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DOCTORAL THESIS

Mention: Biomedical enginnering

The use of heart rate variability along with non-cardiac Muscles to distinguish physical activity from stress

Presented by

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to my parents and grandparents,

to my brothers,

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Abstract

In this work, we are interested in improving the accuracy of the measurement of physical activity in humans when heart rate monitor is used and this without the addition of another device. That by eliminating of the added errors to the heart rate signal, when the presence of stress in the individual in whom physical activity is assessed. It was therefore necessary to develop a method that can separate physical activity and stress. The developed method is based on the use of muscle electrical activity (EMG) of the abdomen in combination with that of the heart (ECG). At first, we developed a device to acquire the two signals (ECG, EMG), then send them to a computer for further signal processing. With the latter, several experiments were conducted in both universities, Tlemcen, Algeria and Linkoping, Sweden. The results were quite positive to conclude that using the electrical activity of the abdomen in combination with of the heart can be used to separate physical activity and stress and so improving the evaluation of physical activity without using other devices but only the heart rate monitor.

Resumé

Dans ce travail, nous nous somme intéresser à améliorer la précision de la mesure de l’activité physique lorsqu’un moniteur de la fréquence cardiaque est utilisé et cela sans ajouter aucun appareil. Cela par l’élimination des erreurs apporté au signal du rythme cardiaque lors de la présence du stress chez l’individu ou l’activité physique est évalué. Il fallait donc développer une méthode qui peut séparer l’activité physique et le stress. La méthode développée est basée sur l’utilisation de l’activité électrique musculaire (EMG) de l’abdomen en combinaison avec celle du cœur (ECG). Dans un premier temps, nous avons développé un appareil pour acquérir les deux signaux (ECG, EMG) et les envoyer à un ordinateur pour l’application des algorithmes développés. Avec ce dernier, plusieurs expériences ont été menées dans les deux universités, Tlemcen, Algérie et Linköping, Suède. Les résultats ont été assez positif pour conclure que l'utilisation de l'activité électrique de l'abdomen en combinaison avec du cœur peut être utilisé pour séparer l'activité physique et le stress et ainsi améliorer l'évaluation de l'activité physique sans utiliser d'autres appareils, mais seulement le moniteur de fréquence cardiaque.

الملخص

هذا العمل كرس لتحسين دقة قياس النشاط البدني عند استخدام جهاز *رصد* معدل نبضات *القلب*، دون إضافة أي جهاز اخر .لقد تم ذلك من خلال حذف الأخطاء الواردة في إشارة ضربات القلب لشخص ما في حالة إجهاد او في حالة نشاط بدني .وهنا تكمن ضرورة توفير طريقة تفيد بفصل النشاط البدني عن الإجهاد.لقد اعتمدنا في هذا العمل على استخدام النشاط الكهربائي لعضلات (EMG) البطن و النشاط الكهربائي للقلب..(ECG)ابتداءا، تناولت الدراسة على تحقيق جهاز للحصول على إشاراتي (ECG, EMG) ثم إرسالها إلى جهاز كمبيوتر،لتطبق عليهما الخوارزميات المقترحة، والتي تمت تجربتها على مستوى جامعة تلمسان بالجزائر و جامعة لينكوبينج بالسويد. النتائج المتحصل عليها كانت جد إيجابية كافية لاستنتاج امكانية استخدام النشاط الكهربائي لعضلات البطن

بالاشتراك مع النشاط الكهربائي للقلب لفصل النشاط البدني عن الإجهاد وكذا امكانية تحسين تقييم النشاط البدني بالاستخدام التام لجهاز رصد ضربات القلب دون اللجوء الى أجهزة أخرى.

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INTRODUCTION

The human being has always and continues to modify his environments to live as comfortable as possible. This means with less effort on daily life and so focus on more specific and important daily tasks. With the incredible technological development, the majority of society becomes quite sedentary and we began to see the effects of this inactivity. Indeed, in the last fifty years, many scientific articles were published and showed that lack of physical activity (PA) may be the cause of many diseases such as diabetes type II, hypertension , obesity, different type of cancers and even mental illnesses such as depression stress, anxiety ... etc. Actually, PA has become so important that in some countries, doctors write exercises in the prescription. This brings us back to say that this is not enough to consume the light products to seem like the person is conscious about his health but it is necessary to remain active in daily life and organising sports programs individually or with groups.

The work presented in this thesis is concerned with the development of hardware platform and software programs so that to measure the PA and also to separate it from stress by using heart rate variability. To describe our contribution, the thesis is divided in two major parts. In the first part, we detail the relationship between PA and many diseases. We will also highlight the necessary recommendations to limit the damage caused by the inactivity. Even if in many countries, PA is not written in prescriptions it is however strongly recommended. Therefore, the need to monitor its levels for patients is highly required. Many methods exist to measure the level of PA. These are first described and synthesised in the second part of the thesis, followed by a detailed description of the main contributions of this work. In fact the proposed approach in measuring PA levels and its separation from stress is based on the analysis of heart rate variability along with non-cardiac muscles. The filing of an international patent rewards our work.

PART 01

BENEFITS OF PHYSICAL ACTIVITY ON HEALTH

PA is associated with lower mortality in both men and women. This is demonstrated by many studies dealing specifically with different age groups, gender or socio-professional classes. Many studies focused on the relationship between mortality and PA during leisure time, occupational time, or sports, such as running or cycling. Subjects on the different studies participating on a sporting activity showed a degree of mortality decreasing such those using the bicycle as a means of transportation. In this first part, we will detail the impact of PA on health.

I. CHAPTER 01 physical activity and vascular risk

PA is, in itself, a recognized vascular risk factor. The practice of daily exercise therefore subtracts this factor. However, PA can also change other risk factors. Here in this chapter, the impact of PA on cardiovascular risk factor is studied such as the influence of PA on hypertension, smoking, diabetes type II, obesity…etc. In addition, we show that PA can be a tool in the prevention on different cardiovascular diseases as both primary and secondary prevention.

1. PHYSICAL ACTIVITY AND CARDIOVASCULAR RISK FACTORS

A. Impact on overweight and obesity

The prevention of the obesity must be ensured at an early age as highlight Clara B Ebbeling [1]. This is because the overweight in children, with a particular early adiposity rebound, is a predictor of risk of obesity, premature death from all causes, and myocardial infarction in adults, as a British cohort study [2] shows. This prevention must go through dietary advice to parents and children, but also by promoting PA, as suggested by the study Trost & co [3]. The monitoring focused on 133 non-obese children and 54 obese, middle-aged 11.4 years. The level of PA was measured by accelerometry and questionnaires. Results show in the "obese" group, a significant decrease in time spent in moderate and intensive PA and also the number PA sessions. This study also focused on the time spent watching television and shows a direct relationship between this time and Body Max Index (BMI). Obesity risk decreases by 10% per hour of moderate or intense PA per day and increased by 12% per hour spent watching television [1]. Prevention is also essential to adulthood through the promotion of PA and the fight against physical inactivity, as shown in the work of Colditz & co [4]. The study involved 50277 women with a BMI less than 30 and with no history of cardiovascular incident. The cohort was followed from 1992 to 1998. During the next 6 years of the track, 7.5 % developed obesity. This risk was statistically associated with the act of watching television (every 2 hours daily spent watching television increased the risk by 23%) and was inversely associated with PA (every hour of brisk walking per day decreases the risk 24%). We will now see the benefits of regular PA in the treatment of obesity in 7.5% of women included in the "obese" category. First, a finding of Adams & Co [5]: obese or overweight reported lower levels of leisure time PA than those with a BMI <25. In a prospective study of one year covering 173 obese and sedentary women, conducted by Irwin & Co [6], randomization led each woman to a "control" group (stretching) or an "intervention" group (moderate daily exercise at home and in center). After 12 months, they found in the "intervention" group, a significant decrease in weight (-1.4kg, 95% CI, -2.5 to 0.3), total fat (1%, 95% CI, -1.6 to -0.4), and intra-abdominal fat and subcutaneous abdominal. Current World Health Organization (WHO) recommendations consider the correct level at 30 minutes of moderate PA per day, 7 days if possible per week. For obese patients, a consensus conference in May 2003 estimated that the prevention of weight regain requires 60-90 minutes of moderate PA per day, or a shorter period of intensive PA [7].

B. Impact on hypertension

In its consensus conference on hypertension, the Canadian Medical Association (CMA) emphasizes that arterial hypertension (AHT) is the third risk factor leading to death, behind malnutrition and smoking. In the same conference, regular PA, moderate (40% to 60% of VO2max) for 50 to 60 minutes, 3-4 times a week is recommended in both the prevention of hypertension or in its treatment [8]. These conclusions are supported by numerous studies and Meta-analyses such as that of Spurgeon & Co. [9] that compares the blood pressure in 810 subjects not taking treatment, whose average age is 50 years. These 810 subjects were divided into 3 groups: "lifestyle advice only 30 min", "advice renewed 18 times in six months" and "repeated advice associated with a well codified regime". The blood pressure fall in the 3 groups but there is a greater decrease in "repeated advice" groups and "repeated with diet advice versus " isolated advice " group. Compared to the prevalence before any intervention (38%), the prevalence was 26% in the "isolated advice," 17% in "repeated advice" group and 12% in the "repeated advice with diet" group without significant difference between the latter two groups, emphasizing the importance of the combination of activity and diet in the prevention of hypertension. Fagard & co [10] confirmed these results in a meta-analysis of intervention studies, highlighting a significant decrease in systolic and diastolic blood pressure, for exercise repeated 3 to 5 times per week for 30 to 60 min, 40% to 50% VO2max.

C. Impact on smoking

The CMA cites smoking as the second risk factor leading to death. About the role of exercise on tobacco, it is possible to see two areas of interest, first in preventing adolescent and in the accompanying cessation. In terms of prevention, a Norwegian study by Holmen and co. [11] between 1995 and 1997, focused on 6811 students from 13 to 18, by measuring the level of PA (self-administered questionnaire), lung function (spirometry), and tobacco consumption. 44% of adolescents had reported never smoking and 20% smoke daily. The frequency of exercise sessions was inversely related to tobacco consumption. Daily smokers did not practice any PA in 53% of cases and occasional smokers in 43% of cases. In the "non-smoking" group, there

was a dose- dependent relationship between the level of PA and respiratory function, whereas no such relationship could be found in the group "daily smokers". Note that among the active subjects, a greater proportion of smokers was observed among those practicing an individual activity other than endurance. The study tends to demonstrate the value of regular PA advise at the pre-adolescence and especially an endurance activity in the prevention of smoking. At weaning, the studies are conflicting about the importance of exercise for both maintain abstinence and for weight gain. Therefore, we will to compare three studies. First experiment is of Usher & co [12] which randomly included 299 smokers in a 7 weeks stop smoking program. It was a first branch " nicotine substitution and exercise repeated advices " (I) and second branch " alternative health education and repeated advice " (II). Abstinence was monitored by measuring the level of CO exhaled. At 6 weeks after cessation of the program, although the level of PA was higher in group I, there was no significant difference between groups I and II at both abstinence and weight gain. However, the participants included in Group I reported a lower level of nervous tension, anxiety and stress, irritability and agitation. We can conclude from the study that if exercise does not change the odds of smoking cessation or weight gain, it reduces psychological symptoms related to withdrawal. This study is consistent with other studies evaluating the impact of the activity on psychiatric illnesses, which will be discussed later. Another randomized study quite close to the first, was conducted in the USA by Marcus & co [13]. It covered 281 women smoking and sedentary. Randomization yielded two groups subjected to almost identical to the previous study programs, but on 12 weeks. Participants in group I were invited to participate 3 times a week to a group exercise session. Abstinence was verified by salivary assay of nicotine, 1 week after stopping at the end of the program, three months and 12 months. The difference between the two groups was statistically significant in favour of exercise group (I) as in the abstinence, when stopping the program, at 3 months, and at 12 months than on the weight gain program. We can conclude from this study that the regular and intensive PA is beneficial to weaning and maintaining abstinence from tobacco as well as weight maintenance.

Even with same methodologies between these two studies, radically different conclusions are presented, It could be explained by several differences: firstly, the study population was purely feminine in the second study. On the other hand, the exercise program was more intense in the second study with group sessions and a 12-week program against 6. Therefore, we can assume that to be beneficial for smoking cessation, the PA must be intensive and prolonged.

Finally, the benefits of exercise on weight gain after smoking cessation is confirmed by a 3rd study using data collected during the "Nurses' Health Study" on 121700 women aged 40 to 75 years. Kawashi & co [14] have, in fact, studied over 2 years, 1474 women who stopped smoking without changing their level of exercise. The average weight gain was greater by 2.3kg comparing to weight gain in women continuing to smoke. This weight gain was only 1.8kg in women who increased their activity level 8-16 METs per week, and 1.3kg if the increase was more than 16 MET week.

D. Impact on type II diabetes

The peripheral insulin resistance is one of the elements agent explaining the type II diabetes. Schmitz & co [15] studied 357 non- diabetic children 10 to 16 years depending on their level of PA. PA was significantly associated with insulin secretion and insulin. These results are even more convincing if we deem that the population figures PA above average. After adjustment for age, sex, ethnicity, and Tanner stage, the results are significant, showing that PA in adolescents could reduce the risk of type II diabetes, and especially among adolescents with risk factors such as hypertension. In adults, many studies observe the impact of changes in lifestyle on the risk of developing type II diabetes. A Finnish randomized study by Tuomiletho & co [16] on 522 adults aged of 55 years on average, overweight (average BMI = 31), with a family history of diabetes and with intolerance to carbohydrates, has shown a 58% decrease in risk of developing type II diabetes over 3.2 years of follow-up. The intervention recommended to lose 5% of their body weight, to eat less than 30% fat and at least 30 minutes per day of moderate PA. Personalized follow-up took place every three months including dietary survey and PA program. "Control" group was informed of the benefits of PA and diet but without individual monitoring (see Figure I.1).

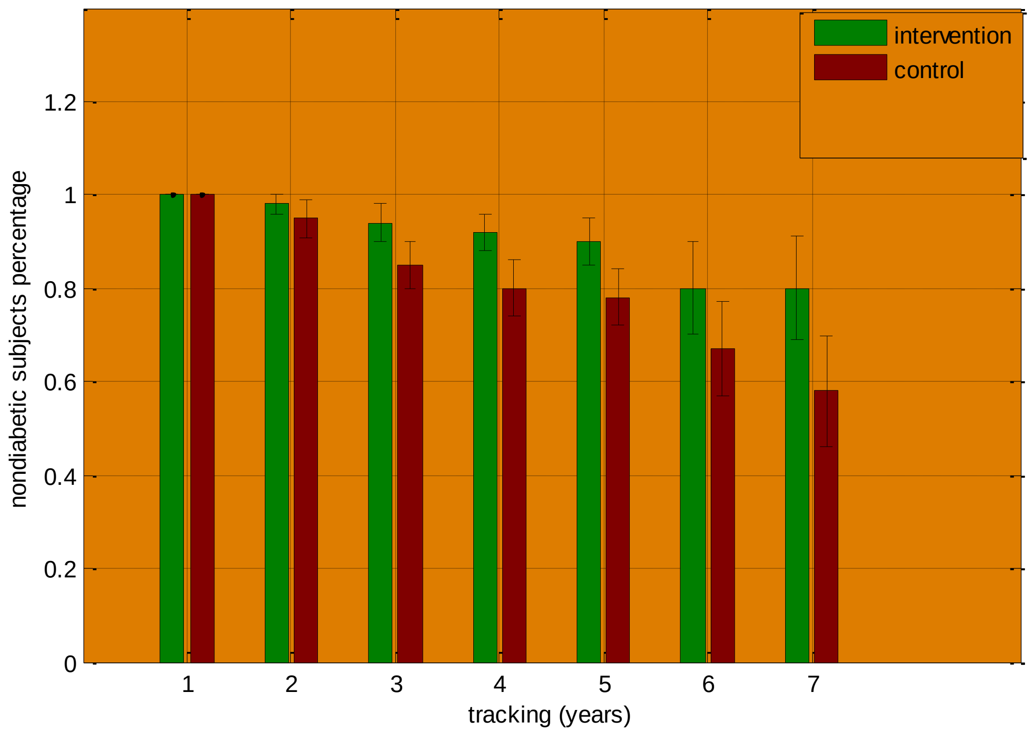
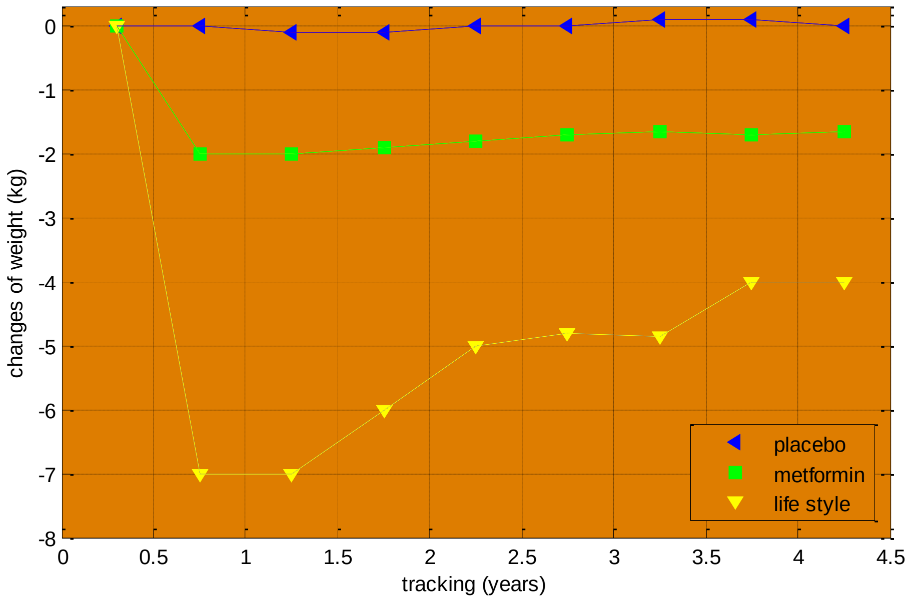


Figure I.1 Proportion of non-diabetic subjects during the study.

Apart from the conclusion that regular and moderate PA associated with a low calorie and low fat diet reduces the risk of developing type II diabetes in subjects at risk (overweight, family history, intolerance to carbohydrates). It is important to note that simple information is insufficient and that the motivation of individuals must be maintained through regular consultations, emphasizing the importance of the association between different stakeholders (endocrinologist, GP, dietician, but also government).

Finally, to finish with type II diabetes, it is important show the study carried out by the "Diabetes Prevention Program Research Group" [17] comparing the effectiveness of changes in the lifestyle of the metformin against a control group (simple lifestyle advice with placebo) in preventing diabetic patients with intolerance to hydrates carbon associated with a BMI> 24. This study included 3234 patients divided into 3 groups. The metformin dose was 2 X 850mg/d. Changes in lifestyle were aimed a decrease of 7% of initial weight, with an hypocaloric diet and hypolipidemic associated with a moderate level of PA such as brisk walking for at least 150 minutes per week. The monitoring covered 2.8 years on average with 7.5% of lost view. The drug adherence was 77% in the "placebo" group and 72% in "metformin" group. The adhesion to the recommendations for PA was 74% after 6 months and 58% at the end of the study. 50% had achieved the 7% weight loss at 6 months and 38% at the end of the study (see Figure I.2).



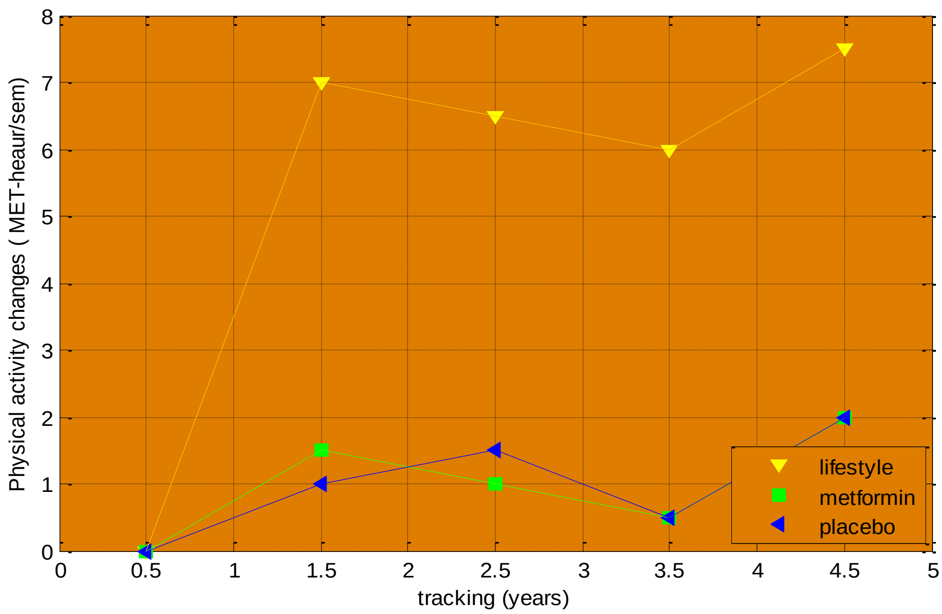


Figure I.2 changes in body mass and physical activity for different groups.

At the onset of diabetes, the incidence was lower in "metformin" groups and "lifestyle changes" (See Figure I.3). The differences between all groups being significant.

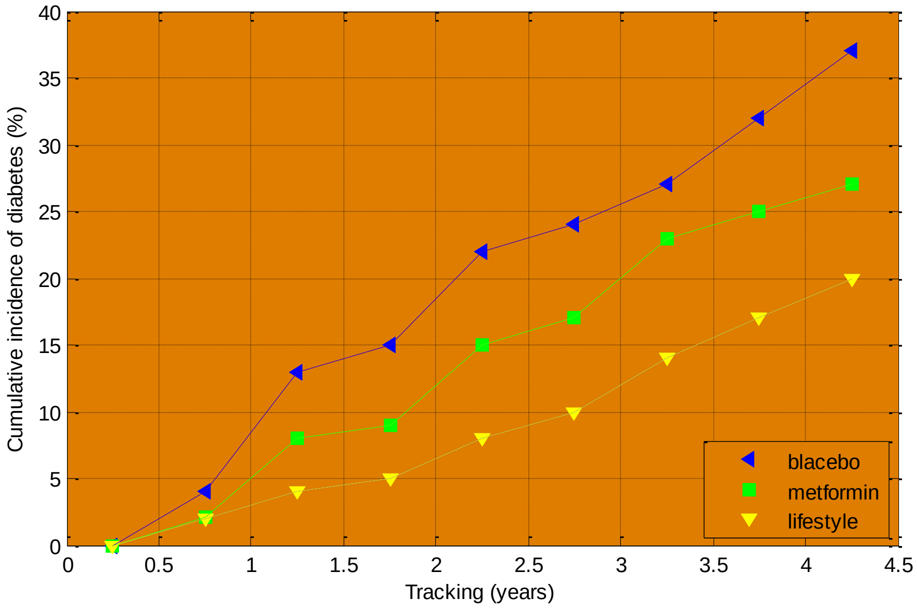


Figure I.3 Cumulative incidence of diabetes type 2 according to the different groups.

