motions. Dealing with such errors has been the inspiration for the work presented in this paper. Rather than filter them out as noise we propose to use muscle shape changes as source of information.

Physiological Background. To understand what type of information can be extracted from muscle shape changes some physiological background is needed. From a physiological point of view the muscle inflation can be explained as follows: Muscle is a contractile form of tissue and it consists of a large number of muscle fibres. A muscle contraction occurs when the muscle fibre shorten. The higher the force production during short-term muscle exercises the more fibres are activated and extended which contributes to larger physiological cross sectional area and this means an increased muscle volume during a muscle contraction. When muscles contract during long-term exercises, blood vessels within the muscle become wider (vasodilation) and blood flow is increased more than 20-fold. Repetitive mechanical muscle contractions consume large amounts of energy and therefore require delivery of considerable amounts of oxygen and substrates, as well as the efficient removal of metabolic waste products (e.g., lactate, CO_2, H^+). Long-term physical activities with higher intensities or motion velocities result in accumulation of lactate and other metabolites within the muscle and reduced muscle blood circulation in small arteries and arterioles. This resistance in arteries yields a blocked muscle blood circulation, an increased blood volume within the muscle, and an inflation of muscle volume during sustained and intensive exercises.

2.2 Measurement Idea

From the above physiological considerations the following sources of muscle shape change and the associated interesting information can be identified:

1. Shape change associated with each muscles contraction, with the amount of volume increase given by the load on the muscle, as can be seen in Fig. 1 (left). Since muscle contraction is the driving force behind limbs motion, detecting contractions will provide us with information about limbs movement. Since, in general, each limb is moved by a combination of muscles looking at the activity pattern of the relevant muscles should provide detailed information on the type of motion.
2. Shape change associated with long term exercise as the blood flow in the muscle is increased to provide more oxygen. This can provide information about the intensity of physical activity, as can be seen in Fig. 1 (right).

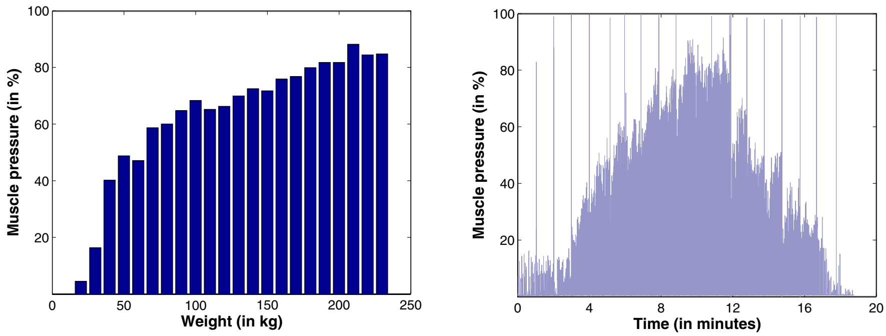

Fig. 1. *Left:* single-leg press with weight increasing in 10kg steps beginning with 20kg (left). The final weight which could be lifted was 230kg. *Right:* Muscle fatigue test using a step mill. Intensity was increased every minute till a maximum point and then decreased again.

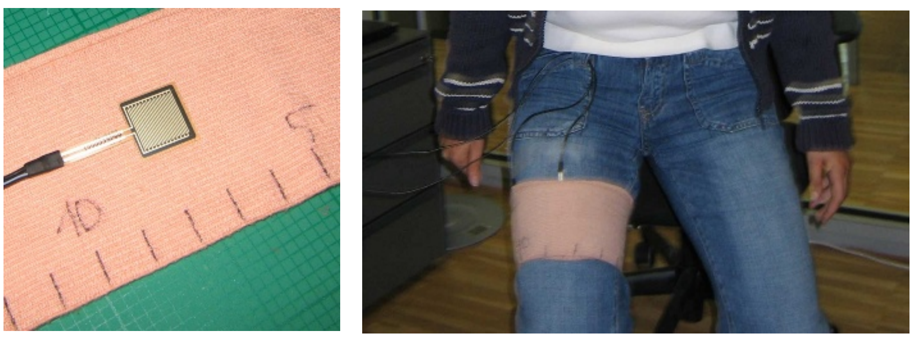

Fig. 2. Left: The force sensor and the elastic band used in our experiments. Right: One of the subjects with the band on the leg doing squats.

3. Shape change associated with muscle fatigue. Such fatigue is an important information on its own.

We propose to detect the shape changes by attaching force sensors integrated in tight fitting garments or elastic bands to the surface of the relevant muscles. The actually employed setup is depicted in Fig. 2.