To prevent the occurrence of diabetes over a period of 2.8 years, it should therefore, according to this study, treat 13.9 patients with metformin and 6.9 by changing lifestyle. This study again demonstrates the benefits of changes in lifestyle, including PA on the occurrence of type II diabetes but also shows the superiority of these changes compared to metformin.

2. PHYSICAL ACTIVITY AND CARDIOVASCULAR DISEASES

Several studies concluded that PA is strongly and inversely correlated with the risk of cardiovascular mortality and coronary events, regardless of age and gender. We will detail the impact of exercise on the various cardiovascular pathologies.

A. Major coronary events

Primary prevention

Wannamethe & co [18] showed a significant reduction in major coronary events compared with an increase in PA at a moderate level, without significant benefit if further increase in the activity level. The relative risk (RR) reached 0.60 (95CI 0.50-0.72) as shown in Figure I.4.

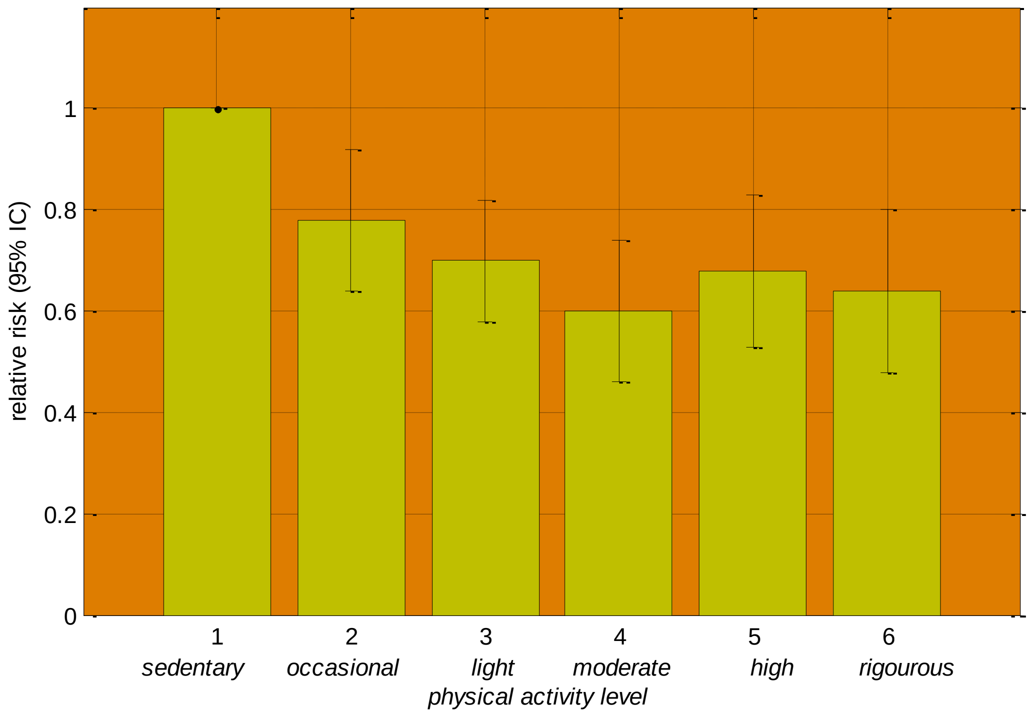


Figure I.4 Relative risk of major coronary events based on PA.

Colditz & co [19], in their meta-analysis found a RR of major coronary events of 0.55 between the least active subjects and the most active subjects. The level of activity does not need to be high as suggested by the study of American nurses on 72488 women aged from 40 to 65 years followed over 8 years: practice 3 hours of walking per week or more is associated with a significant decrease in the risk of coronary events (RR = 0.65).

Secondary prevention

a. Ischemic heart disease

Going back to the 1970s, we find that re-training cardiovascular programs already existed, emphasizing the importance of PA, combined with a healthy lifestyle in the prevention of recurrent myocardial infarction and unstable angina.

Different criteria have been analysed such as end-diastolic and tele-systolic volumes, stroke volume, ejection fraction, coronary diameter, VO2 max, the maximum level of effort and walking distance during 6 min. In 1995, Pitscheider & co [20] assigned 83 patients with myocardial infarction trans-wall, in a control group (no particular program) and re-training group. The monitoring covered three months and permitted to highlight a significant decrease in telediastolic volume by 7% and tele-systolic volume of 12 % in the "intervention" group without significant changes in the "control" group. The decrease in volumes was more significant in patients with a lower infarction. The study of Adachi & co [21] 1996 focused on the measurement of stroke volume by comparing 39 patients with a history of myocardial divided into 3 groups of level of PA (1: control, 2 low intensity 3: high intensity). The monitoring covered two months. Inside group 3, the stroke volume improved both at rest and after a violent effort of 6 min as the ejection fraction. Group 2 has seen an improvement in his stroke volume during exercise without changing the stroke volume at rest or ejection fraction. "Control" group showed no significant change between these two dates. These results confirm the importance of PA in the repackaging effort of coronary patients, and suggests that the level of training should be relatively high. Hambrechet & [22] also divided their patients with coronary artery disease into 2 groups: a control group of 33 patients and an intervention group of 29 patients submitted to a program of re-conditioning effort (group exercises and leisure PA Questionnaire). The monitoring then filed over 1 year. There is a significant improvement in the "intervention" of 7% of VO2 max group, 14% of the maximum efforts intensity while there is a decrease of the data in the "control" group. The author evaluated to 1400 kcal / week the minimum leisure exercise for a benefit. The study also focused on the degree of coronary calibre by angiography; "intervention" group: regression 28%, unchanged 62% increase 10% "control" group: regression 6%, unchanged 49% increase 45%. The minimum of PA level required to stabilize lesions is computed by the author to 1533 kcal /wk, and to2200 kcal / wk for lesions regression (about 3h bike at 16km / h in the first case and 4h30 in the second).

b. Heart failure

Whether it has ischemic origin or secondary to fibrosis, heart failure is associated with fatigue and of effort dyspnoea. Oka & co [4) showed, firstly, that patients with congestive heart failure spontaneously reduce their level of daily PA to avoid these symptoms, and, secondly, that there is a gap between the physical capacity of the subject and its daily exercise level, so that the average level of PA of the patients with heart failure is too low compared to its theoretical possibilities. The comparison made by Silva & co [23] between a group subjected to a training program for 3 months and a control group shows a significant improvement in the covered distance during 6 min (+355 m) in the group "intervention." Another study by Oka and co [24] observed the benefits of PA at home during 3 months in patients with heart failure stage II or III. It showed a significant decrease in fatigue, and improvement of the physical capacity and quality of life without adverse events during this period.

Finally, Beneke & co [25] followed 16 men with heart failure over 3 weeks by subjecting them to a training program (15 min biking for 5 times a week and 10 minutes of treadmill walking 3 times a week). They observed a significant improvement in VO2 max by 18% and increased the rate of spontaneous march speed of 70% (42% of increase due to an increase in muscle power and 58% due to better economy of gesture).

PA therefore improves physical capacity and quality of life of heart failure patients without significant change in mortality.

c. Angina

Schuler & co [26] conducted a study of 113 patients with angina followed during 12 months. After randomization, 56 were included in a program of intensive retraining (2h group training per week and 20 min individual training per day) associated with a lipid-lowering diet without lipid-lowering medication, the other 57 were the control group submitted to "usual care." Each subject received coronarography and myocardial scintigraphy at the beginning and after 12 months. In the "intervention" group, it is found a decrease in body weight of 5%, the total cholesterol by 10%, triglycerides by 24% and an increased of the good cholesterol by 3% (all statistically significant). There is also an improvement in the myocardial oxygen consumption of 10%. On angiographic images, the lesions progressed in 23% of cases (against 48% in the "control" group), stabilized in 45% of cases (control: 35%) and decreased in 32% of cases (control: 17%).

B. Cerebro vascular accidents (CVA)

Cerebral arteries are also affected by atheroma and are not an exception to the protection induced by regular PA; this at low intensities even if there is a dose-dependent relationship between relative risk and PA. in the Northern Manhattan Stroke Study, Sacco & co conducted a case-control study of 1047 patients, 369 of them were presenting ischemic stroke, while the other 678 were selected to be similar in age, sex and ethnicity. After adjustment for other cardiovascular diseases, hypertension, type II diabetes, smoking, alcoholism, obesity, medical limitations in PA, and education, leisure time PA protects significantly against ischemic stroke. As shown in Figure I.5, the protective effect exists regardless of age, gender, and ethnicity. Figure I.6 shows the dose-response relationship between the efficiency level of exercise, duration of exercise, and the protective effect.

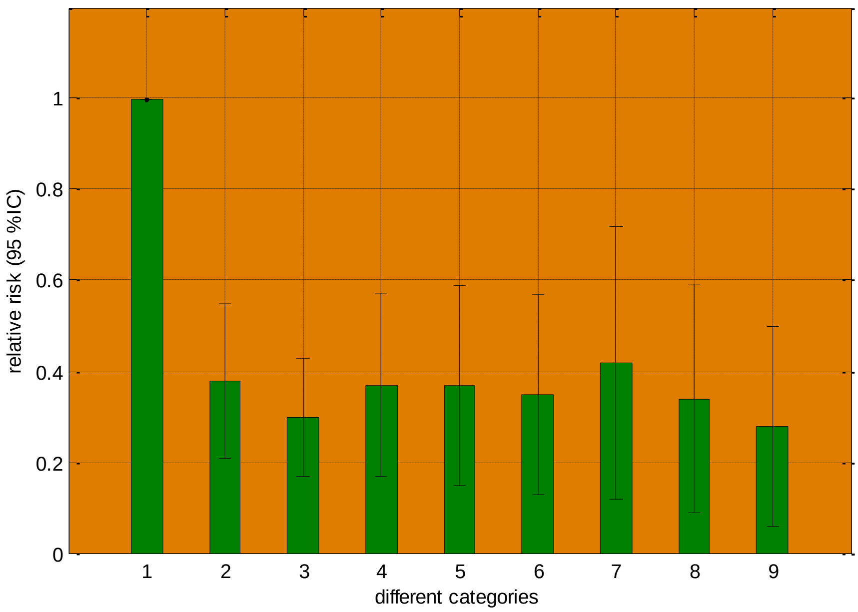


Figure I.5 Relationship between PA and ischemic stroke, 1: sedentary 2: active 3: <65 years old 4: > 65years old 5: men 6: women 7: white 8: black 9: Hispanic

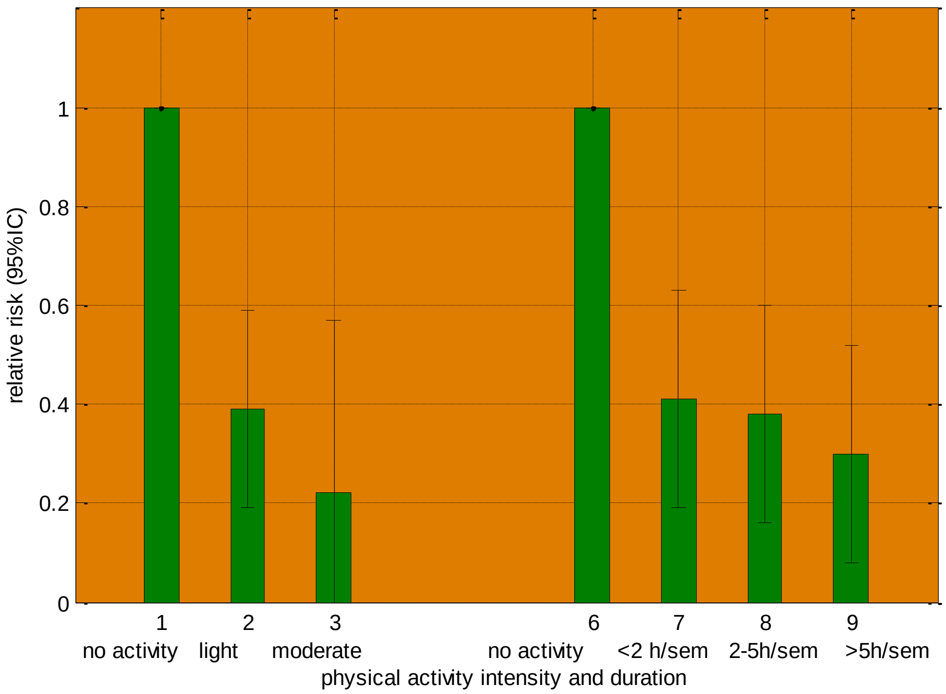


Figure I.6 Dose-response relationship between PA and ischemic stroke

Another study, this time prospective, conducted by Ellekjaer & co [27], focused on 14101 Norwegian women over 50 years, followed for 10 years. It analyzed the relationship between the rate of stroke mortality and level of PA. After adjusting for the same bias, the relative risk of dying from a stroke decreases with increasing levels of PA.

3. CONCLUSION

Throughout this chapter, the impact of PA on the cardiovascular system and the vascular risk factors was described. It is clearly seen that PA is beneficial in both primary and secondary prevention. The PA is also likely to reduce the incidence of other vascular risk factors. However, the presented studies show also that the physical inactivity is clearly identified as a risk factor in itself.

II. CHAPTER 02 Physical Activity And Psychiatric Disorders

According to the British Department of Health, in 1994, mental disorders related to stress represented an expense of 5.3 billion pounds per year [28]. Early studies on the benefits of regular exercise on stress levels are from 1982. So, Kabosa, Madi, and Pucetti highlighted the fact that business leaders with regular PA had a lower frequency of mental illness [29]. In this chapter, we detail the impact of the PA on mental diseases.

1. PHYSICAL ACTIVITY, ANXIETY AND STRESS

Spielberger [30] distinguishes between the "state anxiety" as a temporary emotional state, evolving, in which we subjectively and consciously feel apprehension and tension, associated with a reduction in the autonomic nervous system, from "trait anxiety", which is "a behavioural disposition to perceive a threat in objectively safe situations and react with a disproportionate anxiety. Trait anxiety and state anxiety are often associated. The stress often related to anxiety is defined as substantial "imbalance" between the physical and psychological demands and the ability to respond in circumstances where failure has important consequences [31]. Landers and Arent [32] point out that there was, between 1991 and 1994, six meta-analyzes of 159 articles dealing with the relationship between the practice of PA and the reduction of anxiety, which were included in a meta-analysis summary [33]. These six meta-analyzes concluded that all exercise was significantly associated with reduced anxiety traits and its physiological indicators. Levels of evidence were considered as low or moderate. It appears in this summary that the level of anxiety reduction is mainly found in populations in low fitness and high levels of anxiety, but this reduction also affects the population with normal values for tests. These findings on the effects at the population not anxious were strongly contested by Ragling [34] who highlights the many methodological artefacts. Results show that the anxiolytic effects vary in intensity depending on the subjects initial anxiety. In non-anxious individuals, the effects of PA would be felt at the level of state anxiety [34] and are recorded 30 minutes after the start of the activity; they prolong one hour after stopping the activity and persist for 2 hours. Reducing anxiety status by aerobic exercise is comparable to that obtained by the relaxation or rest in peace [35]. According to Garvin et al. [36], reduction of state anxiety lasts all the time of the activity. If the reduction of the state anxiety is found in most of the work, the necessary or minimum intensity of the activity to produce effects is discussed. It now appears that this reduction is rather correlated with a moderate or low intensity exercise [33]. Conversely, experimental studies have demonstrated an increase in anxiety following intensive and aerobic type programs when subjects with low fitness [37, 38, 39]. The interest of aerobic activities highlighted by Petruzzello [40] was questioned by Bartholomew and Linder [41] who showed the same level of reduction of anxiety by building work muscle. The dose-response effect seems to vary according to levels of fitness and style of living [42]. Similarly, the role of the environment, perception of competence, age and sex on the results has been widely noted [43, 44] further complicating the conclusions to advance. However, we can note that this state anxiety is greatly reduced in pathological subjects with moderate or high anxiety as confirmed by the meta-analysis of Petruzzello Landers [45]. Broocks et al. [46] show that after a 10-week program, reduction of anxiety is higher in the "exercise" group than in the drug-treated and placebo group. The low number of studies on populations with severe psychopathologies does not definitively conclude that PA can be prescribed as a therapy in itself for all the anxious people but leads to strongly suggest PA as "complementary therapy". In summary, it is clear that the observed "state anxiety" before sport decreases rapidly after about 20 min of exercise, resulting in a state of relaxation and well-being which persists during and after the activity. The exercise of moderate intensity appears to have a short term effect on "state anxiety" in non-pathological or pathological populations and can be used to reduce this experience; Intensive physical practice appears instead to quickly trigger an increase in anxiety and cause stress responses in anxious populations, when elderly or poor physical conditions [42]. The current work does not suggest that PA can have effects on "anxiety trait". Some research suggests that trait anxiety is reduced when the improvement of fitness is important reducing physiological manifestations against the "stressors". PA would be a learning function, active coping (problem solving) and serve as an inoculator defence system (physiological and psychological) [47]. Indeed, it is well established that subjects with a good physical condition are more responsive to psychological and social stress and recover better after the confrontation with the stressor at the tension, heart rate (HR), muscle tone ... [48]. In a recent meta-analysis, Larun et al. [49] analysed the results of 16 studies of 1191 adolescents without disorders, aged from 11 to 19 years. They compare the active groups practicing a high intensity PA (3 times per week for up to 20 weeks) to the non-active group at the "traits of anxiety". They found a marginally significant difference ($p = 0.05$) between the two groups. They do not reveal the persistence of this difference and therefore the antidepressant effect of PA over the long term. The importance of the intensity or the type of the practice is not demonstrated. The analysis of some work on the anxious adolescent populations showed no difference between active and inactive groups. Anxiety of the adolescent is very complex, particularly related to the crisis of development of the corpulence sexual, identity, is different from that of adults and explains the specificity of the results.

2. PHYSICAL ACTIVITY AND DEPRESSION

Many investigations have examined whether inactivity was associated with depression and vice versa, if a regular practice was correlated with a low depression score. Close to anxiety, depression affects self-image and body. Meanwhile, body therapies experiments emerged to treat depression and sport is seen by some as a fairly effective therapeutic, inexpensive and accessible to all those that do not support medication or treatment or do not want to engage in psychotherapy.

A. General population

Transverse and longitudinal epidemiological studies on this subject are numerous. Dunn et al showed [50] that the "active" had a lower score than "non-active" to various scales of depression [51]. The investigations have focused on pre-adolescents [52 53], adolescents [54], students in Sport [55], students from all disciplines [56], sedentary adults [57], women postpartum [58 59], depressive adult [60] and older adults [61]. Only one study [62] finds no change in the feeling of depression in 29 patients who have a complement to their treatment a physical therapy program. We can mention here the work of Farmer et al. [63] who followed 1497 depressed and non-depressed subjects aged from 25 to 77 years over 8 years with a depression test, a PA Questionnaire (little or no PA leisure, moderate or severe activity) and physiological assessments. The analysis of interactions between PA and level of depression highlights a correlation between "lack of leisure time PA" and "depression" at the non-depressed population with no difference between man and woman. Longitudinal following shows an increase in depression score in non-pathological populations and no leisure time PA, with a difference between man and woman. For the female population, PA appears to be a predictor of absence of depression eight years later while inactivity can be considered a risk factor.

B. Pathological populations

A recent epidemiological study [64] on a cohort of 424 depressive adults followed over 10 years, emphasizes that with each assessment (1 year / 4 years/10 years) a high level of PA is associated with a low level of depression without any clarification of the causality of this relationship. However, we see today that patients with medical problems (moderate depression, heart disease, arthritis) are motivated to participate in physical rehabilitation activities and are capable of regular practice, which suggests that it is the proposed PA that decreases the level of depression and make better adaptation to medical problems (exercise coping). A summary of Lawlor and Hopker [65] on older pathological populations over 18 years (from 5 computerized bibliography databases, known writings, and reviews of practitioners) highlights the lack of work, corresponding to strict criteria of experimental control, from where the reservations made in the results and conclusions to be drawn. In 77 publications, they have retained only 14 of them considered as having a "correct" methodology and can provide evidence. Eleven studies focus on the comparison between a group doing PA and a group not forming a follow up of 6 to 12 weeks. They all conclude that significant differences between groups at the end of the program with a score of lower depression in "practitioners". According to the authors, "PA can be effective in reducing short-term symptoms of depression in some volunteer patients." However, if the level of the indicator of depression found in the group of "active" versus those who do not exercise is lower, this score, which focuses on the symptoms, does not always have visible clinical implications for physicians and for patients in their experience. The authors then address the work comparing different interventions with patients. In six studies selected, they analyse the evolution of the level of depression of a group engaging in PA with a group following the prescribed treatment (behavioural psychotherapy, brief psychotherapy, classic psychotherapy, relaxation, medication). Results show significant differences between the "exercise" group and other groups "cognitive therapy" (3 trials), treated group with medication (1 trial) and psychotherapy. One publication does not find difference. Similarly, Blumenthal et al. [66] and Lawlor Hopker [65] find no difference between the group practicing PA and group having cognitive psychotherapy in the early weeks and find the same level of depression regardless of the form of support at the end of follow up of 3 to 4 months. On all work reviewed, the type of exercise does not seem to play a major role in depression but the environment seems important (presence of an individual coach or practice in small groups). Score reduction is particularly visible in low or moderate level of depressions and the effects seem to decrease with time. A final meta-analysis of Pedersen and Saltin [67] confirms that the whole works are too heterogeneous at group level, practices, duration, treatment, to be able to conclude that PA is a depression treatment more effective compared with other protocols. They however recognize the very positive effects of PA on depression, which are, are summarized in Table II.1.

Table II-1 Arguments for the prescription of physical activity in the case of depression [from Pedersen and Saltin,[68]

benefits	strong evidence	moderate evidence	limited evidence	No evidence
Pathology				x
Symptoms, secondary disorders	×			
Fitness	×			
Quality of life	×			

There is therefore a consensus shared by researchers and practitioners on the role that PA can play at the negative impact of depression: inactivity, isolation, low self-esteem, impaired body image, somatic concerns ... on all of these side effects, it is clear that PA can play a major role and therefore limit the inadequacies, so improve the quality of life of patients. For these reasons, psychiatrists recommend alongside conventional treatments, physical recreation and moderate intensity in small groups or individual coaching. These positive findings in adults cannot be advanced as clearly at an adolescent population. In another meta-analysis, Larun et al. [69] only find five studies on a population of depressive adolescent and find no differences between the effects of the practice of low intensity PA type aerobic and other supports such as relaxation, or discussion groups...

Dunn et al. [70, 71] have attempted to identify in a program of PA, the necessary conditions to reduce anxiety and depression in an adult population without disease or with treatment. From a meta-analysis, she suggests the following: Aerobic work or not aerobic, Three times per week or five times, moderate intensity: 17.5 kcal / kg / week, 30 min sequences, engagement more than 12 weeks (effect from 8), working in small groups or with an individual coach Practice more than 30. It is important to note that depressed people can certainly participate in sport and PA but depression is associated with psychomotor retardation, a symptom of fatigue and an inability to share [72], these issues will not go voluntarily to an activity or abandon then very quickly. It is therefore essential to accompany, "coach" these topics individually or in small groups.

3. CONLUSION

In conclusion, the effects of regular physical activity on the well-being of the general population and improving the quality of life of people with deficiencies and disability encourage public health policies to advocate the practice of regular physical activity. That means that being able to evaluate PA level, will permit to us to assist people who need to be followed in their practices. In the second part of this thesis, we present the different methods that exist to measure PA and also our developed method and how we can use it to distinguish PA from Stress.

III. CHAPTER 03 Different methods of Physical activity measurement

It exist three types of PA measurement methods: subjective methods, criterion methods, and objective methods. Since PA is defined as any bodily movement resulting in energy expenditure (EE), it is clear that measuring EE by measuring heat production or heat loss process known as direct calorimetry is the gold standard for PA measurement against which the validation of other methods must be made. However, this measurement method is, in most cases, not useful due to practical reasons. EE estimated by oxygen consumption and/or carbon dioxide production measurement, and indirect calorimetry measurement of heat production, can also be used as criterion measurement for validation and are much more useful. Objective measurement methods include HR monitoring and movement monitoring using pedometers and/or accelerometers and are actually, the most useful in daily life monitoring. Finally, questionnaires and activity diaries are considered subjective methods, they are also very useful.

GOLD STANDARD

A. Direct calorimetry

Antoine Lavoisier is the initiator of the direct assessment of body heat production who developed an ice-calorimeter. He determined the metabolic heat production of an animal from the melting of snow that was surrounding the calorimeter [73]. Other authors developed larger isolated metabolic chambers that can hold human bodies [74]. The heat diffused by the subject was transported to a water flow, and heat production was measured from the temperature difference between inflow and outflow. Only some institutes have access to metabolic chambers.

B. Indirect calorimetry using closed and open-circuit respirometry

Indirect calorimetry is based on open or closed circuit respirometry. The precise evaluation of EE using oxygen consumption method requires knowledge of the individual's respiratory quotient and urinary nitrogen excretion, but to make the measurement easy, the computation is generally established on non-protein respiratory quotients [75]. Such computations give acceptable evaluation during periods of rest and moderate PA, but are less accurate when prolonged vigorous PA, when an important quantities of protein are metabolized. open-circuit respirometers are the most used devices for oxygen consumption measurement. Comparing to the early devices, data collection has been significantly simplified when chemical gas analysis was replaced by electronic instruments and gas flows have been determined by turbine flowmeter or pneumotachograph. One of the advantageous of this gold standard method is that miniaturization of equipment now enables collection in the field of breath-by-breath data. For the studies interested by small populations such as with the epidemiologist, oxygen consumption measurement may be very useful. Portable oxygen consumption method is a very used method for validation of objective methods. However, it is not very practical in everyday life due to need of a mask on the face.

C. Metabolic estimates of physical activity

Because the methods mentioned above are not very practical in everyday life, different authors developed new methods and examined PA patterns by studying the associated rate of either metabolism using as overall food consumption or the metabolism of doubly labelled water (DLW). The metabolism of DLW is used as the gold standard criterion to validate other PA measurement techniques such as questionnaires, HR, or accelerometers [76].

Early, radioactive isotopes of hydrogen and oxygen were ingested, but for safety reasons non-radioactive forms of deuterium oxide and water containing the isotope oxygen^{-18} are used rather than the original markers. A precise dose of DLW is administered, and after equilibration with body fluids, the rates of elimination of deuterium and 0^{18} are determined by sampling saliva, urine or blood. The big advantage of this method is that the subject can live a normal life between the administration of the isotopes and the final sampling. In addition to validation studies, DLW has gave estimates of the energy needs of several specific populations undertaking sustained exercise. However, in humans, an interval of 2 weeks is needed between the administration and the final sapling. Consequently, it is only possible to examine long-term averages of accumulated PA.

1. DIRECT OBSERVATION OF SUBJECTS AND FILM ANALYSIS

The direct observation of PA patterns or the analysis of filmed records needs experienced observers and requires lot of work. Mostly, direct observation of PA patterns or the analysis of filmed records are used for assessing the physical demands of team sports. The analysis of records, mostly recorded using multiple cameras, are essential in the investigation of performance in team sports such as soccer. Information can be acquired on the proportion of a game when a player is sprinting, running, jogging or standing. In most cases, movement patterns are filmed for a single individual, although systems are now available that allow video records to be used with HR for an entire team [77]. Recently mechanical tracker can convert video records to velocity categories, mean velocity and estimate the total distance covered by players [78]. Recently, computerized tracking was able to evaluate the distance covered with a small error comparing to a trundle-wheel pedometer. However, the sampling rate is generally low (e.g., 15 frames/s), and elaborated network of cameras and processors is needed to investigate the total game. In addition, an action from an observer is usually needed.

2. SUBJECTIVE REPORTS: QUESTIONNAIRE AND DIARY RECORDS

Attentive questionnaires and immediate diary records of a subject's PA appeared attractive sources of information for numerous epidemiologists, because they offer simple and cheap estimates of human habitual PA. In fact, until recently, techniques of questionnaires were the most frequent approach to the epidemiologist. Diaries have been used not only in their own right, but also in partnership with physiological recordings, to help the interpretation of these observations as a sudden increase in HR of a subject.

Questionnaires

Questionnaires were used most often when estimates of PA were required on large populations. Instruments have requested information on not only global activity, but also its intensity, frequency, duration and type. Questionnaires are available in a simple, requiring only two or three answers [79, 80, 81], to elaborate instruments for more than 20 pages, that included all types PA imaginable. Sometimes the answers were supplemented with a qualified assistant who made nuanced interpretations of the data [82] although this immediately cancels the first questionnaires benefits: simplicity and low cost.

3. OBJECTIVE TECHNICS

A. Recording of body movements

Studies of body movement patterns have conventionally been based upon the assessment of the distance walked and information collected from mechanical odometers and pedometers. More recently uniaxial and triaxial accelerometers have increased their popularity.

Odometers

Odometers were used to assess walking distances. For instance, allowing cardiologists to recommend an appropriate PA intensity for patients who were undergoing recuperation following myocardial infarction [83].

Pedometer/accelerometers

Original device have joint the characteristics of both pedometer and accelerometer, as electronic mechanisms were used rather than mechanical parts. The Seiko and Epson firms started developing an electronic digital timepiece in the years leading up to the Tokyo Olympic Games of 1964. In electronic forms of the pedometer, a lever arm moves with each gait, creating an electrical contact or compacting a piezoelectric crystal. The generated electrical impulse is then measured as a step. Many simple and cheap instruments now allow the user to input an expected gait length, so that the accumulated step count can be transformed to an estimate of the distance walked. Instruments such as the Kenz Lifecorder also integrate a filter that sets appropriate limits to measured accelerations (for instance, activation requires a minimum acceleration of 0.15 g); this decreases the extent of false counts from incidental movements. The simpler models have sustained to accumulate steps using a digital counter, but more sophisticated apparatus now permits electronic storage of information for 60 or even 200 days. Some models are also capable to measure the power of impulses, permitting a categorizing of rapid rates of EE [84]. To date, almost the total reports have suggested that pedometer/accelerometers are more reliable than pedometers alone; a previous review details performance characteristics of 25 presently available devices [84]. One study looked at counts recorded on test platforms. Under these conditions, the correlation between the instrument oscillations values and the real number of oscillations of the platform was 0.996 [85]. Unfortunately, this type of assessment does not verify that the device will respond correctly when measuring the varied movement patterns during daily life. Another technique of measuring the reproducibility of data was to wear two instruments, fitted to the left and right hand sides of a subject’s waist belt, respectively [86]. Those tests showed good reliability for some devices [87]. Pedometers and accelerometers usually react reliably to a coherent movement pattern such as level walking [88]. At the two moderate and slow walking velocities, the Yamax instrument provided the best estate of five devices over a 4.8-km estimated walking course, with an average systematic error of about 2%; in some of the other instrument, the error was higher than 10% [86]. Almost all from the 10 tested pedometer / accelerometers were able to approximate the treadmill walking distance to within ± 10% and the gross EE to within ± 30% of the real value at a walking velocity of 4.8 km/h [89]. Values had a tendency to be undervalued at velocities lower than 4.8 km/h [90], and at 3.2 km/h the Kenz Lifecorder and Actigraph produced step counts that were, respectively, 92 ± 6% and 64 ± 15% of the correct values [91]. Additional assessments of absolute precision comprised comparisons with a heel-mounted resistance pad with an error of 460 ± 1,080 steps/days. [92], with the directly assessed oxygen consumption and a Pearson correlation coefficient of 0.97, with mean changes of -3.2 to +0.1 kJ/min [93], and against metabolic chamber data an extra considerable 9% error for entire EE and 8% for PA EE [94]. In [95], they accepted that both reliability and validity were degreased significantly on changing from the laboratory to free-living environments. Recorded errors are augmented if individuals can choose their own activity types rather than walking on a stable course and/or at a fixed pace. Imprecisions are introduced by slow march speed, a brief pitch length and Abnormalities of gait [96]. When evaluating old individuals whose main source of PA is moderate walking, accelerometers may give an accurate result. Thus in such populations their accuracy may be enough for some clinical goals, such as the measurement of PA related with health benefits. However, the response of Pedometers and accelerometers is not very accurate when cycling, skating, load carrying, household chores, and many other non-standard activities [97]. Furthermore, the accelerometer take no account of the extra energy expenditures when movements against resistance or mounting hills. In addition, artefacts may appear when using a vehicle [98]. Thus, information from pedometer/accelerometer on the absolute energy expenditures of younger adults when everyday life conditions rests much more debateable. In some studies, they underestimated measurements by about 30 to 60% compared to DLW assessments [99]. The uniaxial accelerometer evaluates the acceleration forces rather than making the summation of electrical contacts. Changes of the acceleration of minor weights to discreet electrical impulses happens when Capacitive, piezoresistive, or piezoelectric component are used. Even if the most used position of the accelerometer is around the waist using a belt, sometimes they are positioned on other parts of the body. As an example, a type of accelerometer known as the ‘‘footpod’’ is positioned around the feet, sensing the impact related with every gait. Another type of accelerometer that was developed is a small inertia sensing device that may be positioned on the ear lobe; this measures posture and linear acceleration in the same time, the information sent by the device can be used to estimate the EE of the individual. A first report of this device claimed a good correlation between the counts of the accelerometer and Cosmed K4b2 oxygen consumption estimation when individuals were practicing 11 typical activities. They also claimed a good accuracy in classifying the type of the activities that were being practiced [100]. Many methods differ on the epoch that must be used. Some of them use the integration of the accelerometer counts over intervals that vary from 1 to 15 s. Other methods use secret and complex equations to improve the accuracy of the measurement. Actually, a 3-part algorithm are included in the Actical instrument:

1- If the values are smaller than the inactivity threshold, the individual is credited with an EE of 1 MET;
2- If the values are bigger than the inactivity threshold but the coefficient of variation (CV) during four successive 15-s epochs is<13%, a second, walk/run regression equation is used.
3- If the values are bigger than the inactivity threshold and the CV is>13% [101], a third, daily life regression equation must be used.

The advantageous of the triaxial accelerometers is that it is possible to measure the accelerations of the three body axes, so being able to measure a larger range of body movements. In a recent study, differences were found when the comparison between the uniaxial and the triaxial accelerometer [102]. Uniaxial accelerometer have a tendency to underestimate step count. However, the step frequency affects the performance of both types of accelerometers at any walking velocity.

B. Multiphasic devices

In order to improve the accuracy of the measurement when using accelerometer or HR method, multiphasic devices can be used, especially when measuring the EE related with non-standard movements [103]. Corder et al. [104] claimed some enhancement of the result when measuring PA of children when they used electrocardiogram (ECG) data in addition to accelerometer counts. Both uniaxial and triaxial accelerometers were used and positioned on wrist and thigh respectively with the combination of three ECG leads Haskell et al. [105]. Coefficient of correlation (0.73) was used to study the strongest of the relation between the estimated oxygen consumption across a variety of activities. The result was not especially impressive. Another new novelty has been to use GPS with accelerometer information [106]. When using with a vehicle, a GPS is very helpful to detect the side effect. However, tall buildings can affect the quality of the signal and so is critical if data are to be measured in urban areas [107]. In addition, the signal can be lost when passing under tunnels. Furthermore, rapid movements are hard to detect when using the low sampling frequency. In a recent study, they developed a recent device, which uses a GPS with triaxial accelerometer, temperature, barometric pressure, light, audio and humidity recording [108]. It is claimed that the new device can be used to define the fraction of activities performed out of doors, distant versus local travel (with the possibility to detect accelerations due to traveling in a car. The Sensewear armband includes data from heat flux with two accelerometers, galvanic skin response and skin temperature [109]. The company that manufactures this device states that it is possible for the device to make the difference between the activities accomplished by the upper and by lower limbs. The device can also detect activities of load carriage, hill climbing, and non-ambulatory activities. However, one comparison with a respirometer showed an under-estimation of EE of 24–56% when skating. Another study reported an important underestimation of EE when high-speed running (40%) and cycling (25–50%) [110].

C. Physiological responses to physical activity

HR, respiratory minute volume, body temperature and sweat gland activity are physiological responses that are used to estimate PA. They can be measured individually or in combination.

1. HR monitors

Since the Astrand nomogram [111], it was evident that HR can be used as an indicator of PA. The relatively linear increase that was found between HR and oxygen consumption when from 50% of an individual's maximal oxygen intake to close peak effort. Many evident limitations about the exploitation of this connexion exist: age, sex, physical fitness and posture of the subject affect considerably the slope of the line. The slope also differs radically between arm and legs work. Furthermore, the slope is augmented by the exposure to high altitudes or to a hot environment, by static work and /or anxiety, [112]. Booyens and Hervey [113] are first who defend HR recording for PA estimation. When analysing the ECG data and depending on the contact electrode and the degree of muscles tremor, RR intervals can be detected and HR can be calculated and used to estimate PA. Some devices may indicate when specific activities start, and in the most, sophisticated recent monitors, a triaxial accelerometer are included to the ECG device and it automatically signals lying, standing and walking events. Electrochemical integration of pulse signals, tape recording, ear-lobe photocells, and ECG telemetry are the possible systems for the field measuring of HR.

a. Telemetry

Since using cables to measure the ECG signal to derive HR for PA estimations, is not very practical,, the telemetric transmission of ECG signal through a wireless connected device was the earliest methods for PA estimation developed by Norman J (''Jeff'') Holter. This method is still very used, generally in the evaluation of athletes and patients taking part in cardiac rehabilitation programs. The first Holter backpack weighed about 34 kg, but after that, telemeters rapidly became quite lighter. With the light telemeters, the subject rests mostly autonomous, but has to stay inside the range of the recorder. However, many systems cannot be used in a wet environment. Now it is possible to transmit data to central laboratory where automated interpretation of data can be performed [114], [115]. During the 1970, the company Polar system first introduced a telemeter that could measure the ECG signal through chest strap and transmit it to wristwatch-type recorder. The device allows many athletes to evaluate their HR level. Actually, more advanced devices exist using a conductive dry fabric for the chest strap and can incorporate microcontrollers that analyses the ECG signal to measure HR and other versions that even include accelerometers to improve the diagnostic.

b. Ear lobe photo cell

Changes in pulse wave induces changes in optical density when using small photo-cell to the subject's ear lobe. In Other studies, they applied the same type of detector to the fingertip. One problem that can happen is the slippage of the earpiece, which is source or erroneous signals. Another problem that could happen when using this method is that because sometimes the dicrotic pulse wave could be large enough when exercising, and so rather than having only one impulse corresponding with one pulse, two impulses are generate with only one pulse.

c. Respiratory minute volume

For the ergonomist, the ventilatory measurements was used for long time as an estimator of energy expenditure, and so for several years portable respirometers were used to estimate the average oxygen consumption during periods of 5–30 min. An early study showed that the EE (kJ/min) of workers could be predicted by an equation, [116]. The respiratory minute volume has a linear relationship with the oxygen consumption at moderate work rates, although as with the HR, the connection is vulnerable to some parameters such as which muscle groups are activated, isometric contractions, anxiety and environmental temperature. Furthermore, when low work rates, the relationship is much less linear [116]. Also the ventilatory method is not accurate when subjects are at a given age. Also their maximal respiratory minute volume differs significantly with their body size and cardiorespiratory fitness. In a study, they found that the error in estimate when using respiratory method during moderate intensities of work is around 10% [117]. The main limitation of respiratory method is that the subjects need to wear a facemask and so it's not very particle in everyday life. In [118], they argued that they could estimate the respiratory volume from pressure fluctuations with a small chest pneumograph, [119]. The precision of this method has been enhanced by using algorithms connecting the abdominal and thoracic movements [120]. In the future, clothes will be used to make easy the method when everyday life. However, the errors are still large, even when walking [±7 l/min, [121].

2. Body temperature

During the beginning of PA, the temperature of the body rises, after some time it tends to a plateau. The value is related with the rate of EE. Certain studies [122] claimed that it exist a linear relationship between this value and the individual's rate of working. However, the temperature interpretation is affected by many factors such as body size, air temperature, air movement and air humidity [123]. Furthermore, when a specific muscle is working, it is in that area where the temperature increases; equilibration between the numerous parts of the body may be very slow, and rectal readings can be biased.

3. Sweat rate

In an earlier study, Marius Nielsen [124], they established that when a subject is practicing exercises in a dry and warm environment, most body's heat is lost by sweating, and when a steady state is attained, sweat production is related to the level of the work. Generally, to determine the sweating, repeated weighting of the subject are performed, although this approach presents a direct source of error. In fact, when moving, not all of the secreted sweat is evaporated. In addition to this limitation, the rate of sweating is influenced by the environment and by the aerobic fitness of the individual.

4. Multiple physiological measurements

Treuth et al. [125] rather than using only one variable to estimate PA, they combined HR information with data from a leg-mounted vibration sensor, and found that this combination enhanced the accuracy of measurements of 24-h EE relative to respiration calorimetry. In a recent study, Zakeri et al. [126], combined HR data with acceleromer information. In a another study, [127] the authors developed a multifunction ambulatory garment able to instantaneously measure the ECG, activity posture, the respiration and optionally the blood pressure and body temperature. In addition to all of those parameters, a patient report is generated. However, using all of those devices and sensors is not very practical when everyday living.

5. CONCLUSION

Actually and after many years of developing methods for measuring PA, it is still hard to make precise field evaluation of PA and the related EE, especially in wide populations. In this chapter, we saw that questionnaires focus on the different types of activities (work, home, leisure, sport, or specific activities) with open or closed answers. Carefully made questionnaires are acceptable to make a three or four level classification of PA patterns, and this can be enough for some epidemiological purposes. However, the total significance of questionnaire data rests very questionable. In addition, this method is time consuming, which is not practical, especially in our society when time is very precious. We also saw that one of the movement sensors that exists, is the pedometer that measures the number of steps. The device is in the form of a box of the size of a match box, small and laterally fixed to the belt over the hip by means of a clip. After measuring the length of the normal pace of the subject, the result can be converted to distance. The pedometer measures the number of steps or pulses made by walking or running and does not allow assessing the intensity of movement or energy expenditure related to the activity. The accuracy in estimating the number of steps taken and distance varies depending on the available models. The pedometer can be useful when walking but not when movement on site. Another device presented here is the accelerometer. It permit to measure the acceleration-deceleration and obtain an estimate of the movement and intensity signal in daily life. The results are expressed in units of movements ("counts") per unit of time or energy expenditure related to the activity. Individual PA patterns can be defined. However, static activities (charges, cycling, rowing, and moving on site ...) are poorly taken into account. Thus, the accelerometer can be used to detect walking, but it cannot be used to detect movement on site. We have seen that actually, the most spread method in the market is the HR method, it is based on the existence of a linear relationship between HR and oxygen consumption in an individual subject to a period of gradually increasing power. In addition, in certain circumstances (stress, high external temperature ...), HR can be increased without relation to PA. Thus, the HR is not an accurate method to measure low level of PA, since it cannot make the difference between HR increases due to walking or due to mental stress. After we have seen the most used methods, their type of data, their relation with PA, their advantageous and disadvantageous. In the next chapter a detailed description of the developed approach is given.

IV. CHAPTER 04 Physical Activity, Cardiac And Non-Cardiac Electrical Activity

As PA is conventionally defined as any body movement produced by the contraction of skeletal muscle that increases energy expenditure above a basal level [128] we understand that skeletal muscle is the central organ of PA; it is the only organ able to ensure the conversion of biochemical energy into external mechanical work. From this, we can understand that muscle contraction is related to the movement intensity. We decided to investigate this relationship.We know that the most used method to measure muscle contraction intensity is to measure its electrical impulses amplitudes and frequencies. The goal is not to study the relation between one muscle fiber contraction intensity or even a motor unit action potential but the relation of a set of muscles contraction intensity with a specific movement. We will not study all body muscles but only trunk muscles. Why? Because we wanted to use an already well spread method and device in the market, that can measure the electrical activity of muscles. We know that any electrodes positioned over the skin can detect muscle electrical activity. ECG electrodes were chosen since as we saw in the previous chapter, HR method, using ECG chest device, is the most used method to measure PA. We also know that the most used electrodes positions when HR measuring is under the pectorals over trunk muscles. For these reasons, trunk muscles was chosen.