2.3 Measurement System

The force sensors used in our experiments are so-called force sensitive resistors (FSR). Such sensors consist of thin ($<< 1\,\mathrm{mm}$) electrodes that change their electrical resistance when subjected to pressure. Specifically, we have used the FSR-153NS device from Conrad Electronics. It is 0.09 mm thick and has an area of $13 \times 13\,\mathrm{mm}^2$. The measurement range is between 0.1 and 100 N with a corresponding resistance between $2\,\mathrm{k\Omega}$ and $2\,\mathrm{M\Omega}$. The maximum achievable sampling rate is between 100 and 1000 Hz.

For signal acquisition a module from a standard platform developed at ETH Zürich (PadNET [19]) is used. Its main components are a TI MSP 430 mixed signal processor with a built-in analogue digital converter, some analogue signal processing circuits, a voltage regulator and a serial interface. The force sensors are connected to the analogue input of the MSP in a voltage divider configuration with a 47 kΩ resistor. The sensors are sampled with 100 Hz and 12-Bit resolution.

3 Measuring Muscle Activity

For our approach to be viable for a widespread use in pervasive applications we must ensure that acceptable signal quality can be achieved without excessively complex attachment and adjustment procedures. We envision the sensors to be integrated in garment such as pants or in an elastic band that is put on top of clothing. In both cases two issues are critical for signal acquisition:

1. The baseline pressure between the sensor and the muscle. As described in the previous section our system detects muscle activity through variation on mechanical pressure that the muscle surface exerts on the sensor. Thus, obviously, the signal that we will get depends on how tight the garment or the band is put on the muscle.
2. The sensor position; The sensor must be placed on a part of the muscle where a detectable inflation occurs. For each muscle it is well known from human physiology where such a spot is. It can also easily be felt when flexing the muscle. For practical applications the key question is how sensitive the signal quality is to small displacements.

Below we describe the results of a systematic experimental evaluation of the above issues on the example of upper-leg muscles.

3.1 Sensor Attachment

Due to the complexity of garment integration in our initial work we consider the elastic band variant as shown in Fig. 2.

1. The band is wrapped around the upper-leg in such a way that it exerts no perceivable pressure.
2. The band is tightened in increments of two centimeters. After each increment the user bends his knees about 90 degree in a partial squat and the maximum of the signal is noted.
3. Point two is repeated after the signal with bent knees reaches between 15% and 20% of the maximum (as given by sensor range).

The above procedure was performed on 10 subjects, each repeating it three times. We used a commercial elastic bandage which was folded in half wrapped around the upper-leg between two and three times. On all subjects signal in the desired range was achieved by tightening the band between a minimum of 4 cm and a maximum of 16 cm. For all subjects the required amount of tightening was the same in all three attempts.

The results of this experiment mean that an individual value has been established for tightening the band and that it can be put on in a single deterministic step. The search for the right value is matter of a view simple steps not much different from fitting a shoe.

3.2 Sensor Placement

The placement of the sensor on the muscle is performed according to international standards for EMG written by Merletti [4]. To evaluate the effect of sensor displacement on the signal quality we systematically displaced the sensor from the above position in increments of 1 cm and then looked at the signal produced during squats. An example result is shown in Fig. 3. The measurements have revealed two things:

1. The optimal EMG placement spot does not correspond with the best placement for our sensors, although it does produce good signals.
2. Depending on the direction of sensor displacement even a 1 cm move from the original position can lead to a loss of signal. However, within a 4 cm $\times$ 4 cm square around the optimal position there are many points with good signal quality.

The above means that for practical applications one would have to work with a sensor array rather then with a single sensors. Since the force sensors are thin and easily integrable this is not a problem. Such 4×4 arrays with about the right area have even been demonstrated as purely textile devices. In summary, it can be said that, as long as we can work with an array, sensor placement is not a serious obstacle to achieving good signal quality with realistic setups.