1. MUSCLE CONTRACTION AND ENERGY

To be able to contract, the muscle needs a suitable supply of energy substrates and oxygen. The energy supply to the muscle depends on many other integrated operating systems, particularly the liver and adipose tissue for storage of energy reserves, the endocrine system for controlling the distribution of energy in the muscle and cardiorespiratory system for the supply of oxygen. Energy substrates are represented by carbohydrate reserves, lipid reserves and the pool of underlying amino acids. The type of energy substrates depends on the characteristics of muscle activity (intensity, duration), the initial stock and the level of training. We distinguish very short and intense physical activities that seek primarily anaerobic metabolism (without oxygen), prolonged activities, which involve mainly aerobic metabolism (with oxygen). According to muscles, there is a predominance of fast-twitch fibers and slow-twitch fibers. Anaerobic capacity concern mainly the fast twitch fibers when the aerobic capacity. The slow-twitch fibers have a high mitochondrial density and enzymes orienting metabolism toward oxidative pathways. Cardiac output increases by increasing the HR and the stroke volume. The alveolocapillary diffusion increases as the arteriovenous difference in O_2 with increasing of tissue sample of O_2 throughout the body. The increased cardiac output associated with an aperture of capillary bed allows preferential irrigation of muscle territories to work. Thus, we can understand that using HR to estimate the intensity of the exercise is a correct idea and it was well documented as we saw earlier (chapter 03). It is also obvious that the intensity of the exercise is related with the intensity of the muscle contraction and so with the bioelectrical activity. Because of this relationship, we tray in our work to understand how we can use muscle contraction to estimate PA intensity. It is therefore important to first understand the muscle contraction process.

2. MUSCLE CONTRACTION AND ELECTRICAL ACTIVITY

Depending on its purpose, the muscle may be categorized as either skeletal, smooth, or cardiac. Skeletal muscle is attached to the skeleton and facilitates movement and position of the body, whereas smooth muscle is found within the intestines and blood vessels. Skeletal muscle is the type of interest in this thesis. Cardiac muscle builds the heart walls and produces the contraction of the heart, creating a heartbeat; the function of the heart is described separately (chapter 04). In skeletal muscle such as rectus abdominus (RA) and oblique externus (OE) (trunk muscles), contraction is controlled by electrical impulses, i.e., action potentials, which propagate between the central and peripheral nervous systems and muscles. The action potentials are transmitted down the axons of the motor neurons, originating in the brain or the spinal cord, to the muscle fibers. Each motor neuron is connected to muscle fibers through a specialized synapse called the neuromuscular junction which allows the action potentials to stimulate contraction. Taken together, a motor neuron and the fibers to which it connects (innervates) comprise a motor unit and represent a functional unit of contraction. Depending on the purpose of the muscle, a single motor unit may comprise just a few muscle fibers or more than a thousand muscle fibers [129 130]. Muscles that control fine movements, for example, of an eye or a finger, have fewer muscle fibers per motor unit than muscles that control gross movements, for example, activated trunk muscles during walking and jogging. The contraction of a muscle fiber is initiated when neuronal action potentials reach the neuromuscular junction and fire action potentials that spread along the excitable membranes of the muscle fiber. A motor unit action potential (MUAP) results from spatial and temporal summation of individual action potentials as they spread through the different muscle fibers of a single motor unit, see Figure IV.1.

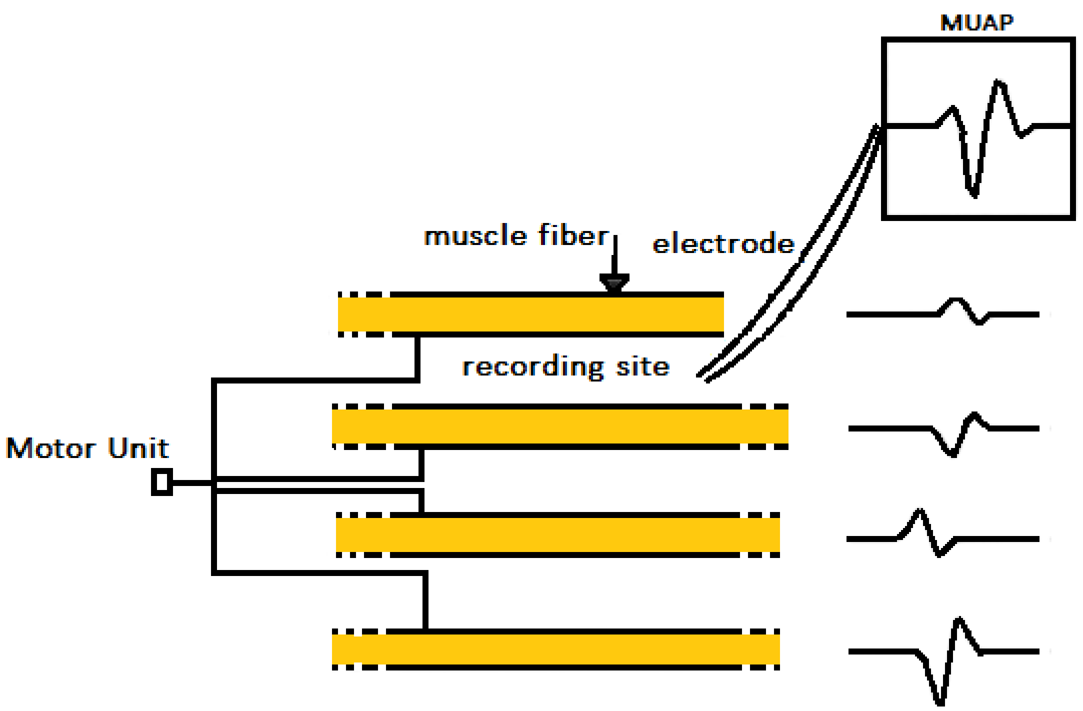


Figure IV.1 The generation of a MUAP of a single motor unit with four muscle fibers. The amplitude of the MUAP decrease when the electrode become more distant from the fibers.

The electromyogram (EMG) signal results, in turn, from summation of the different MUAPs which are sufficiently near the recording electrode. The number of MUAPs within the pick-up (detection) area of the electrode depends on the selected type of electrode. Motor unit recruitment is a fundamental muscular process in which the force exerted by muscle contraction is controlled by the central nervous system through spatial and temporal recruitment of motor units. Spatial recruitment means that force is increased by recruiting more motor units, whereas temporal recruitment means that force is increased by firing of action potentials at faster rates. Although both types of recruitment can occur at the same time, spatial recruitment dominates from lower levels of muscle contraction until most motor units have been recruited. At high levels of muscle contraction, temporal recruitment dominates and drives the motor units with firing rates at about 50 Hz and faster. A high firing rate implies that individual MUAP waveforms no longer can be discerned due to temporal superimposition, and the resulting EMG signal exhibits a noise-like, random appearance, referred to as an interference pattern. Usually, the placement of surface electrodes depends on the muscle of interest and involves factors such as muscle fiber orientation, anatomical landmarks, and minimization of electrical cross-talk from other muscles. However, in our case, the position of the electrodes is not a choice but a consequence; initially the electrodes are used to detect ECG signal measured on trunk muscles position. When subject's movement, those muscles generate bioelectrical signals called trunk muscles signals (TMS). These signals are usually considered as EMG noises when measuring the ECG for HR detection. The surface ECG electrodes detect the gross activity produced by a large number of motor units. Its spatial resolution is more limited than that of the needle EMG, and the high-frequency content of a MUAP is smoothed. The surface ECG electrodes does not allow the detection of individual MUAPs, although MUAP trains may be detected at low levels of muscle contraction [130]. The surface EMG can be recorded at lower sampling rates than the needle EMG since the intervening tissue between the motor units and the surface electrode acts as a lowpass filter of the electrical signal. A sampling rate of 500 Hz can be used to detect the trunk intensity. The ECG trunk muscles signals (ECG-TMS) intensity depends on the intensity of the muscle contraction. In the proposed method, we computed the ECG-trunk muscles signals amplitude (ECG-TMSA) and compared it to HR evolution derived from the same ECG signal. If the correlation is linear, ECG-TMSA can be considered as a new method to estimate PA. Such an approach has not been investigated before.

3. TRUNK MUSCLES AND LOCOMOTION MOVEMENT

When an individual moves from sitting to a walking state, a set of muscles are contracted and although leg and hip muscles are the main walking actuators, the whole body is involved. Opposite arm swings and rotational movements of the trunk are examples of typical attributes of walking activities [131]. Trunk muscles can further be divided into two different muscle systems: the global system enabling movements and the local system ensuring stability. Local system muscles are permanently active at low levels [132], independent of movements. Conversely, muscles of the global system act to initiate movements leading to movement dependent phasic activation patterns. The global system was subdivided further into the global stabilizing and the global mobilizing systems respectively. Global stabilizers complement the function of the local system by controlling and limiting movements by means of eccentric activation characteristic when global mobilizers initiate movements [132]. RA is global mobilizer, whereas OE belongs to the global stabilizers. As we said earlier, the initial signal is the ECG and the electrical activity of the trunk muscles is superimposed on it. To be able to evaluate the amplitude of ECG-TMSA, we need to separate it from ECG, for this we need to know the origin of both of them. We have developed the necessary about the EMG and we said that it exhibits a noise-like, random appearance and is limited on a band frequency from 50 to 250 Hz with sample frequency of 500 HZ. Now we need to understand the origin of the ECG Signal. We present here the general functioning of the cardiovascular system, and then, in more detail, the principle of the ECG. This presentation is limited to the minimum necessary for an understanding for this thesis and the reader interested in a rigorous medical approach may refer to many medical literature available on the subject.

4. THE CARDIOVASCULAR SYSTEM

The cardiovascular system provides blood circulation in the body and thus makes the supply of oxygen and nutrients. It consists of the heart, a kind of double pump, which circulates in two complementary systems: that of the arteries and the veins.

A. Arterial and venous circulation

The arterial network of the large circulation is a high-pressure circuit, it led the oxygenated blood through the body in blood vessels called, depending on their size, arteries, arterioles and arterial capillaries. The latter level is comprised of multiple small branches which facilitate the transfer of oxygen from the blood to the organs. The blood, now poor in oxygen, comes back to the heart into the veins, then is sent by the small pulmonary arteries in the circulation where it is oxygenated in the lungs. The venous system is the major reservoir of blood and contains about 70% of the total volume, which is 5 to 6 liters for an adult.

B. Heart

The heart is the central element of the cardiovascular system. We describe the anatomy and the electrical functioning of a healthy heart.

1. Anatomy

The heart pumps blood through the contractions of muscle tissue called the myocardium. A thick wall divides it into two halves (left heart / right heart), and each has two chambers: the atrium and the ventricle. With each beat, the myocardium following the same sequence of movement: the oxygen-poor blood reaches the heart through the vena cava. There enters the right atrium, and is driven by its contraction called atrial systole which moves it in the right ventricle. Ventricular systole (contraction of the ventricles) in turn propels blood from the right ventricle to the lungs where it will be loaded with oxygen. Returning to the heart through the pulmonary veins, blood pools in the left atrium and then, during the atrial systole, passes into the left ventricle when the ventricular systole sends it to the organs by the aorta.

2. Electrical Activity of the Heart

As for all the body's muscles, myocardial contraction is caused by the propagation of an electrical pulse along the cardiac muscle fibers induced by depolarization of muscle cells. In the heart, the depolarization is normally incurred at the top of the right atrium (sinus) and then propagates through the atria, inducing atrial systole, which is followed by a diastole (relaxation of the muscle). The electrical impulse then reaches the atrioventricular (AV) node, single path point possible for the electrical current between the atria and ventricles. Here, the electrical pulse undergoes a short break allowing blood to enter the ventricles. It then follows the bundle of His, which is made up of two main branches in each ventricle. The fibers constituting the bundle, supplemented by the Purkinje fibers, due to their rapid conduction, the electrical pulse propagated in several points of the ventricles, and thus enable an almost instantaneous depolarization of the entire ventricular muscle, despite its large size, this ensures optimum efficiency in propulsion of blood that is the contraction phase of ventricular systole. Then follows the ventricular diastole (relaxation of the muscle) muscle fibers re-polarize and thus return to their initial state.

C. The electrocardiography

1. The principle of the electrocardiogram

The principle of modern ECG recording is very nearly to the developed by Einthoven who used two electrodes stuck to the skin surface, it records the potential difference between two points diametrically opposite to the heart, this signal being directly correlated to the displacement of the electric pulse in the cardiac muscle fibers. The instantaneous electrical activity may be defined by a vector oriented following the potential difference present in the heart, and is proportional to it. At each instant the pair of electrodes records the amplitude of the projection of this vector along their axis and, when the electric vector is directed from the electrode - to the + electrode, we observe on the recorder a positive deflection , and when the vector is directed in opposite direction, the negative deflection. In cardiology, the exam the most commonly practiced is the 12-lead ECG, where the ECG signal is visualized by 12 privileged axes: six axis in the frontal plane and 6-axis in the transverse plane. Its length can vary from a few seconds to one or two minute. It allows the precise location and diagnosis of certain pathologies, which leave permanent marks such as deficient myocardium areas following an infarction. However, when measuring HR, the necessity of 12 derivations disappears and only one lead is sufficient. For this, the most used device is the ECG chest strap, which is composed from the unit, and the strap. The signal is detected through two electrodes fixed on the strap. With the position of the electrodes when the ECG chest strap is used, the heart electrical activity is visualized with the second derivation (II).

2. ECG Waves and Time intervals

The heartbeat can be monitored through the surface recording of the electrical signal that accompanies it. In fact, each phase of the beat has a particular electrical trace. A trained eye can therefore, in most cases, differentiate quickly the trace of atrial contraction from the trace of ventricular contraction. The initial impulse comes from the sinus but it is not visible on the ECG. The electric wave which then propagates through the atria, causing their contraction, leaves the trace as a small positive deflection on the ECG: the P wave (Figure IV.6 a). The impulse then reaches the AV node, which produces short break reflected on the ECG by a small flat segment, then it borrows rapid conduction pathways (the bundle of His) to drive the contraction of the ventricles, followed by their repolarization. This propagation of the pulse, and the brief and powerful contraction of all the ventricular muscle, draw on a series of three

ECG waves (Q, R and S) called QRS complex (Figure IV.2 b). The Q wave is the first; it is a wave downward, which is not always visible on the plot, the second is the R wave; it is high amplitude and upward, the last is directed downwards; it is the S-wave. It is the combination of these three waves is the QRS complex. After each QRS complex, it is observed on the ECG a wave called T wave. Between this wave and the previous one, there is a short break called the ST segment, the study is very important for the identification of certain pathologies . The T wave reflects the repolarization phase of cells constituting the ventricles, it is a purely electrical phenomenon and during this phase, the heart is mechanically inactive (Figure IV.2 c).

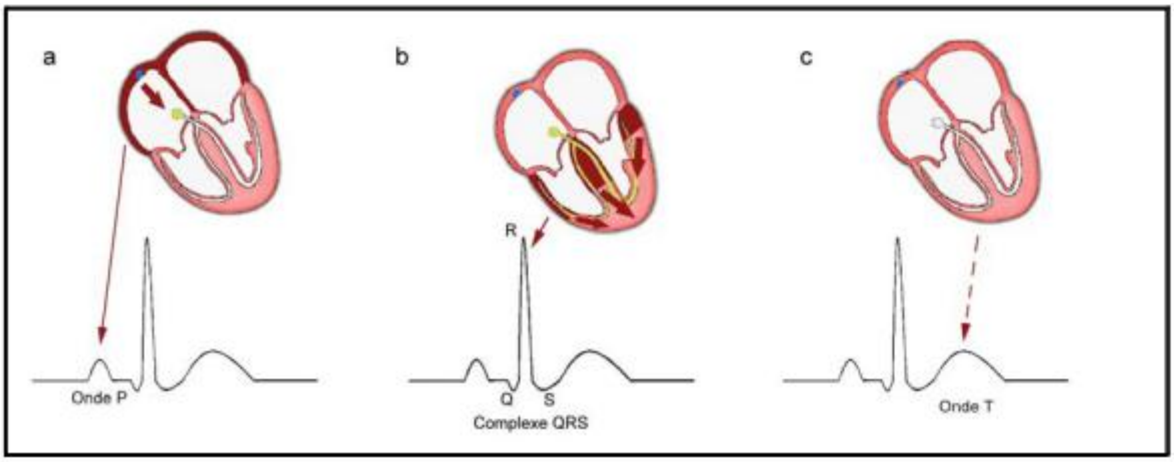


Figure IV.2 A one period heart contraction

The contraction of the atria is reflected in the ECG by a positive wave called the P-wave (a). It is followed by a short break corresponding to the delay made by the (AV) node. The short and powerful contraction of both ventricles is represented by three waves: the Q wave, the R wave and the S wave This is called the QRS complex (b). Q is the first early negative wave complex, it is not always visible, the R wave is the second wavelength, it is positive and large amplitude, the third wavelength being the S. The T wave corresponds to cell repolarization muscle ventricles (c). Between this wave and the S wave is the ST segment.

3. ECG Noises and Artefacts Sources

The ECG is often contaminated by noise and artifacts that can be within the frequency band of interest and can manifest with similar morphologies as the ECG itself. Broadly speaking, ECG contaminants can be classified as:

1. Power line interference: 50 ±0.2 Hz main noise (or 60 Hz in many data sets10) with an amplitude of up to 50% of full scale deflection (FSD), the peak-to-peak ECG amplitude,

2. Electrode contact noise: Loss of contact between the electrode and the skin manifesting as sharp changes with saturation at FSD levels for periods of around 1 second on the ECG (usually due to an electrode being nearly or completely pulled off),

3. Patient–electrode motion artefacts: Movement of the electrode away from the contact area on the skin, leading to variations in the impedance between the electrode and skin causing potential variations in the ECG and usually manifesting themselves as rapid (but continuous) baseline jumps or complete saturation for up to 0.5 second,

4. EMG noise: Electrical activity due to muscle contractions lasting around 50 ms between dc and 10000 Hz with an average amplitude of 10% FSD level,

5. Baseline drift: Usually from respiration with amplitude of around 15% FSD at frequencies drifting between 0.15 and 0.3 Hz,

6. Data collecting device noise: Artefacts generated by the signal processing hardware, such as signal saturation,

7. Electrosurgical noise: Noise generated by other medical equipment present in the patient care environment at frequencies between 100 kHz and 1 MHz, lasting for approximately 1 and 10 seconds,

8. Quantization noise and aliasing,

9. Signal processing artefacts (e.g., Gibbs oscillations).

The intensity of the different noises depends on many parameters such as the environment, the quality of the hardware, the electrode positions and the movement intensity of the subject. As we saw earlier, we are interested to detect and evaluate the ECG noises and since the electrodes are under pectorals over trunk muscles, the EMG noises are originating from trunk muscles contractions; their amplitudes differ and are related with the subject’s movement intensity.

5. CONCLUSION

Cardiac and non-cardiac muscles are related, this relation is originated from the need of skeletal muscles, when contraction, to energy substrates and oxygen. The contraction of cardiac muscle pumps blood to the vascular system and supply muscle with the needed energy and since any PA needs the contraction of muscles, we conclude in this chapter that PA is related with both cardiac and non-cardiac muscles activity. Cardiac activity represented by HR is well used in measuring PA. However, non-cardiac muscles activity is not used to this purpose. In this thesis, we decided to investigate if it is possible to use the intensity of muscles contractions to estimate the PA level. We have seen that ECG chest strap device can detect trunk muscles electrical activity. We detailed the anatomy and the electrical activity of both cardiac and non-cardiac muscles. After this background we can go thought practical experiment and study in more detail the relation that exist between PA and trunk muscles activity intensity.

V. CHAPTER 05 Materials And Methods

In this chapter, we describe the three experiments performed in both laboratories in Linkoping and Tlemcen universities. The goal of the experiments is to study the correlation between ECG-TMSA and PA (walking on treadmill with different velocities) and the influence of mental stress on the ECG-TMSA in laboratory and real life conditions.

1. INSTRUMENTATION

The device used throughout the experiment is a wearable ECG sensor and data storage device. The small size (length 6 cm, width 3.5 cm, thickness 1.1 cm) wearable ECG device was developed at the department of biomedical engineering, Linköping University, Sweden. Connection to the electrode chest belt is made by means of standard buttons for clothes. In this study, the device comprises receiving port, which is configured to receive the ECG signal from electrodes positioned on the chest of the individual under the pectoral muscles and preferably distributed on both left and right body halves. The ECG amplifier is a two lead type input with fixed 10 Mohm load resisters to a virtual ground that will keep the DC potential of the electrodes close to the virtual ground without the need of a third reference electrode. A high and low pass filter with cut of frequencies of 0.3-240 Hz respectively are used. The resulting ECG signal is then sampled in a 16 bit analog-to-digital (ADC) converter at a sampling frequency of 500 Hz. The signal is sent wireless through a Bluetooth 2.0 module (®Free2move F2M03AC2) to a computer where it can be displayed in real time and digitally stored.

Chest belt/electrodes:

Every subject used the same chest belt for the whole experiment. It uses a chest belt wrap made of a combination of fabric and plastic from brand ®Polar. The electrodes as well are fabric based designed with metalized plastic fibers.

The most used electrodes position when HR is measured by an ECG bipolar chest strap, is under the pectorals over the trunk muscles see figure V.1. Because of its close proximity to the heart, this position permits to have high ECG signal amplitude.

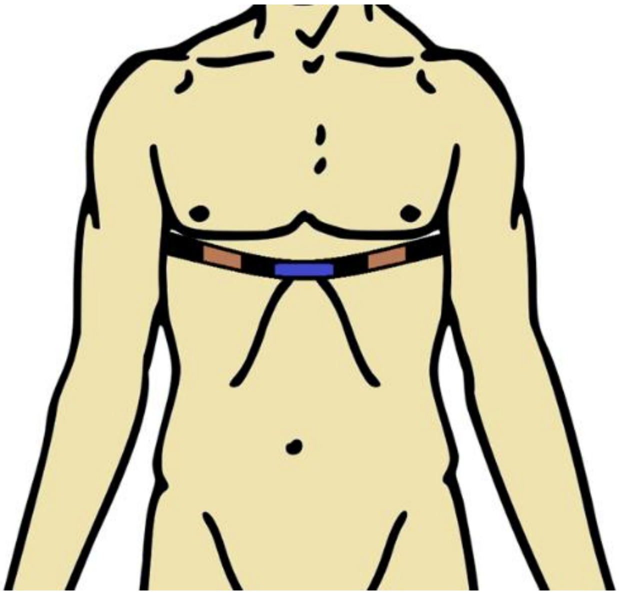


Figure V.1 ECG chest-strap-type, most used position

2. SUBJECTS

In the first laboratory experiment, sixteen male voluntary subjects, students at the department of biomedical engineering, (body mass = 82±18 kg, height = 1.80±0.06 m, age = 28±4 yrs, and BMI= 25±5 kgm^{-2}), participated and gave informed consent. All subjects were healthy, with no evidence of past or present disorders. No intake of drugs known to affect energy metabolism, having a balanced diet, and non-smoking. Subjects were encouraged to maintain their normal daily PA and food intake. Four subjects token from the initial sixteen, participated on the second experiment. During the third experiment, other fifteen voluntary subjects, some of them are students at the department of biomedical engineering of Linkoping university and the others are employees at different companies in Sweden, participated in this study and gave informed consent. All subjects were healthy, with no evidence of past or present disorders, no intake of drugs known to affect energy metabolism, having a balanced diet, and non-smoking. Subjects were encouraged to maintain their normal daily PA and food intake.

3. PROTOCOL

During the first experiment, Subjects were asked to refrain from exercise and caffeine intake less than 5h before the test. Before the start of the measurement, an adequate habituation phase of 5 minutes was used. The subject walked barefoot with a normal arm swing on a treadmill for 6 minutes at the following speeds: slow walking at 4 and 5 (kmh^{-1}), fast walking at 6 (kmh^{-1}), and running at 7, 8, 9, and 10 (kmh^{-1}). Between each walking exercise, there is a

5 minutes resting period and 15 minutes resting period between the jogging exercises. The measurements started at the lowest speed and followed an ascending order. The same experimental procedure was repeated during 8 days, with 2 persons per day and with the same instructions. Since HR is influenced by mental activity, after the experiment, each subject reported if his apparent stress level was elevated during the experience or not. Stressed subjects were excluded to remove any influence of mental stress on HR. After the first Experiment, A second one was performed; on the ninth day of the study, a subgroup of 4 male subjects (body mass = 72 ±12 kg, height = 1.76±0.03 m, age = 28±3 yrs, and BMI= 23±3 kgm^{-2}) were exposed to a mental stress experiment. A computer application was used to randomly present Stroop Colour-word interference tests and arithmetic problems to the subject. To prevent habituation of the Stroop test, subjects were asked to select either colour-name or font colour (figure V.2). Subjects had to provide an answer before the end of pre-set time limit (1 seconds) and the feedback \correct", \wrong", elapsed time and accuracy rate was displayed on the screen.

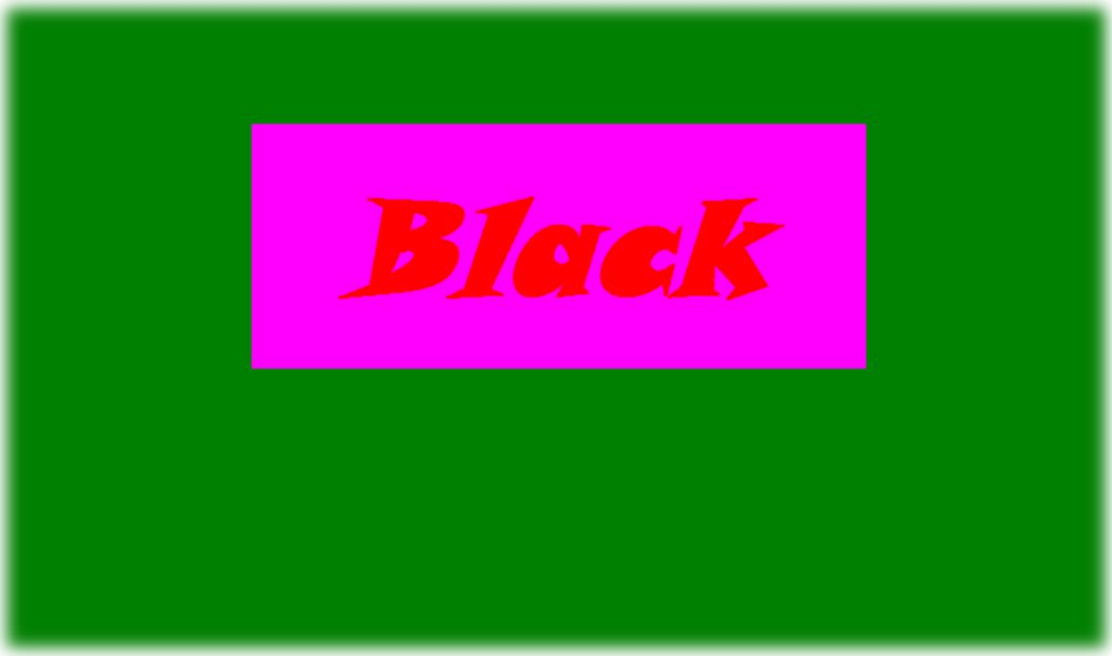


Figure V.2 Stroop test

HR and ECG-TMSA were derived from ECG-recordings in the absence of stressors and when stressors applied for each physical condition.

1. Absence of stressors: (12 minutes): Listen to meditation music (in sitting and walking conditions).

2. Presence of stressors (12 minutes): Complete Stroop test and mental arithmetic under time pressure while sitting, and walking.

During the third experiment, in the morning, subjects put on the chest belt according to the instructions. They had to moisten the electrode surfaces (the two grey areas at the front of the belt). After a few seconds, the green diode should start to blink, and the subject should write the starting time of the measurement on the diary. Subjects tried to wear the device all time awake, they had to do the provocations (below) and note them and all activities they do in between the provocations in the diary. It is ok to not measure some periods and to miss a provocation now and then. Instructions were clear: It is much more important that the diary and measurements are truthful and correct than complete! During the experiment, the instructions were to try to live normal life with respect to training (or not), eating habits, sleeping habits etc. They just had to add the provocations (below). Also, the instructions were to not perform the provocations if they have an ongoing infection! It is important that the watch they use is exactly on time. Otherwise, our analysis is much more complicated.

The instructions concerning the provocations are as follow:

A. Provocation 1 – Relaxation

One time each day, find some time to relax. It is Preferable (but not necessarily) at about the same time each day, for instance directly in the morning. It is however important that you do not have performed any heavy exercise on the same day before.

The steps of the provocation are:

Note the exact start time so you can put it in your diary after the provocation.

- Sit in a comfortable posture, without any movement, and keep your eyes open.
- Try to think of nothing (which is not easy). At least try to avoid thinking on stressful things.
- Try to breathe deeply and slowly.
- Sit like this for about 15 minutes.

- Note the exact start and end time in your diary, and if you felt that you were not very relaxed or if something else was worth noting.

Note 1: If you already have a relaxation or meditation routine, feel free to use this. But keep the time to about 15 minutes and write down your routine in the diary.

Note 2: If you want help with relaxing, feel free to use mobile applications or other tools for relaxation, meditation etc. of your own choice. But keep the time to about 15 minutes and write down what application you use in the diary.

B. Provocation 2 – Walking

At 5 up to 7 times each week, take a brisk walk for about 20 minutes. It is preferable (but not necessarily) at about the same time of day each time, for instance in the afternoon or evening. Brisk means that the pace is on a level where your respiration is almost affected. We like you to use the same route and about the same tempo each time you do this provocation. Before you start walking and directly after, stand still and relax about two minutes. If you want to walk longer than 20 minutes that is ok, but don't forget to stop and wait after 20 minutes as described above. Important here as well that you do not have performed any heavy exercise on the same day before. Note the exact start and end time in your diary. In addition, write if something special happened, if you were walking and talking to a friend, if you had to stop for a while etc.

C. Provocation 3 – Sitting vs. moving

Do this provocation 2 times each week, at approximately the same time of day each time. No heavy exercise on the day before. Note the exact time of start and end in your diary. The steps of the provocation are: Sit down and relax for 5 minutes, similar to the relaxation provocation.

- Remain seated and do motions during 5 minutes as if you were working at a desktop, for instance keyboard writing, moving papers, doing exercises, etc. To do real desktop work is of course ok, but remain seated, make continuous movements.
- After that, walk slowly for 5 minutes, in a tempo as you normally walk in your home. You can walk anywhere as long as you avoid stairs or uphill walking.

D. Provocation 4 – Mental activity

Do this provocation 2 times each week, at approximately the same time of day each time. No heavy exercise on the day before. Note the exact time of start and end in your diary. For this provocation you have to run the program we have sent to you. The steps of the provocation include:

- Click on the mental stress button an follow the instructions, when the provocation will finish, all your program time details and stroop test result will be displayed.
- So during this provocation you have to Sit down and relax for 5 minutes, similar to the relaxation provocation.
- Stay in the comfortable posture and run the "Stroop test" for 5 minutes.
- Try to not move during the test, only as necessary for using the mouse. Be sure to do your best and don't give up. Your clicks are recorded by the program and that you do your best is important for the results.
- After the Stroop test there is a period of moving on site during 5 minutes, such as in the desktop work provocation in Provocation 3.

E. The Diary

You will receive a prepared diary. What you have to do is write down when you do the different provocations and events that happen in between provocations in your daily life. For activities you perform when you are not wearing the chest belt you do not have to fill in the diary.

4. DATA PROCESSING

After the acquisition, ECG data are sent from the unit via Bluetooth module and through software to a computer for storage. The stored ECG signals are digitally processed, in a first step to generate HR and in a second step to identify ECG-TMS.

A. Detection of HR

To generate HR signal, the ECG signal is analysed in order to detect QRS complexes positions and then generate RR intervals. Therefore, an accurate determination of QRS complexes is essential for a correct measurement of HR.

QRS detection

The difficulties in QRS complex detection, when subjects are walking and jogging on a treadmill, are due to the artefacts and noises that appear in the ECG signal. Usually, before applying QRS complexes algorithm detection, the signal is passed through filters to make the detection easier and more accurate. However, due to the real time demands, many algorithms are developed to detect QRS complexes without ECG pre-processing step. Based on these considerations, a fast computation method for real-time QRS complex detection is developed. The developed algorithm is then applied on the detected ECG signals from all the subjects for evaluation.

a. QRS features

The slope of the R wave is the steepest slope comparing to the other ECG waves slopes, especially the descendant slope of the R wave. In fact, in healthy people, the absolute value of the descending slope of the R wave is higher than that of the ascending slope. The features: Wave Right Distance (WRD) (according to the descending slope) and Wave Left Distance (WLD) (according to the ascending slope) are computed using equation Eq 5.1:

$$WRD = Y(x_0) - Y(x_1) \text{ and } WLD = Y(x_0) - Y(x_2) \tag{5.1}$$

Such as $\forall\, x \in I_1,\ \exists x_1,\ \ y(x_1 - x) \leq 0, \forall\, x \in I_2,\ \exists x_2,\ \ y(x_2 - x) \leq 0$

And $\forall\, x \in I_0,\ \exists x_0,\ \ y(x_0 - x) \geq 0$

Where

x_0: The position of the expected R peak.

I_1: $[x_0\ \ x_0 + 6]$, I_2: $[x_0\ \ x_0 - 6]$

I_0: [xl xr] is a bounded interval.

The value of WRD is higher when it is computed from the R wave. This is true in a noise free ECG signal. However, to be accepted as a pertinent feature that characterizes R wave during mental and/or PA assessment, WRD must not to be influenced by the presence of high noise level and artefacts. Hence, the issue is: whether this property is true in a noisy ECG signal with different levels of noises. After the analysis of several signals measured in the laboratory, the conclusion is: even if WRD is influenced by noise, it remains less sensitive and is the best indicator of an R wave. In Figure V.3, one can see that unlike the amplitudes of R waves, the WRD has the same value in successive R waves even in the presence of high level of noise (SNR=-6) and therefore it better characterizes the R wave.

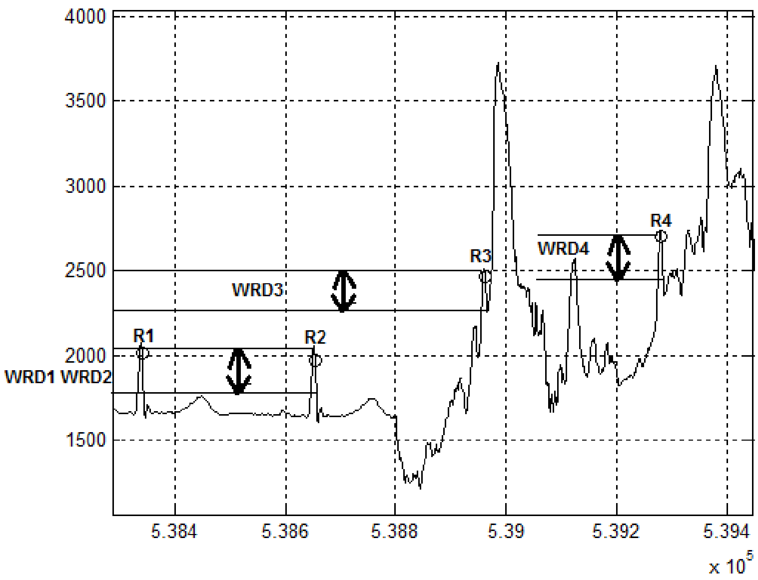


Figure V.3 File 119e_6 from MIT-Noise Stress database (segment of the signal (3 sec): No large differences of WRD between successive R waves while high level of noise.

The QRS complex detection algorithm stores the mean value of WRD and WLD of the seven last R-peaks using equation Eq 5.2:

$$WRD_{Avrg}(k) = \frac{\sum_{n=0}^{6}\big(WRD(k-n)\big)}{7}$$

$$WLD_{Avrg}(k) = \frac{\sum_{n=0}^{6}\big(WLD(k-n)\big)}{7} \qquad (5.2)$$

Where K: The detected peak number.

WLD alone does not characterize the R waves very well and is therefore combined with WRD to be pertinent. With these two features, it is easier to differentiate between R waves and non-R waves. However, in order to improve the algorithm regarding the detection of the R-wave mainly in the presence of high noise waves, a narrow time window is used. The window is positioned where the R wave is predicted. While positioning the window, the two features (WRD, WLD) should be computed but before that, the sample x_0 that represents the position of the probable R peak should be estimated. This is done by finding the maximum value of the ECG inside the window. However, the correct peak can be missed; due to the presence of a false R wave (FR) which can be confused with the correct one as shown in Figure V.4 when we used a large window (50 milliseconds (ms)).

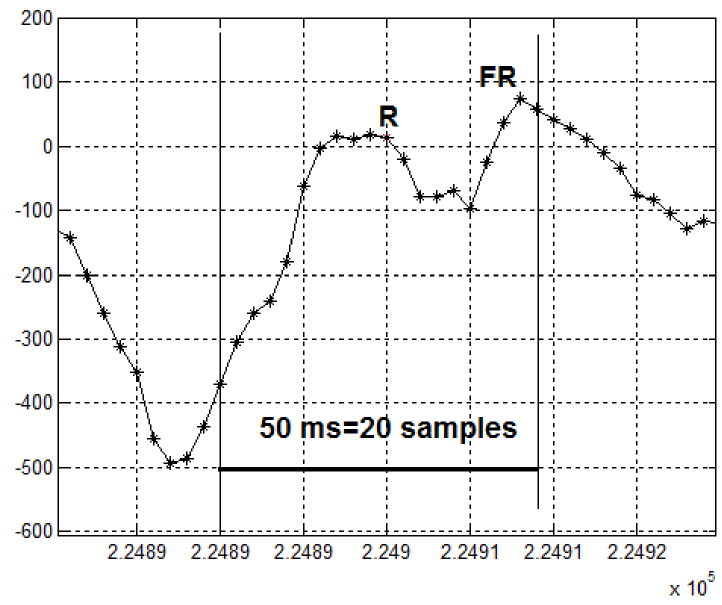


Figure V.4 File 118e00 from MIT-Noise Stress database (segment of the signal (0.105 sec)): Window of 50 ms (20samples) as width is placed where the R wave is predicted.

After positioning the window on the predicted region, equations Eq 5.3 and Eq 5.4 should be true to confirm the presence of a probable R Peak:

All the following equations are applied to signals with 360 Hz as sample rate.

$$(y(x_0) - y(x_0 + j)) > 0, \text{ if } 4 \leq |j| \leq 6 \qquad (5.3)$$

$$\left(y(x_0) - y(x_0 + j)\right) \geq 0, if \quad -3 \leq j \leq 3 \qquad (5.4)$$

Theoretically, the window size must be as small as possible (3 samples) to be sure to avoid the confusion between two close peaks. However, due to the effect of high resolution and/or a wide R wave, using 3 samples is not practical; experimentally, and using 360 Hz as sample frequency, we found that 7 samples is the best length of the window. In figure V.5, we can see that the two peaks, the true one (R) and the FR, are separated and each peak has its own window, then each peak has its own WRD and WLD which will be used in the decision step to find which wave correspond to the correct R wave.

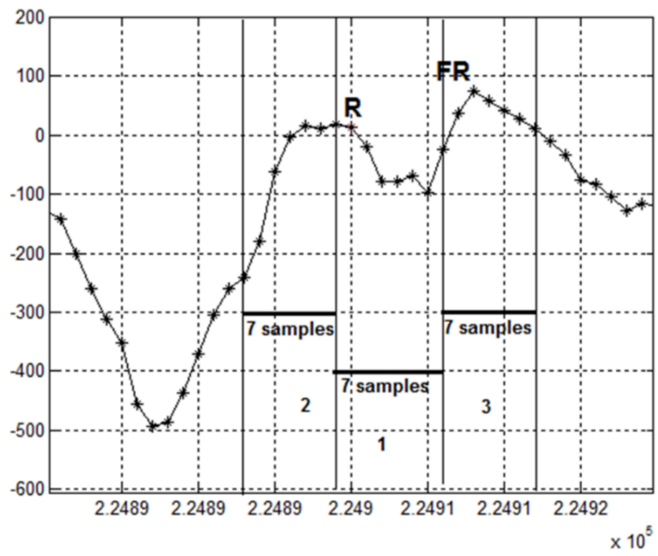


Figure V.5 File 118e00 from MIT-Noise Stress database (segment of the signal (0.105 sec)): Window of 17 ms (7 samples) as width is placed where the R wave is predicted.

b. Predicting the window's position

After the initialization of the detection, (detection of the seven first R wave in a noise free ECG segment), we compute the average of RR interval (RR_{Avrg}), and then equations Eq 5.5 and Eq 5.6 are used to predict the position of the next R wave:

$$xr(k) = (R(k-1)+3) + RR_{Avrg}(k) \qquad (5.5)$$

$$xl(k) = (R(k-1)-3) + RR_{Avrg}(k) \qquad (5.6)$$

Such as $$RR_{Avrg}(k) = \begin{cases} \frac{\sum_{n=0}^{6} RR'(n)}{i+1}, & if\ i \geq 0 \\ RR_{Avrg}(k-1), & if\ i = -1 \end{cases}$$

and $$RR'(n) = \begin{cases} RR(k-n), & if\ |RR(k-n) - RR(k-n-1)| < 5 \\ & and\ \left|RR(k-n) - RR_{Avrg}(k-1)\right| < 40 \\ 0 & ,if\ |RR(k-n) - RR(k-n-1)| > 5 \\ & or\ \left|RR(k-n) - RR_{Avrg}(k-1)\right| > 40 \end{cases}$$

With $$RR(k) = R(k-1) - R(k-2)$$

$R(k)$ is the position of the last detected R peak.

- $xl(k)$And $xr(k)$are the limits of the window.
- i : The number of positive$RR'(n)$minus one,with$-1 \leq i \leq 6$

c. Decision step

When the window is positioned at the first predicted R region, the features are computed and the result is that the algorithm either validates the R wave or not. If not, the algorithm looks in the vicinity of the first predicted region by shifting the window. For each new position, a number is assigned to the window, (36 positions); 1 ≤n≤ 36. To validate the position of the R wave, we need to compare WRD (n) and WLD (n) with their thresholds WRD_{th1} and $WLDt_{h1}$ respectively. Eq 5.7 is used to compute the threshold:

$$WRD_{th1} = \left(0.9 \times WRD_{Avrg}\right)$$

and

$$WLD_{th1} = \left(0.4 \times WLD_{Avrg}\right) \tag{5.7}$$

If WRD (1)>WRD_{th1} and WLD(1)>WLD_{th1}, R wave is validated and detected. If not, the window is shifted to the left and its assigned number is incremented n=2. If WRD (2)>WRD_{th1} and WLD(2)>WLD_{th1},the R wave is validated and detected. If not, the window is shifted to the right and its assigned number is incremented n=3. The same procedure is repeated until n=12 (n=12 is an experimental choice). The window is shifted using equations Eq 5.8

$$xr(n) = xr(n-1) + (xr(1) - xl(1)) \times n^{(-1)}$$

And

$$xl(n) = xl(n-1) + \left(xr(1) - xl(1)\right) \times n^{(-1)} \tag{5.8}$$

If for n=12, the R wave is not detected, WRD and WLD values are computed for all the windows' positions and are stored. For n>12, the window is shifted following a new equation Eq 5.9:

$$xr(n) = xr(n-1) + \left(xr(1) - xl(1)\right) \times (-n)$$

$$xl(n) = xl(n-1) + \left(xr(1) - xl(1)\right) \times (-n) \tag{5.9}$$

Except for n=21, 22, 23, and 25 (because for those values of n, the window is positioned too left from the next R wave and so it less probable to find it for a normal ECG) where:

$$xr(n) = xr(n-1) + \big(xr(1) - xl(1)\big) \times (n)$$

$$xl(n) = xl(n-1) + \big(xr(1) - xl(1)\big) \times (n) \qquad (5.10)$$

A coefficient called R wave presence coefficient (RPC) is computed from WRD and WLD using the Eq 5.11:

$$RPC(n) = \begin{cases} 3 \times WLD(n) + 4 \times WRD(n)\,, if\ 1 \leq n < 4 \\ 2 \times WLD(n) + 3 \times WRD(n)\,, if\ 3 < n < 9 \\ 1 \times WLD(n) + 2 \times WRD(n)\,, if\ 8 < n < 26 \\ 0.5 \times WLD(n) + 1 \times WRD(n)\,, if\ 25 < n \leq 36 \end{cases} \qquad (5.11)$$

The algorithm compares WRD and WLD of the window, which has the highest value of RPC (n=n0), with their thresholds WRD_{th2}, WLD_{th2} respectively, following Eq 5.12 and Eq 5.13:

$$WRD_{th2} = \big(0.5 \times WRD_{Avrg}\big)$$

And

$$WLD_{th2} = \big(0.1 \times WLD_{Avrg}\big) \qquad (5.12)$$

If WRD (n_0)>WRDth2 and WLD (n_0)>WLD_{th2}, for n<26, the R wave is detected. If not, WRD and WLD are compared to other thresholds (WRD_{th3},WLD_{th3}).

$$WRD_{th3} = \big(0.2 \times WRD_{Avrg}\big)$$

And

$$WLD_{th3} = (0.6 \times WLD_{Avrg})$$
(5.13)

If WRD (n_0)>WRD_{th3} and WLD (n_0)>WLD_{th3}, for n<16, the R wave is detected. If not, third and fourth features are computed and used to detect the presence of premature ventricular contraction (PVC).PVCs have two major characteristics: first, they are premature and arise before the next normal beat, and second they have abnormal appearances; the QRS complex is always abnormally wide and high. The PVC is usually followed by a compensatory pause. In order to well characterize PVC, the large wave right distance and left wave distance (LWRD, LWLD) features are computed, following Eq 5.14:

$$LWRD = y(x_0) - Y(x_3),\ LWLD = y(x_0) – Y(x_4) \tag{5.14}$$

Such as

$\forall\, x \in I_3,\ \ \exists x_3,\quad y(x_3 - x) \leq 0$,

and

$\forall\, x \in I_4,\ \ \exists x_4,\quad y(x_4 - x) \leq 0,$

$I_3 : [x_0 x_0 + 20];$

$I_4 : [x_0 x_0 - 20]$

The average values of LWRD, LWLD are computed using the same approach needed to compute WRD_{Avrg}, WLD_{Avrg} in equation Eq 5.2.