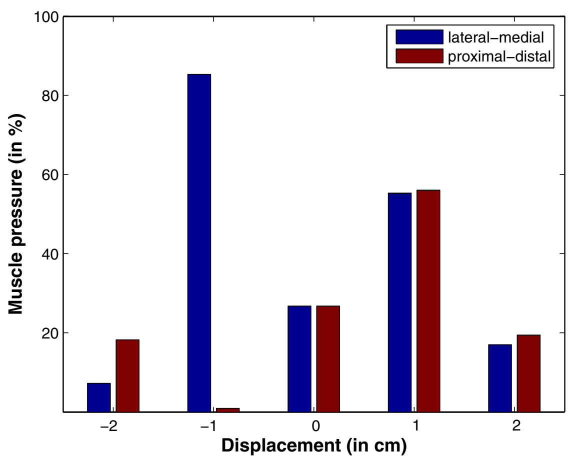

Fig. 3. The effect of sensor displacement on signal quality

4 Interpreting Muscle Activity

The previous section showed that reliable acquisition of muscle activity signals is possible under realistic conditions. Staying with the example of upper-leg muscles this section leverages physiological knowledge to extract from those signals information relevant to a wide range of pervasive applications.

4.1 Modes of Locomotion

The recognition of different modes of locomotion is a standard context problem that has become sort of a benchmark for new approaches. In the following we investigate the problem of distinguishing between level walking with normal stride, level walking with extra long stride, walking downstairs, and walking upstairs.

Physiological Foundations. To monitor motion patterns in level walking, going upstairs and downstairs by using force sensors, muscle activity of the front-leg muscles (m. vastus lateralis) and back-leg muscles (m. biceps femoris) were selected. For the purpose of analysis, steps are usually divided into the swing phase and the stance phase. In the swing phase the leg is brought forward without ground contact. The stance phase begins with the leg being put down and ends with the leg pushing off the ground.

While walking styles differ between people, there are some general considerations valid for the majority of people. Also wherever variations are present they are consistent in the sense that a given person will always display certain muscle activation patterns for a particular mode of locomotion.

1. For all types of walking there can be expected to be little to no muscle signal during the swing phase.
2. Typically, during level walking the stance phase contains two distinct muscle activities: (1) cushioning the impact when the leg is put down and (2) pushing off the ground. In general, the front muscle is more active during

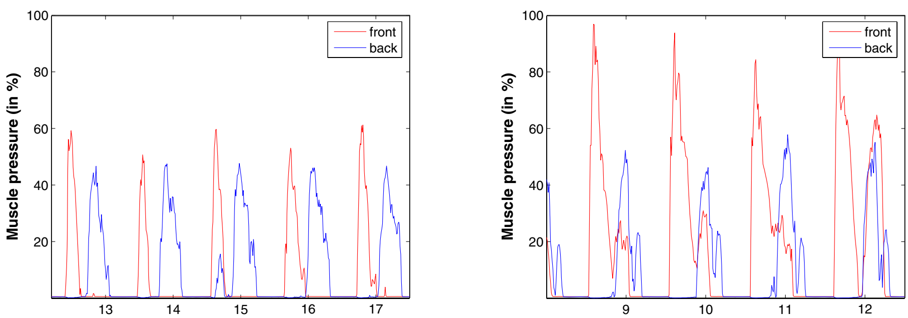

Fig. 4. Example of level walking signals from the front-leg and the back-leg muscle with normal step size (left) and long step size (right)

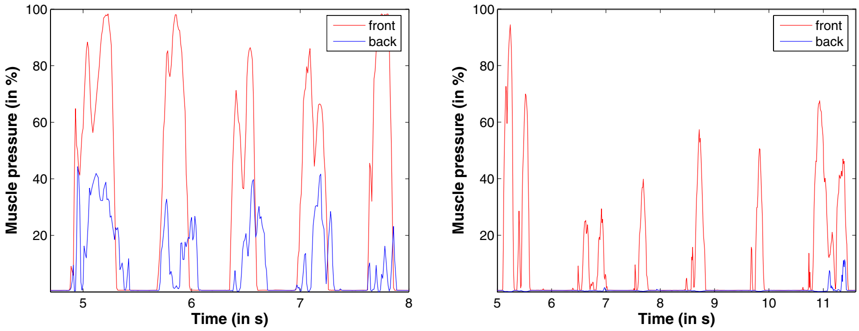

Fig. 5. Example of signals from the front-leg and the back-leg muscle for walking downstairs (left) and upstairs (right)

impact, whereas the back muscle tends to dominate the push-off. While the activity between the impact and the push-off as well as signal ratios will vary between people the presence of a front muscle dominated peak in the beginning and a back muscle dominated one at the end is a very strong indication of level walking, as can be seen in Fig. 4 (left).