Then, a coefficient called ectopic presence coefficient (EPC) is computed for each window using the Eq 5.15:

$$EPC(n) = 1 \times LWLD(n) + 2 \times\ LWRD(n), 12 \leq n \leq 36 \tag{5.15}$$

LWRD, LWLD of the window, which has the highest EPC (n=n1) are compared to the following thresholds, thresholds are computed using the Eq 5.16:

$LWRD_{th1} =\ \left(0.7 \times LWRD_{Avrg}\right)$ And $LWRD_{th1} = \left(0.1 \times LWRD_{Avrg}\right)$
(5.16)

IfLRWD (n_1)> $LWRD_{th1}$ and LRLD (n_1)> $LWLD_{th1}$, with $12 \leq n \leq 36$, and $n \neq 21\text{-}25$, the R wave is detected. If no, LWRD, LWLD are compared to new thresholds, thresholds are computed using the Eq 5.17:

$LWRD_{th2} = (0.4 \times LWRD_{Avrg})$

And

$$LWLD_{th2} = \left(0.7 \times LWLD_{Avrg}\right) \quad (5.17)$$

If $LWRD(n_1) > LWRD_{th2}$ and $LWLD(n_1) > LWLD_{th2}$, with $12 \leq n \leq 36$, and $n \neq 21\text{-}25$, the R wave is detected. If not, the algorithm fails to detect the R wave and try to detect the next R wave starting from predicting its probable position.

d. Performance of QRS detection

Before using the QRS detection algorithm in the acquired signals, its performance was estimated over a large set of ECG signals taken from internationally recognized ECG databases, representing for various types of noises and arrhythmias. The robustness of the method in the presence of noise is quantified by the noise stress test using recordings from the MIT-BIH Noise Stress Database and against the whole noisy MIT-BIH record 105. This latter is used through the literature to test QRS detection, therefore comparisons are possible. MIT Noise Stress Test database includes 12 half-hour ECG recordings and 3 half-hour recordings of noise typical in ambulatory ECG recordings. The noise recordings were made using physically active volunteers and standard ECG recorders, leads, and electrodes; the electrodes were placed on the limbs in positions in which the subjects' ECGs were not visible. The three noisy records were assembled from the recordings by selecting intervals that contained predominantly baseline wander (in record 'bw'), muscle (EMG) artefact (in record 'ma'), and electrode motion artefact (in record 'em'). Electrode motion artefact is generally considered the most troublesome, since it can mimic the appearance of ectopic beats and cannot be removed easily by simple filters, as noise of other types [133]. The MIT-BIH arrhythmia database was also used to test the performance of the algorithm. The complete database was analysed, except for record 208; (many fusion of ventricular with normal beats) and 222: nodal, junctional escape beat, for 112448 beats tested. The analysis software operates automatically. The R detection is validated when it is within the interval, which begins 50 ms before and ends 100 ms after the annotation time mark [134]. Three statistical indices were used to report the performance of the developed QRS detection algorithm: The sensitivity (Se), the positive predictive value (PPV), and detection error rate (DER), [135] are computed using Eq 5.18:

$$Se = \frac{TP}{TP + FN} \times 100\ (\%), PPV = \frac{TP}{TP + FP} \times 100\ (\%)$$

and

$$DER = \frac{TP + FN}{TotalQRScomplex}(\%) \tag{5.18}$$

Where TP(true positive) is the number of correctly detected beats, FN is the number of undetected beats (false negatives) and FP (false positives) is the number of falsely detected beats. In the case of the noise tolerance test, the performance of the proposed QRS detection is tested using signals with different type of noise and SNR values, the results obtained are compared with three other algorithms developed in two different studies [136, 137] and the results are shown in Table V.1.

Table V-1 (a): Comparison of three QRS complex detection methods with the proposed method applied to the signal 118e
(b): Comparison of three QRS complex detection methods with the proposed method applied to the 119ea

SNR	indices/method	a	b	c	proposed
24	SE (%) PP(%) DER(%)	99.32 99.79 .	100 100 0.00	100.00 99.64 .	99.95 99.95 0.06
18	SE (%) PP(%) DER(%)	98.49 99 .	99.96 99.82 0.22	100.00 99.46 .	99.93 99.95 0.06
12	SE (%) PP(%) DER(%)	96.66 97.78 .	98.81 97.28 3.95	99.90 89.32 .	99.93 99.95 0.10
06	SE (%) PP(%) DER(%)	91.23 81.11 .	94.69 91.13 14.53	99.63 73.34 .	96.36 96.29 1.33
00	SE (%) PP(%) DER(%)	77.3 71.34 .	84.15 82.66 33.49	99.53 57.68 .	96.90 96.60 6.49
-06	SE (%) PP(%) DER(%)	63.47 72.04 .	78.45 77.16 44.78	89.93 52.01 .	80.02 80.71 39.09

b

SNR	indices/method	a	b	c	proposed
24	SE (%) PP (%) DER (%)	100.00 98.17 .	100 99.95 0.05	100.00 99.58 .	99.97 100 0.02
18	SE (%) PP (%) DER (%)	99.28 98.04 .	99.95 99.80 0.25	99.88 98.99 .	99.97 100 0.02
12	SE (%) PP (%) DER (%)	98.25 97.37 .	99.14 95.12 5.94	99.28 88.52 .	99.75 99.78 0.46
06	SE (%) PP (%) DER (%)	96.33 89.99 .	95.87 88.85 16.16	99.63 70.24 .	98.06 98.02 3.90
00	SE (%)	89.58	89.73	99.28	90.04

	PP (%) **DER (%)**	**75.38** **.**	**81.34** **30.85**	**53.38** **.**	**90.70** **18.83**
-06	**SE (%)** **PP (%)** **DER (%)**	**78.09** **66.27** **.**	**81.08** **74.17** **47.16**	**98.01** **49.14** **.**	**80.77** **80.82** **38.38**

With: (a).Benitez [138], (b). Huaming [139], (c).Benitez [138]

The performance of the proposed QRS detection algorithm is better than the three other algorithms especially when the SNR equals -6dB, with high sensitivity values (about 80%) as well as high positive prediction (about 80%). The same conclusion can be made for respectively high SNR as well as low SNR. In this case, the detection error rate (DER) for our detection is superior to the other techniques found in literature.

The MIT-BIH arrhythmia database was also used. The detection result is listed in Table V.2. The proposed algorithm produces 96 false positive (FP) beats and 331 false negative (FN) beats for an error rate of (0.40%). Most of the FN and FP QRS complexes were found in records 108, 200,203,210 and 223. The ECG waveforms in these records are characterized by high complexity due to cardiac abnormalities.

Table V-2 Performance of the proposed method

Tape	Total	FN	FP	SE (%)	PP (%)	DER (%)
100	2273	0	0	100	100	0
101	1865	4	0	99.78	100	0.21
102	2187	0	0	100	100	0
103	2084	0	0	100	100	0
104	2247	1	1	99.95	99.95	0.08
105	2572	3	0	99.84	100	0.15
106	2027	3	1	99.85	99.95	0.19
107	2137	3	0	99.85	100	0.14
108	1763	52	12	97.05	99.30	3.63
109	2532	2	1	99.92	99.96	0.11
111	2124	2	0	99.92	100	0.07
112	2539	0	0	100	100	0
113	1797	0	0	100	100	0
114	1879	0	0	100	100	0
115	1953	0	0	100	100	0
116	2412	2	0	99.92	100	0.07
117	1535	0	0	100	100	0
118	2278	0	0	100	100	0
119	1987	1	0	99.94	100	0.05
121	1863	1	0	99.94	100	0.05
122	2476	0	0	100	100	0
123	1518	0	0	100	100	0
124	1619	1	9	99.93	99.44	0.61
200	2601	24	11	99.07	99.57	1.34
201	1963	4	0	99.79	100	0.20
202	2136	1	0	99.95	100	0.04
203	2980	99	22	96.77	99.24	4.06
205	2656	20	0	99.24	100	0.75
209	3005	1	0	99.96	100	0.03
210	2647	25	10	99.05	99.62	1.32
212	2748	0	3	100	99.89	0.10
213	3251	5	1	99.84	99.96	0.18
214	2263	21	0	99.07	100	0.92
215	3363	7	0	99.79	100	0.20
217	2208	2	1	99.90	99.95	0.13
219	2154	2	0	99.90	100	0.09
220	2048	5	0	99.75	99.90	0.34
221	2427	0	0	100	100	0
223	2605	10	25	99.61	99.04	1.34
228	2053	21	1	99.97	99.95	1.07
230	2256	0	1	100	99.95	0.04
231	1571	0	0	100	100	0
233	3080	7	0	99.60	100	0.39
234	2753	1	0	99.96	100	0.03
total	105241	331	96	99.68	99.89	0.39

In the case of a very noisy, but not complex, record number 105, the QRS detection errors of the proposed algorithm is lower than that of the well-known and recent algorithms shown in Table V.3. The proposed algorithm is based on derivative methods, adaptive thresholds and a powerful approach using a moving window; it allows R waves to be differentiated from large, peaked T and P waves, present in record 105, with a high degree of accuracy. Without any filtering, the algorithm eliminates the errors of detection associated with baseline drift and minimizes errors related to motion artefacts and muscular noises generated during the movement of the subject.

Table V-3 Performance comparison with other algorithms

Method	FN	FP	DER (%)	REF
Wavelet transform1	**6**	**14**	**0.77**	**Sun [218[140]**
Wavelet transform2	**21**	**15**	**1.3997**	**Mohamed [219[141]**
BPF/search-back	**42**	**67**	**4.2379**	**Jung [220[142]**
Wavelet denoising	**44**	**15**	**2.2939**	**Zidelmal [221[143]**
Filter banks	**13**	**16**	**1.1275**	**Zhang [222[144]**
Hilbert transform	**23**	**1**	**0.9331**	**Xiaomeng [223[145]**
Hilbert transform2	**7**	**3**	**0.3888**	**Sahoo [224[146]**
Linear adaptive filter	**13**	**10**	**0.8942**	**RuYang [225[147]**
3M method	**7**	**9**	**0.6221**	**Zhang [226[148]**
Proposed method	**3**	**0**	**0.1166**	**…………………………….**

The proposed approach eliminates errors due to the baseline wander without removing it, increases robustness of the QRS complexes detector to the most common problems related with high noise level. The false negative detections of consecutive QRSs with altering amplitude are also eliminated. The robustness of the method can be emphasized on the record 105 of MIT-BIH arrhythmia database as it is reported in table V.3. The method used for the prediction of the next R wave, significantly increases the accuracy and the speed of the detection. The developed QRS detector provides a powerful tool for long-term HR monitoring systems for the assessment of physical and/or mental activity, especially for those with small computation resources. The proposed method performs well in the detection of the QRS complexes in the presence of high level of noises and PVCs in the same time. This algorithm therefore may be used in our acquired signals.

Heart rate

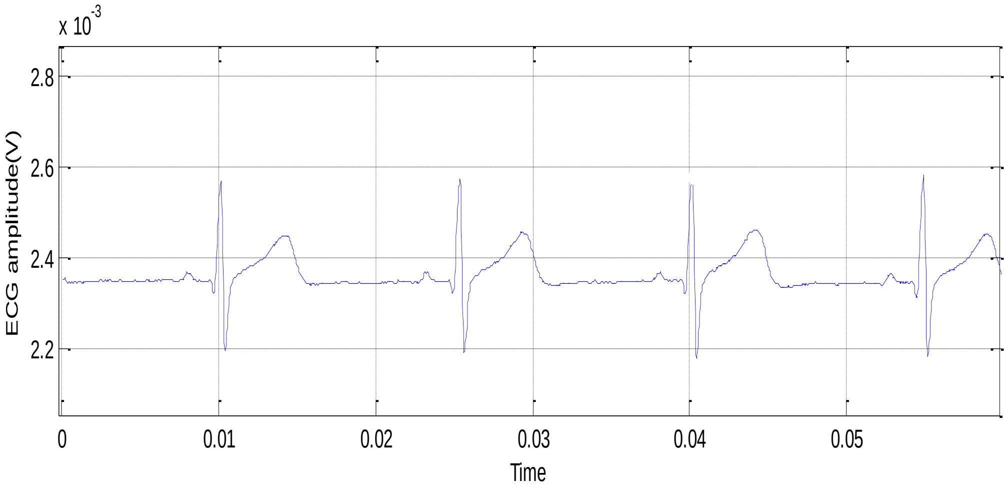
After the detection of QRS complexes, RR intervals are used to generate HR signal using Eq 5.19:

$$HR(Hz)\frac{500}{RR\ (samples)}\times 60, \qquad \text{(With sample rate of 500 Hz)} \qquad (5.19)$$

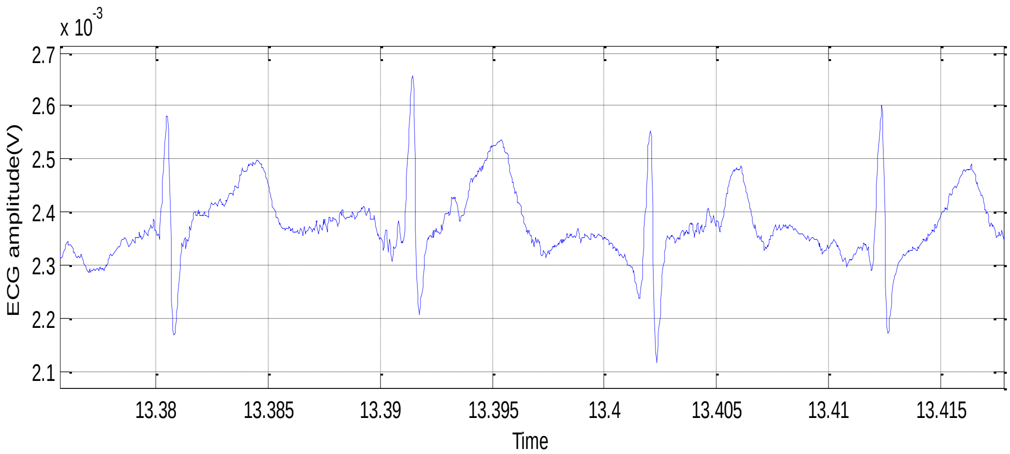
A 4-seconds epoch is used and HR average is computed, non-physiological values of HR (≥ 215 or ≤45 bpm) are replaced by more appropriate values using the interpolation method.

B. ECG-TMS identification

As previously presented (chapter 04), the ECG is often contaminated by noise and artefacts such as power line interference, electrode contact noise, patient–electrode motion artefacts, and EMG noise. The EMG noise is originated from muscles contractions, in our case from trunk muscles contractions. In this study, such a signal is not considered as noise but as the signal of interest. Consequently, ECG waves are considered as non-desired and must be separated from ECG-TMS. ECG-TMS appear as large fluctuations and vary faster than the other ECG waves but have smaller amplitudes as shown in figure V.6



a



B

Figure V.6 a: clear ECG signal, b: noised ECG signal with superimposed TMS

The simplest method to separate ECG-TMS and ECG waves is to eliminate periods that contain the ECG waves (gating method). This method is simple to apply and is potentially efficient as a method for ECG waves' removal. However, this method suffers from losing the portions of the ECG-TMS which overlap with the ECG waves and is therefore not accurate, especially not for non-stationary signals. Several other methods are proposed to separate EMG signals from ECG [149, 150, 151, 152, 153]. In this study, the signals are separated using Discrete Wavelet Transform (DWT).

Wavelet Transform

ECG-TMS can be analysed in time domain, frequency domain, or time-frequency domain.

Fourier analysis, using the Fourier transform, is a powerful tool for analysing the components of a stationary signal but it is less useful in analysing non-stationary data, [154, 155, 156].

The wavelet transform is one of the important methods that are used to analyse the components of non-stationary signals and to separate signals from noises. The wavelet transform is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal, [157]. To analyse signal structures of very different sizes, it is necessary to use time-frequency atoms with different time supports. The wavelet transform decomposes signals over dilated and translated wavelets, [154, 155, 158]. Mathematically speaking, the wavelet transform of $f \in L^2(\Re)$ at time u and scale s is a convolution of the mother wavelet function $\Psi \in L^2(\Re)$ with the signal $f \in L^2(\Re)$

$$Wf(u,s) = \int^{\infty} f(t) \times \frac{1}{\sqrt{s}}\, \Psi^*\left(\frac{t-u}{s}\right) dt = f * \overline{\Psi}_s(u) \tag{5.20}$$

A wavelet function can be seen as a high-pass filter, which approximates a data set (a signal or time series), [154, 155, 156, 159, 160]. It exist a set of wavelets such as Haar wavelets, Meyer, Symlet, Daubechies, Morlet, etc. The choice of the wavelet depends on the application.

a. Multi-resolution analysis

DWT is used to decompose hierarchically discrete time signals into a series of successively lower resolution approximation signals and their associated detail signals. At each level, the approximation and the detail signals that contain the information are needed to be reconstructed back to the next higher resolution level, [161, 162]. The DWT has two parameters: the wavelet mother ψ and the number of iterations. Discrete wavelets can be scaled and translated in discrete steps wavelet representation as the following:

$$\Psi_{j,s} = \frac{1}{\sqrt{2^j}}\,\Psi\left(\frac{t-n2^j}{s2^j}\right) \tag{5.21}$$

Where *j* is the scale factor and *n* is the translation factor, [161]

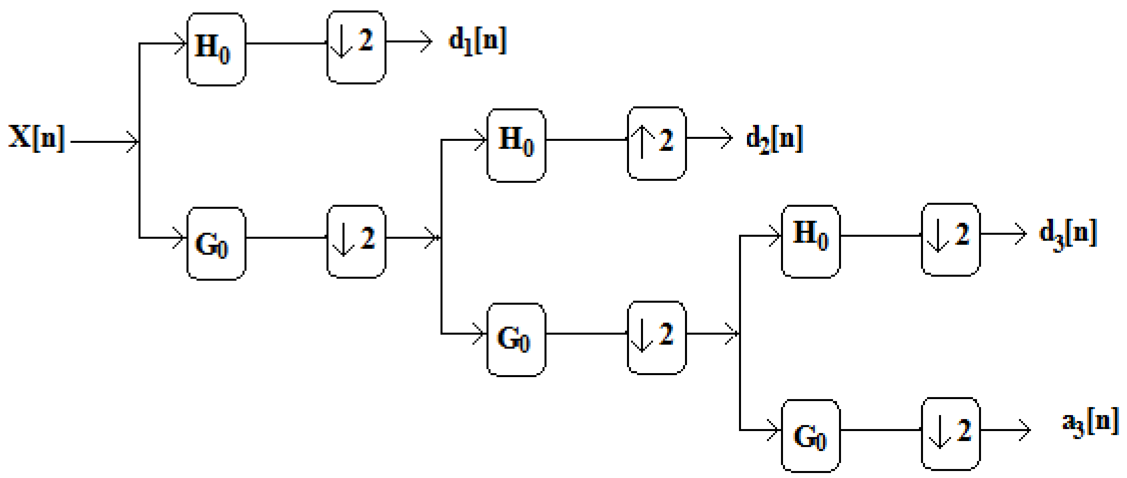


Figure V.7 Three-level wavelet decomposition tree.

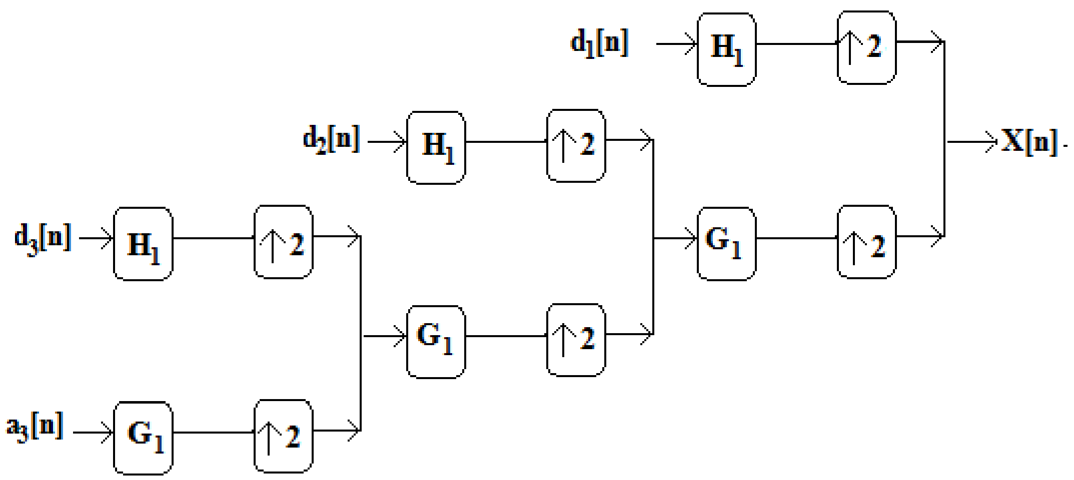


Figure V.8 Three-level wavelet reconstruction tree.

When this type of wavelet transform is applied, filters of different cut-off frequencies are used to analyse the signal at different scales. The signal is passed through a series of high pass filters to analyse the high frequencies and it is passed through a series of low pass filters to analyse the low frequencies. The low-pass filter is denoted by G_0, while the high-pass filter is denoted by H_0. At each level, the high-pass filter produces the detail information d[n], while the low-pass filter associated with scaling function produces coarse approximations, a[n].

The filtering operations determine the signal's resolution, meaning the quantity of detail information in the signal, while the scale is determined by up-sampling and sub-sampling operations. The decomposition algorithm, also known as Mallat-tree decomposition is shown in figure V.7, while the details for eleven wavelet scales of an ECG signal are presented in figure V.9. The DWT of the original signal is obtained by concatening all the coefficients a[n] and d[n], starting from the last level of decomposition. Due to successive sub-sampling by 2, the signal length must be a power of 2, or at least a multiple of power of 2 and it determines the number of levels that the signal can be decomposed to. Figure V.8 shows the three-level wavelet reconstruction tree. In our case, the ECGs are decomposed in eleven levels so the signal can be written:

$$A_0 f \approx D_{-1} f + D_{-2} f + D_{-3} f + \ldots + D_{-11} f \qquad (5.22)$$

Where *A* and *D* represent the detail and the approximation information respectively.

When applied to ECG signal, the first two details re affected by the fast changing of the QRS complex and are also affected by the EMG noises (high-frequency component) [154, 155].

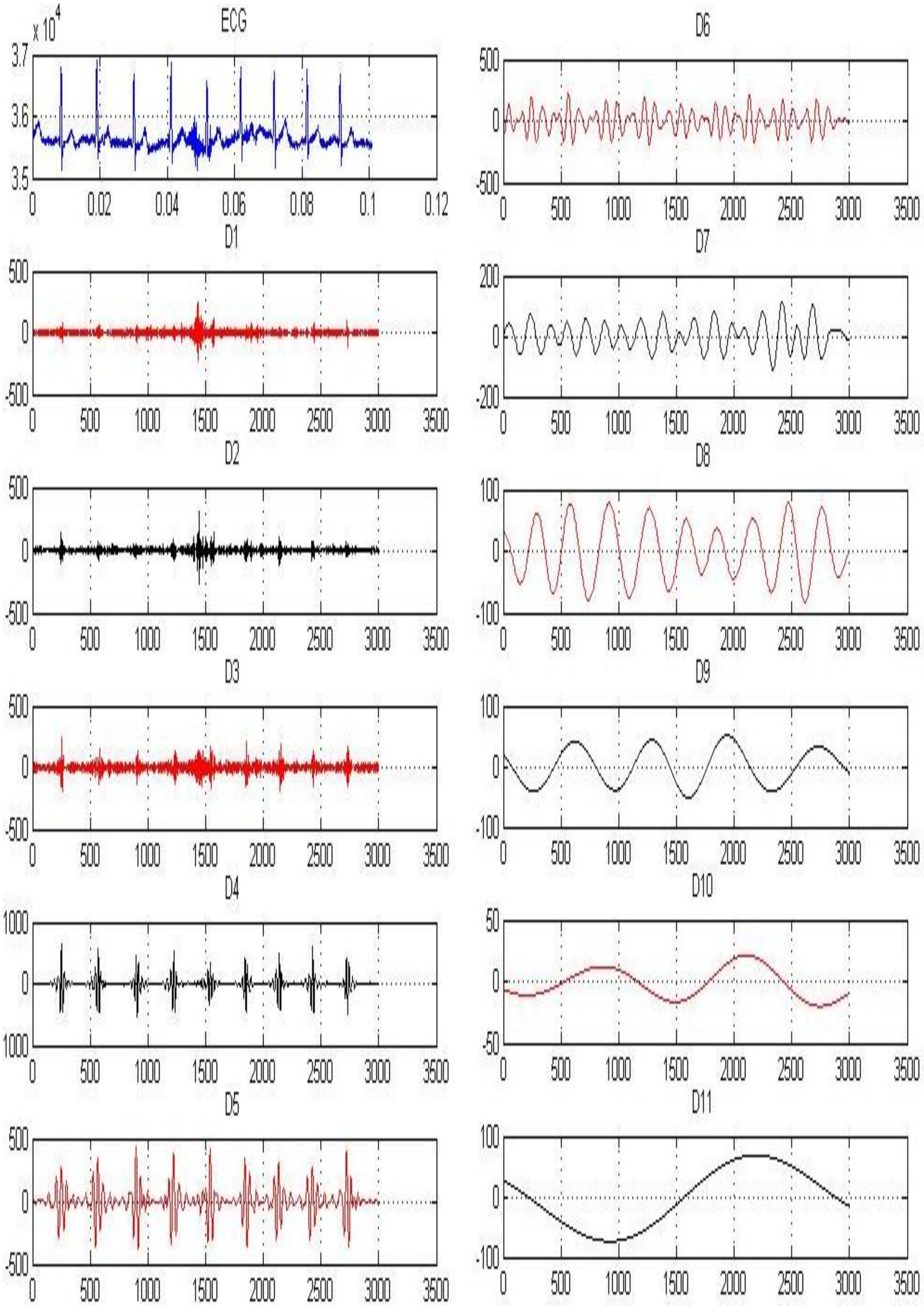


Figure V.9 Multi-resolution decomposition of ECG signal.

DWT is used to decompose hierarchically the ECG signal into a series of successively lower resolution approximation signals and their associated detailed signals. Several wavelet bases, e.g. Daubechies (db4, db8), Symlets (sym4, sym7, sym8, sym10), Coiflets (coif5), discrete Meyer (dmey), and Biorthogonal (bior4.4), have been used to separate different types of noises from ECG. The enhancement is significant if the dilated version of the wavelet (or the scaling function) at some scale matches the shape of the signal or noise components. However, noises originate from trunk muscles do not have a characteristic shape and all the above wavelet bases showed a similarity when applied to separate noises from signal. In this study, the discrete Meyer (dmey) and the decomposition algorithm known as Mallat-tree decomposition are used. It consists on passing the signals through a series of high pass filters and series of low pass filters depending on the level of decomposition chosen. The high-pass filters produced the detail information d[n], while the low-pass filters associated with scaling function produced coarse approximations, a[n]. After the decomposition, the details signals can be processed by integration, root mean square or low-pass filtering to obtain a representation of the level of the electrical activity in the muscle. With 500 Hz as sampling frequency of the ECG signal, the TMS are predominantly represented in the initial four details but particularly in detail2 (D2) and detail1 (D1) since the Root Mean Square (RMS) of D1 and D2 have the highest amplitudes when segments of the ECG signals are affected by TMS; see figure V.10. Even if the D2 is more sensitive than D1 to trunk muscle activities it is however more sensitive to the QRS complexes. Therefore, D1 is chosen as the signal which represents the ECG-TMSA.

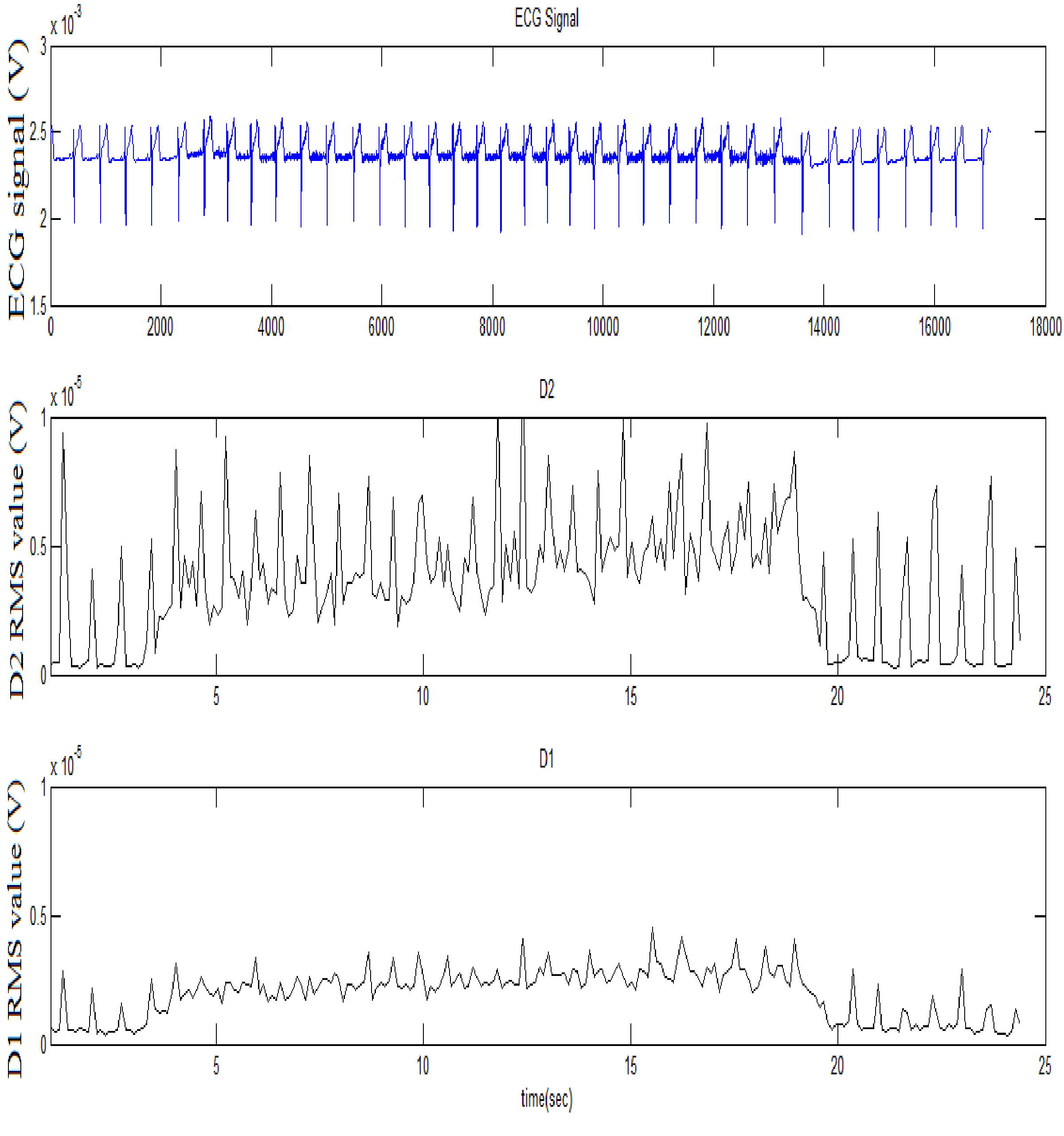


Figure V.10 ECG-signal with an ECG-TMSA signal noise b: RMS value of D2, c: RMS value of D1.

A 4 seconds HR epoch is used and both of HR and ECG-TMSA are expressed as the average amplitude over the last 3 minutes of each exercise. Correlation coefficients and linear regression line are calculated in order to analyze the relationship between ECG-TMSA and HR for all sixteen subjects when walking on a treadmill and when no stressor applied. Because the algorithm used to identify TMS uses ECG signal fluctuations, ECG-

TMSA value can be influenced by R-R intervals changes when HR is increasing due to a non-physical activity event. To investigate this, a 9 minutes epoch is used during the second experiment and both HR and ECG-TMSA are expressed as the average amplitude over the last 9 minutes when the fourth conditions, results are compared. During the third experiment and after the HR was detected using the same developed QRS detection algorithm, A 5 minutes epoch is used and the HR average is computed. A correlation coefficient for horizontal position, siting and walking between two sets of responses is used as a quantitative measure of the test-retest reliability. Another statistical test is applied to determine the accuracy of the algorithm to separate the three conditions (walking slowly and moving on site either with the presence or not of mental stress).

5. CONCLUSION

We began the chapter by the presentation of subjects that participated to the three experiments. They were student and employees on both countries, Algeria and Sweden. After that, the developed instrument used to measure ECG signal was detailed. All subjects used the same device with a chest strap and followed the protocols. After the acquisition of signals, data analysis was applied to detect ECG-TMSA and separate it from ECG signal. In addition, HR was derived from the same ECG signal with the use of a QRS detection algorithm that we developed.

To study the correlation of PA and ECG-TMSA, a comparison between HR and ECG-TMSA was performed. To study the influence of mental stress on the ECG-TMSA, a second experiment were performed. Finally, to study the validity and reliability of the method a third experiment was performed. All the results are presented and discussed in the next chapter.

VI. Chapter 06 Results and Discussion

The chapter illustrates the different experiments carried out on the proposed hardware platform and the developed software along with the obtained results. The correlation of ECG-TMSA and HR of one subject is presented. Then the same presentation is shown but this time for many individuals. Results are discussed. Then, the result of the second experiment is discussed when the subjects were in four conditions practising or not PA in the presence or not of mental stress. Finally, the changes of the ECG-TMSA during different periods is discussed after the presentation of the test retest results.

1. MAIN RESULTS

ECG is a recording of small (mV) surface potentials, generated during heart muscles activity. However, the ECG electrodes record both cardiac muscles as well as non-cardiac muscles electrical potentials but with differences in amplitude and frequency range. In this thesis, we investigated how to use ECG-TMSA to estimate PA. The obtained results was compared and validated against HR. We found that ECG-TMSA derived from ECG signal is correlated with the HR derived from the same signal, we did not find any study with the same goals, and therefore we cannot use a comparison analysis here in this thesis.

2. ECG-TMSA, HR AND WALKING INTENSITY RELATIONSHIP

Depending on the ECG-electrodes' size and position, different muscle groups have different impacts on the recorded ECG signal. The electrical potentials generated when muscle contraction can be recorded as bursts of muscle action potentials superimposed onto the ECG signal. The onset and duration of the electrical activity is well coordinated to the duration of the muscle contraction and the signal intensity is directly proportional to the strength of the contraction. From this, we developed our idea that we can use the intensity of the muscle electrical activity to estimate the intensity of the muscle contraction and so the intensity of PA in general. The most used electrodes position, when the main purpose of measuring ECG signal is to measure HR, is under the pectorals over the RA and the OE muscles. Therefore, they are the muscles that most affect the ECG signal. Electrodes can also pick up the biosignal of other muscles such as the oblique internus, which is deep to the OE, but has a minor influence on the ECG signal. Because of the size (16 cm^2) and shape (bare) of the electrodes used in this thesis, ECG-TMS are not a selective representation of the electrical activity of the RA or OE but a general electrical view of both of them. It has been known since the earliest studies of electrical activity of muscles that, except for such muscles as those of respiration, the skeletal musculature of the body is electrically silent during rest in the horizontal position, when walking requires an upset of the delicate balance of the trunk, which is maintained by minimum muscle activity during standing. During ambulation, the pelvis undergoes significant translational and rotary motion in the sagittal, coronal and transverse planes. Therefore, the requirements for balancing the trunk by action of the trunk muscles are much more complex than during standing. During walking, the trunk must balance on the pelvis, which moves along vertical and lateral as well as horizontal axes. Along the vertical axis, the trunk reaches maximum downwards displacement when its weight is centred approximately between both feet in double support phase; maximum upwards displacement occurs when it is centred over the supporting foot during single stance. The force exerted by the ground on subjects' feet during walking has been measured in force plate studies [163]. Shortly after heel strike an upwards force, which exceeds body weight, is exerted on the foot by the ground. This force is transmitted by the leg to the pelvis and trunk and accounts for the up-and-down displacement of the trunk. Bending forwards from a standing position requires no activity on the part of the RA [164]. Walking is associated with phasic electrical activity in the RA, the major portion of which is observed to occur before significant activity on the back muscles. The rectus exerts a stabilizing flexion force. During walking, the trunk moves laterally to balance itself over the supporting foot [165]. Activity of the erector spinae, multifidus, rotatores and quadratus lumborum muscles provides stabilization of the trunk in the lateral plane. The electrical activity, measured by the ECG-chest belt, of those muscles can be used to distinguish between horizontal position, standing at rest and walking. The ECG-TMSA value of one subject, man (body mass = 75 kg, height = 1.80 m, age = 35 yrs, and BMI= 25±5 kgm^{-2}) during horizontal position, standing at rest and walking at 4 ($km.h^{-1}$) are shown in figure VI.1.

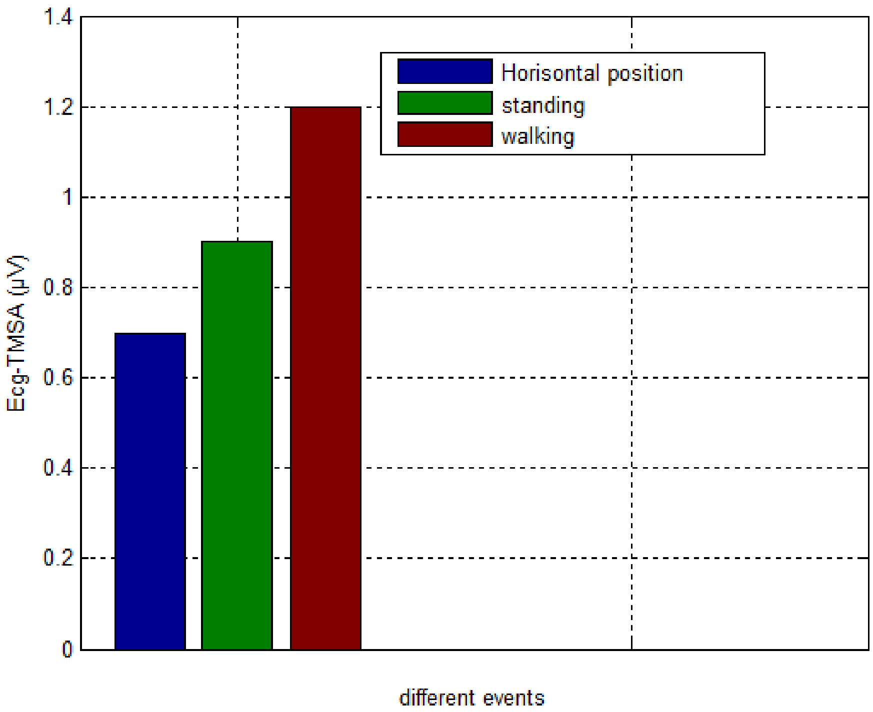


Figure VI.1 ECG-TMSA when subject is at rest (horizontal body position), standing at rest, and at walking.

Running and walking gaits are usually adopted for different speeds of locomotion, with a preferred transition occurring at 7 $km.h^{-1}$ for most human subjects [166]. During walking, the leg tends to behave like a rigid strut, and the joints remain relatively extended throughout the stance phase. In contrast, during running, the major leg joints undergo substantial flexion and extension during stance as the leg behaves in a more spring-like manner. Both running and walking can occur, however, over a wide range of speeds [167]. Subjects performed the treadmill experiment as following: slow walking at 4 and 5 (kmh^{-1}), fast walking at 6 (kmh^{-1}), and running at 7, 8, 9, and 10 (kmh^{-1}). At low velocity, the ECG-TMSA is small and matches results found in [168], where at small velocities, small and constant low amplitudes for RA was observed; peaks occurred at ipsilateral heel strike and at ipsilateral as well as contralateral propulsion, but amplitudes remained at comparably low levels. For the OE, and in the same study, they reported small amplitudes were observed at small velocities and the amplitude peaks were identified during contralateral propulsion phase. Smaller but distinct amplitude with contralateral heel and pad contact was also observed. Moreover, they concluded that the cumulative amplitude of all investigated trunk muscles reflect general speed dependent activation characteristics. Similar to our data recorded, with the large bipolar electrodes ,situated on both sides of the abdomen, where the cumulative amplitude of RA and OE muscles increased with increasing speed (figure VI.2).

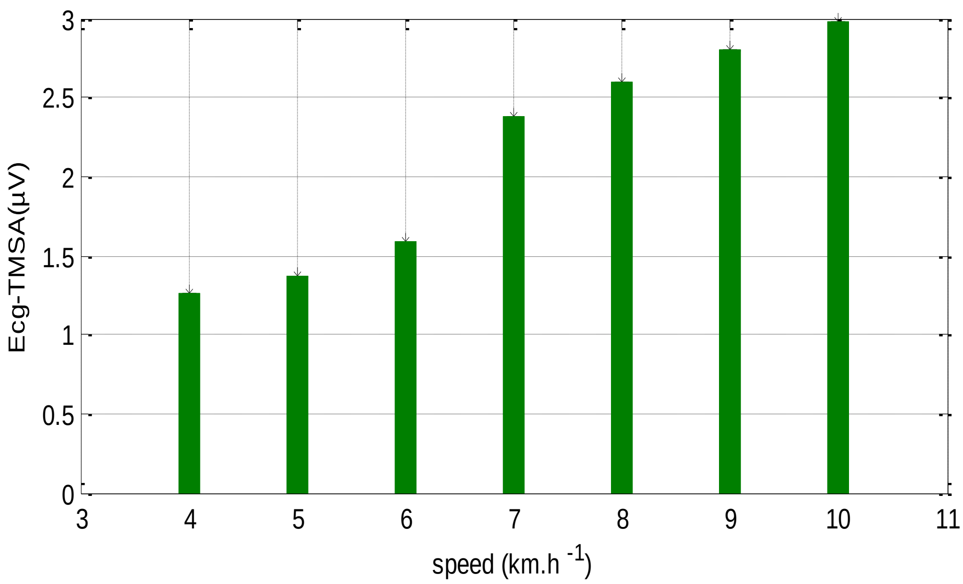


Figure VI.2 Evolution of mean ECG-TMSA of the fourteen subjects with treadmill velocity.