3. For faster walking and longer strides we will see a decrease in the delay between the peaks and an increase in the muscle activity amplitudes. This illustrates Fig. 4 (right).
4. The main activity when going downstairs is the cushioning of impact. Except for very wide steps there is nearly no push-off observed. The cushioning involves both front-leg and back-leg muscles working synchronously. While the exact ratio differs from person to person, the front muscle plays a clearly dominant role. This can be seen in Fig. 5 (left).
5. When going upstairs, front-leg muscles are dominantly used at the beginning of the stance phase to lift the body up. There is no similar synchronized front and back muscle activity as considered in going downstairs. This trend was already presented in elderly by using electromyographic measuring method [20]. An example of walking upstairs, can be seen in Fig. 5 (right).

From the above considerations the ratio of front-leg to back-leg muscle activity and the delay between the two (both during the stance phase) can be derived as appropriate features to separate the four modes of locomotion under consideration. The swing phase with a null or near null activity level from both muscles provides an excellent way to segment the signal into individual steps.

Experiment. To verify the above hypothesis 4 subjects were asked to walk around the hall. Part of the distance was to be covered with normal steps and with particularly long steps. At the end of the hall the subject were to walk down and then back up a flight of stairs. For each subject the data was segmented into steps using the swing phases and the two features suggested above were computed for each step segment. The result is shown in Fig. 6. It indicates

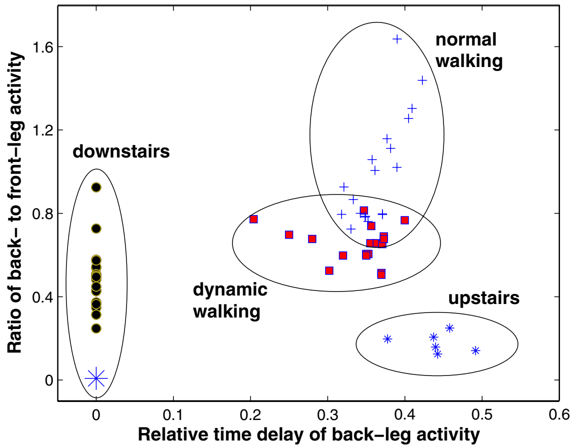

Fig. 6. The separation between the four investigated modes of locomotion using the features described in the text. Asterisk indicates the accumulation of downstairs steps with identical feature values.

excellent separation, even though we have combined data from all four persons in a single plot (8 user independent case).

4.2 Muscle Fatigue

The level of user muscle fatigue is an important piece of information for a variety of applications. Straining the muscles to the point of volitional fatigue may lead to loss of muscular reflexes and may increase the risk for injury as a consequence of proprioceptive deficit in muscle receptors and joint proprioception. Thus detecting fatigue can prevent accidents in areas such as sports, emergency response teams and in elderly, frail persons. In addition, the level of fatigue is also relevant for many classical pervasive applications such as for a context sensitive-tourist guide. A tired user is more interested in the next restaurant then in the nearby hiking trail.

General Considerations. Fatigue is a vague term that can describe a wide range of condition and is often difficult to quantify. In our work we focus on muscle fatigue. As described in section 2.2 sustained, strenuous muscle activity leads to increased production of lactate and other metabolites. This, in turn, leads to an increased blood circulation and with it to an inflation of the muscle. In general terms, it can be said that in medicine the level of production of such metabolites is taken as a measure of muscle fatigue, as it causes the muscle performance to deteriorate.

From the above we can conclude that the amount of muscle inflation can be seen as an objective fatigue indicator. Obviously, with our setup and without detailed large-scale experimental calibrations we can not hope to have any sort of medically accurate fatigue measurement. However, for the majority of applications mentioned above this is not needed. Instead, a rough scale with a small

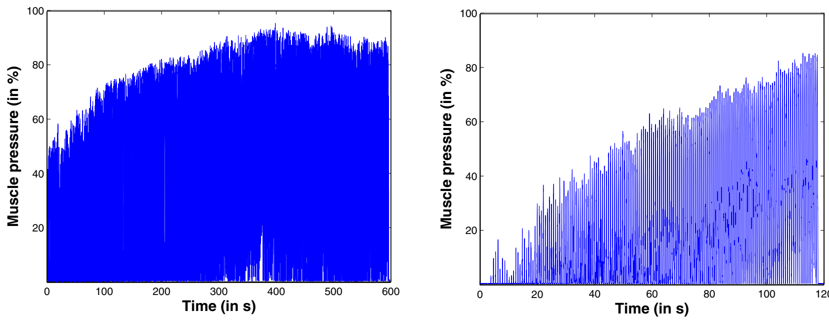

Fig. 7. Two examples of signals acquired from the front-leg muscle during the squats fatigue experiments

number of discrete states between 'fresh', and 'totaly exhausted' is sufficient. To this end the following is required:

1. A definition of 'totally exhausted' must be found that can be applied to all subjects.
2. Between the 'fresh' and the 'totally exhausted' states there must be enough difference in signal intensity to allow reliable, repeatable discrimination between states.
3. The signal must follow a deterministic, repeatable trajectory that agrees with established facts about fatigue. In general terms the relation between the duration of a strenuous activity and the level of fatigue should be vaguely linear with a saturation towards the top as an equilibrium is reached. The slope, level of saturation, and level of linearity are obviously likely to vary between subjects depending on physical condition and individual anatomy.

Experiment. To evaluate the feasibility of assessing fatigue with our system 12 subjects were asked to perform squats for as long as possible with a force sensor attached to the front-leg muscle surface as described in section 3. An example of the resulting signal for two subjects is shown in Fig. 7. An overview of the results for all 12 subjects is given in Table 1. The key results of the experiment are:

1. Only two subjects have managed to reached saturation (steady state). All others gave up before coming that far. This is not surprising since it is well known that only well trained persons can get into the equilibrium state and continue exercise. As a consequence 'totally exhausted' must be defined as either a value corresponding to the steady state or a value at which the user is unable to continue putting strain on the muscle.
2. For all subjects a significant signal difference was registered between fresh and exhausted (between 25 and 85% of the overall sensor range).
3. For all subject the increase of the signal intensity (filtered with a moving average) was close to linear.

Table 1. Muscle fatigue data summary; Increase depicted in percent of the total sensor range

Subject	1	2	3	4	5	6	7	8	9	10	11	12
Period [s]	113	530	600	150	211	80	144	550	441	125	203	188
Increase [%]	85	56	37	61	61	46	51	61	88	53	66	25
Steady state [s]	—	—	400	—	—	—	—	372	—	—	—	—

In conclusion it can be said that the muscle activity signals acquired with our system fullfill the requirements for the envisioned, rough, discrete fatigue detection.

5 Outlook: Further Information

This section presents several additional observations that we made during our experiments. In each case we provide example data and a quantitative physiological explanation. The data presented below is meant as an illustration of the richness of information available from the muscle signals and motivation for further study. Using the respective phenomena in an application would require a detailed experimental study amounting to a publication on its own.

Physical Effort. As described in section 4 without fatigue the amount by which a muscle inflates during action is determined by the load which it has to bear. This is illustrated in Fig. 1. Whereas fatigue is a trend that develops over a longer period of time load-related inflation is a short-term phenomenon directly associated with a certain action. Thus short-term variations in the signal can be interpreted as an indication of the effort that the user puts into a given activity. This could be the weight of an object that the user is lifting, the amount of force put into operating a tool or the load that the user is carrying. Clearly, this is an information that is relevant for a variety of context recognition tasks and can not be extracted from inertial sensors.

Personal Walking Style. It is well known that people have different walking styles. While humans are good at spotting such individual patterns, the actual difference in terms of physical motion is often small and difficult to capture with inertial sensors (although gait-based person recognition has been demonstrated [21]). On the other hand, as shown in Fig. 8, the different styles show very clearly in the muscle activation pattern. Interesting application of walking style evaluation emerge in monitoring rehabilitation progress and in assissitive systems for elderly care. In the latter case changes in the walking pattern might indicate a deterioration of the physical state and an increased risk of falls.

Joint Stress Reduction. An important feature of a personal walking style is illustrated in Fig. 9. It shows the signals from the front-leg and back-leg muscles during walking downstairs. When compared with the signals in Fig. 5 an additional, large peak in the front-leg muscle activity can be seen for each step. This

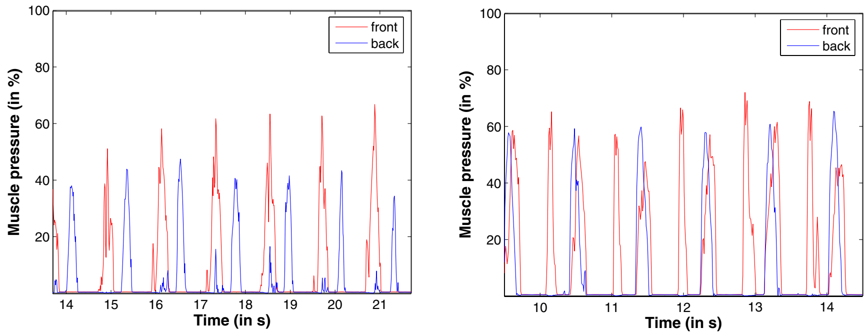

Fig. 8. Example of signals from the front-leg and the back-leg muscle for level walking with long strides

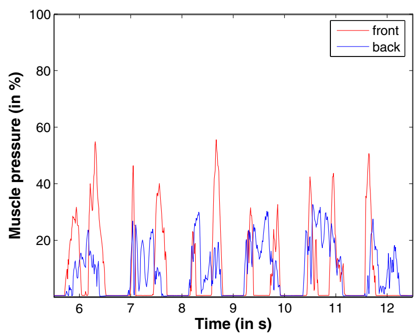

Fig. 9. Example of signals from the front-leg and the back-leg muscle for walking downstairs *in a joint friendly way that manifests itself through the initial peak in the front muscle signal*

peak is an artifact of a downward walking style that cushions step impact in a particularly joint-friendly way [22, 23]. Joint damage is one of the key concerns of many popular recreational sports such as hiking or nordic walking, in particular for overweight people. Thus, the ability to detect joint-friendly walking styles with an unobtrusive setup opens up interesting applications in terms of 'wearable electronic trainer' systems.

Correctness of Exercise Patterns. Like with walking styles in many other physical activities differences that look very subtle when looking at a motion 'from the outside' can have very different muscle 'signatures'. Examples encountered during our fatigue experiments are shown in Fig. 10. In those specific experiments two front-leg muscles (vas. lat. and rec. fem. muscle) were monitored. In the first upper graph on the left the signal amplitude is similar for both muscles and steadily increases for both muscles with the level of fatigue. This indicates user doing the squats in the 'correct way'. In the lower graph on the left we see the data from a user that starts the exercise with a stance and weight distribution that puts all the load of the squats on vas. lat. muscle. It is only after a certain

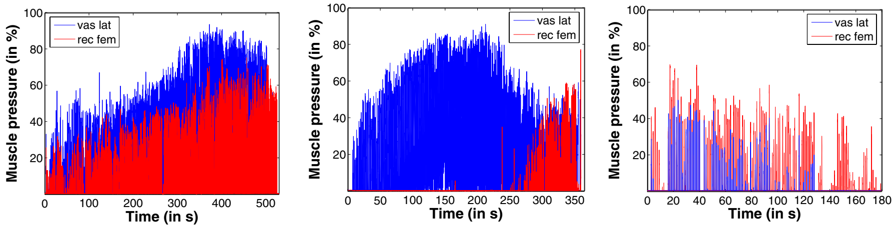

Fig. 10. Example of different muscle fatigue condition for two muscles (vas. lat. and rec. fem. muscle) when doing the squats experiment with different weight distributions and stances. The right picture shows a 'cheating' person.

level of muscle fatigue had been reached that the subject changed his technique to activate the rec. fem. muscle. We then see a decrease in the vas. lat. muscle signal that is nearly perfectly matched by an increase in the signal from the rec. fem. muscle until the muscles share the load almost equally. Finally, the figure on the right shows a person 'cheating'. We see only sporadic signal from the rec. fem. muscle with little sign of fatigue. In this case the user takes the gross of the load from the legs by 'swinging' the squats from the hips and the upper body.

The above is another example of our system providing information that is hard or impossible to get from inertial sensors which currently dominate context recognition and motion analysis. It again underscores the value of our system for sports, recreation- and rehabilitation-based pervasive computing applications.

6 Conclusion

We demonstrated that muscle activity signals can be detected through force sensors attached to the muscle surfaces. We showed that using an array of thin sensors and a conventional elastic band good quality signals can be acquired with an easily usable setup suitable for real world applications. From a physiological understanding of muscle role in walking behavior we proved that modes of locomotion recognition can be implemented by looking at the relation between signals from the front-leg and the back-leg muscles. Furthermore, we have established that long-term muscle inflation detected by our system is suitable as a simple muscle fatigue indicator. Finally, a qualitative discussion of selected interesting data collected during our experiments indicates that our concept can provide a wide range of relevant activity information.

In summary we showed that what others consider a source of noise when working with inertial sensors can be turned into a source of valuable information. Clearly, the results presented in this paper are no more then a starting point towards real life use of force-sensor-based motion analysis and activity recognition. Our group is currently working on more detailed investigation of recognition performance for different tasks. We are also looking into sports applications in which muscle activity information is combined with signals from inertial sensors to produce an even more complete picture of user motion.

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