3. HR DETECTION

As we saw above, the heart is strongly related to all body muscles, every part of the body requires the oxygen and blood, the heart pumps, to thrive and functions correctly. Naturally, as with larger muscles involved a higher cardiac output is needed when speed is increasing leading to an increased HR (figure VI.3).

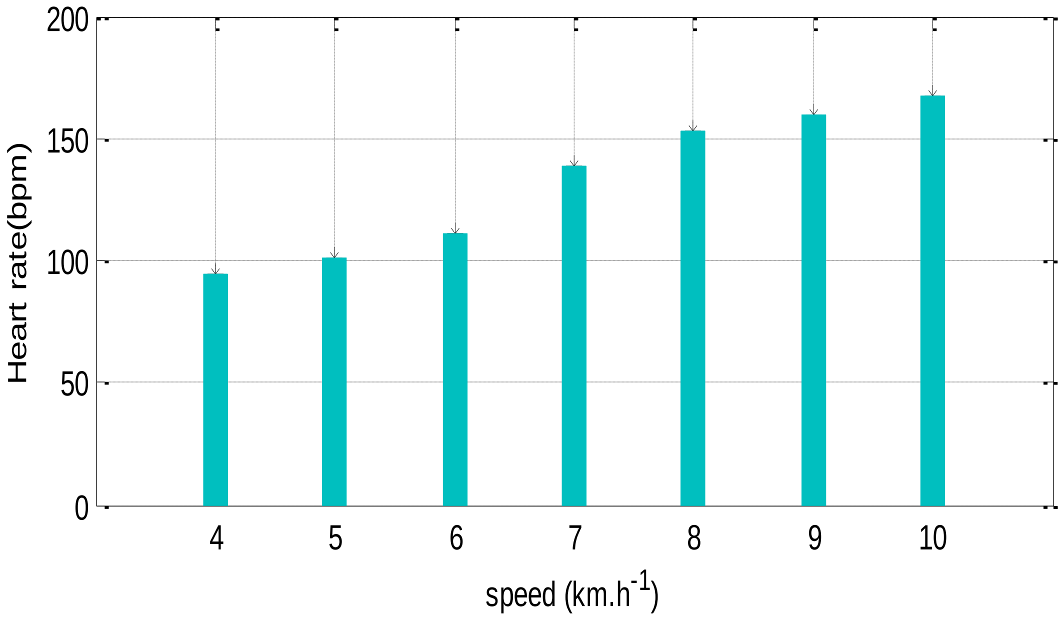


Figure VI.3 Evolution of mean HR of the fourteen subjects with treadmill velocity.

HR is derived from the ECG, This is done by the detection of QRS complexes; we have developed an algorithm to this purpose. The difficulties in QRS complex detection were due to the artefacts and noises that appeared in the ECG signal when subjects were moving. The proposed method does not need any post-filtering of the digital signal; therefore, making the detection speed faster than other existing methods. It can be implemented in a miniature ECG device that is able to measure HR anytime and anywhere. To validate the method, the algorithm was applied to the MIT-Noise Stress Test Database. Results show a QRS complex detection error rate (ER) of 9.06%, a sensitivity of 95.18 % and a positive prediction of 95.23%. This method was also tested against MIT-BIH Arrhythmia Database; results are 99.68% of sensitivity and 99.89% of positive predictivity, with ER of 0.40%. After the validation, the algorithm was used to detect QRS complexes of ECG signals measured in the participating subjects and then HR was generated and used.

4. CORRELATION BETWEEN HR AND ECG-TMSA

HR as a predictor of PA is well known, and extensively documented in literature [169, 170, 171, 172], when the influence of mental activity is removed. To investigate if ECG-TMSA can be used to estimate PA, it can be compared and validated against HR. However, because HR method is influenced by mental activity, this last should not be allowed during the experiment. To this purpose, and after the experiment, subjects reported if they had an apparent stress or not. Two subjects reported they were stressed when walking on the treadmill, and so their data were excluded. After the exclusion, it left fourteen subjects men (body mass = 82 ±19kg, Height = 1.80 m, age = 28±4 yrs, and BMI= 25±5 kgm^{-2}). A result of one subject, male (68 kg) while walking and running at different speeds on a treadmill, 4-10 (km h-1) for 21 minutes, is shown in figure VI.4, and if using a simple linear regression model between the two variables a high squared correlation coefficient is acquired (r2 =0.93, N=336, p<0.001). An increase in the variability about the regression line evident at 130 (bpm) and above in comparison to the activity response observed from 90 to 120 (bpm). Few data points are available for the 116-132 (bpm) range since these intensities represent the walk-run transition interval. When running, the body is more instable than in walking; when the body flex enough, more trunk muscle forces are needed to stabilize the body, this causes higher difference between forces needed for each running step.

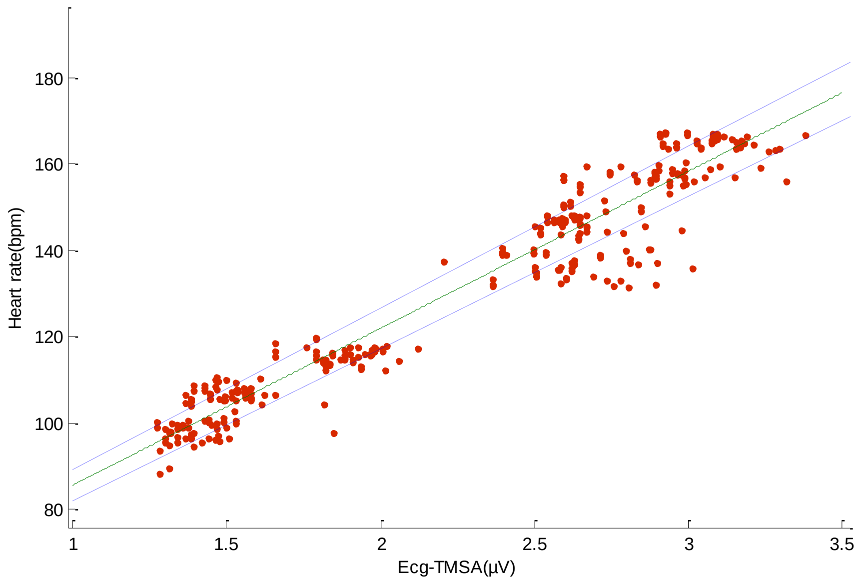


Figure VI.4 Linear regression between ECG-TMSA and HR in a subject. The solid line is the least squares regression line and the dashed line represents the 95% confidence interval about the regression line.

Using Tukey statistical test 46 pairs out of 91 regression lines and their slopes were found statistically significant. A similar result was found for another 23 pairs of the elevations. (See table VI.1).

Table VI-1 Details of Tukey multicomparison tests on the slopes and intercepts of the linear regression lines shown in Figure VI.5.

Regression line numbers	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
						slopes							
1	NS	NS	NS	S	NS	S	S	S	S	NS	S	NS	S
2		NS	NS	S	NS	S	NS	S	S	NS	S	NS	S
3			NS	S	NS	S	NS	S	S	NS	S	NS	S
4				S	S	S	S	S	S	S	S	S	S
5					NS	NS	NS	NS	S	NS	NS	NS	S
6						S	S	S	S	NS	S	NS	S
7							NS	NS	NS	NS	NS	NS	S
8								NS	S	NS	NS	NS	S
9									S	NS	NS	NS	S
10										NS	NS	NS	S
11											S	NS	S
12												NS	S
13													S
						elevations							
1	NS	NS	S	—	S	—	—	—	—	NS	—	S	—
2		NS	S	—	S	—	NS	—	—	NS	—	S	—
3			S	—	S	—	NS	—	—	NS	—	S	—
4				—	—	—	—	—	—	—	—	—	—
5					S	S	S	S	—	S	NS	S	—
6						—	—	—	—	S	—	S	—
7							S	NS	NS	NS	NS	NS	—
8								NS	—	NS	S	S	—
9									—	NS	S	NS	—
10										S	NS	NS	—
11											—	S	—
12												NS	—
13													—

S indicates a significant difference while NS Non-significant difference between two regression lines. ($\alpha<0.05$, q_critic=4.842).

Plotting the individual data pairs, HR versus ECG-TMSA as in figure VI.5, for all the individual linear regression lines, and the mean of these, are illustrated (figure VI.5). The slopes of the individual lines vary between 18 and 70 (bpm μV^{-1}), and the intercepts between 19 and 72 (bpm) respectively.

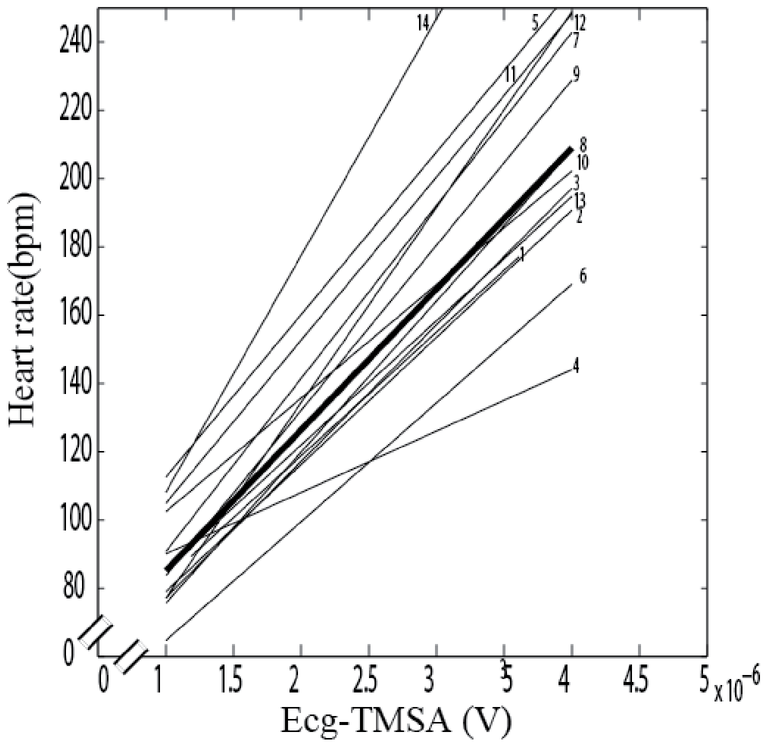


Figure VI.5 Linear regression lines of the relationship between ECG-TMSA

Table VI-2 Values of a (intercept), b (regression coefficient or slope) ±S.E, and of r2 (coefficient of determination) for the linear regression equations of HR in fourteen subjects, where HR=a+b (ECG-TMSA)

No.	Body mass (Kg)	a (bpm)	b (bpm. μV^{-1})	r^2
1	59.1	46.4±3.2	3.62±0.1	0.88
2	72.2	41.8±3.2	3.7±0.1	0.91
3	89.5	37.2±2.4	4.0±0.9	0.93
4	68.2	72.1±1.7	1.8±0.4	0.94
5	71.3	64.9±3.0	4.8±0.2	0.86
6	80.5	29.9±2.3	3.4±0.1	0.94
7	97.5	40.1±3.2	5.1±0.2	0.89
8	75.0	31.4±2.4	4.4±0.1	0.95
9	73.0	35.4±1.8	4.8±0.1	0.96
10	121.0	19.9±4.8	5.7±0.2	0.88
11	83.3	49.2±2.5	3.6±0.1	0.93
12	112.0	57.2±2.3	4.8±0.1	0.92
13	101.0	69.2±2.4	3.3±0.1	0.93
14	57.0	38.8±4.5	6.9±0.3	0.88
Mean	82.9	45.3±2.9	4.3±0.2	0.91

The different slopes and intercepts can be explained by the fact that the HR and the ECG-TMSA are affected by different factors. Variations of HR are caused by Non-modifiable determinants such as age, sex and race, physiologic determinants such as influence of circadian cycle, of posture, blood pressure, lifestyle factors, PA, mental stress, smoking, alcohol, and body weight, and by genetic determinants [173]. The ECG-TMSA is also influenced by different factors, main of them are muscle mass, muscle fibre composition, and tissue filter properties.

5. MAIN ASPECT OF THE THESIS

The important aspect, as far as the present study is concerned, is that the HR and ECG-TMSA relationship was tested from low speed to levels that are probably routinely reached when running on a treadmill and a linear relation was found between ECG-TMSA and HR. This indicates that TMS recorded using ECG chest strap device, can be used as indicator of PA level when locomotion movement and after a calibration phase. Because we removed the influence of stress during the first experiment, and because the mental stress can affect the HR, we do not know how the computed ECG-TMSA value will behave.

6. INFLUENCE OF MENTAL STRESS ON ECG-TMSA

Even if the influence of QRS complexes is minimized by using DWT, it is not eliminated and might affect the ECG-TMSA computed value when changes of HR. When the subject is stressed, the HR increases, HR increasing means that the ECG-RR intervals are shorter than at rest. Because the RMS value is computed using a fixed window, its value can increase if RR interval are shorter and so the calculated ECG-TMSA value will increase. If the calculated ECG-TMSA value is affected by mental stress, this means that it cannot be used to estimate PA in the presence of mental activity. This was certified with the second experiment when HR and ECG-TMSA values of the fourth subjects were compared during four conditions. From Figure VI.6, we can see that HR value increases with physical activities and when applied mental stressors. This is exactly the limitation of HR method; if we use only the HR derived from ECG measured by the HR monitors, the diagnostic will be walking relax for three conditions (sited stressed, walking relax, and walking stressed) since we can’t know if the increasing of HR was due the stressor or due to walking movement.

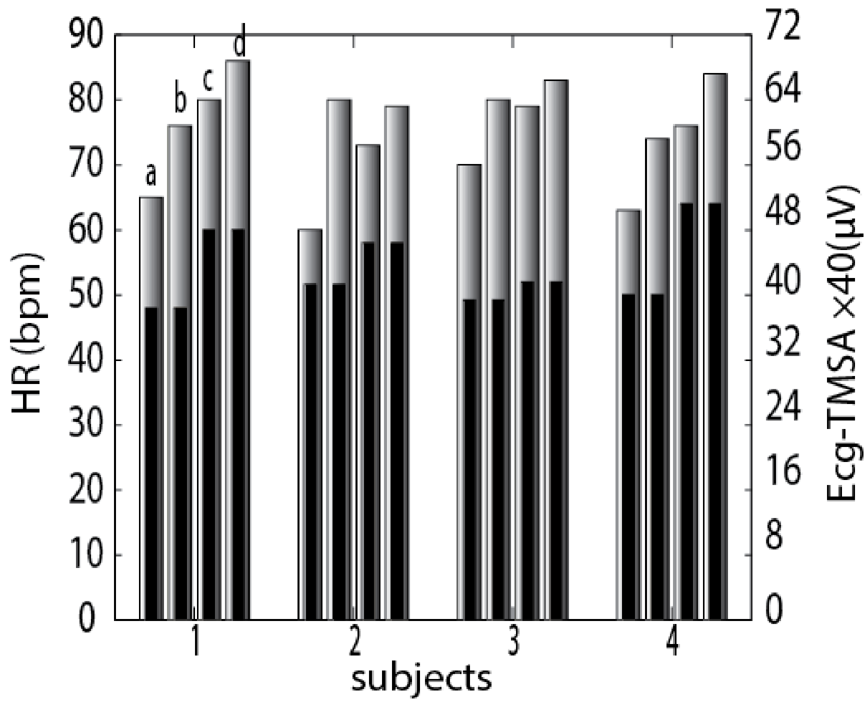


Figure VI.6 HR (non-filled bar) and ECG-TMSA (dark bar) values in four subjects and in four conditions, (a) sitting relaxed, (b) sitting stressed, (c) walking relaxed, (d) walking stressed.

ECG-TMSA increases only during physical activities and stay stable when applying mental stressors. This means that the influence of the QRS complex is minim and mental stress does not affect the calculated ECG-TMSA value. Therefore, unless HR, ECG-TMSA can also be used to distinguish mental stress and PA.

7. RELIABILITY IN REAL LIFE

The two first experiments were conducted in laboratory conditions. To study the robustness of the proposed method, a real life experiment was required. The result of the third experiment is described in the following. We applied the developed algorithm to the data collected from subjects when living their normal daily life during 3 weeks; the estimated levels are compared to the diaries written by the users during all the period. Although the instructions were very clear, the bad aspect of this experiment is that six subjects were excluded from the experiment because they provided duration of measurement less than the fixed limit (almost no data). The data of four other subjects were also excluded from the comparison step because they did not provide correct format of the diaries. A 5 minutes epoch is used and the HR average is computed. The data below (Table VI.3), and the figure VI.7, show a high reliability for measurement of ECG-TMSA in three different situations (Horizontal position HP, siting ST, and walking WK at 4 km.h^{-1}), for six measures, twice with a gap of two weeks between tests.

Table VI-3 ECG-TMSA for three different situations leading to two different measurements separated by two weeks.

Test 1			Test2		
Hp(µV)	**St(µV)**	**Wk(µV)**	**Hp(µV)**	**St(µV)**	**Wk(µV)**
0.60	**0.84**	**1.25**	**0.54**	**0.93**	**1.36**
0.75	**1.02**	**1.54**	**0.70**	**1.13**	**1.43**
0.63	**0.92**	**1.37**	**0.69**	**0.77**	**1.28**
0.78	**1.3**	**1.91**	**0.71**	**1.61**	**1.82**
0.5	**0.82**	**1.19**	**0.59**	**0.93**	**1.07**
0.72	**1.2**	**1.85**	**0.79**	**1.31**	**1.94**

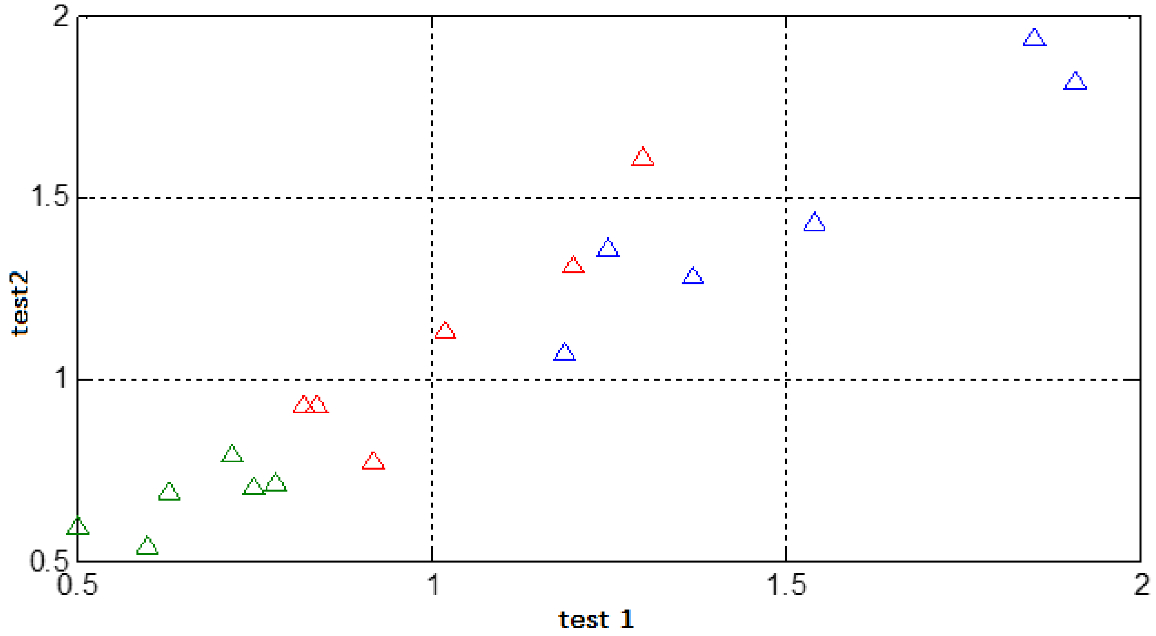


Figure VI.7 Scatter plot of test 1 against test 2; green, red, and blue triangles concern horizontal, siting and walking positions respectively.

The correlation coefficient between the two sets of responses is used as a quantitative measure of the test-retest reliability. 0.73, 0.92, and 0.94 are the correlation coefficients for horizontal position, siting and walking respectively. The three coefficients can be considered as satisfactory. To affect a number on the change in ECG-TMSA, we subtracted the mean of all the subjects for $Test_1$ (0.6633) $_{Hp}$, $Test_1$ (1.0167) $_{St}$, $Test_1$ (1.5183) $_{Wk}$ from that for Test $_2$ (0.6617) $_{Hp}$, $Test_2$ (1.0067) $_{St}$, $Test_2$ (1.5150) $_{Wk}$. The result (0.0016) $_{Hp}$, (0.01) $_{St}$, (0.0033) $_{Wk}$ is the change in the means for the three situations. The variation could be due to a random change and/or a systematic change. Random change in the mean is due to so-called sampling error. This kind of change arises only from the typical error, which is like a randomly chosen number added to or subtracted from the real value every time you make a measure. We speak of the variation in the measures of error, but it is important to realize that only part of the variation is due to an error in the meaning of technological error arising from the device and / or from electrode position (procedure). Indeed, the variation may be due to biological variation, such as weight and/or body fat composition of the subjects. In that case, we should talk about systematic change not random change. Since the period between the two tests is short, the influence of biological effect is relatively small. However, it is important to study if the biological changes that can affect the amplitude of the electrical activity of muscles. For this, we must perform an experience with higher number of participants and longer period between the two or several tests. The most important aspect here is that if the same situation, the ECG-TMSA does not change when measured at different moments within the same subject. However, one issue we found with some subjects is that the identified ECG-TMSA was higher than it should be. That is because when the electrodes get dry, more noises are introduced in the ECG signal and so will influence the measure. However, the frequency of those noises is enclosed in certain band. We used filtering methods to delete those noises. We got good results.

8. MOVING ON SITE AND WALKING SLOWLY

Three other statistical indices are used to report the performance of the algorithm to detect the two following situations: walking slowly and moving on site either with the presence or not of mental stress. The sensitivity (Se), the positive predictive value (PPV), and detection error rate (DER), are computed using equation Eq 6.1.

$$Se = \frac{TP}{TP + FN} \times 100\ (\%) \quad , PPV = \frac{TP}{TP + FP} \times 100\ (\%)$$

$$DER = \frac{TP+FN}{TotalPeriods}\ (\%) \qquad (6.1)$$

Where TP(true positive) is the number of correctly detected periods, FN (false negatives) is the number of undetected periods and FP (false positives) is the number of falsely detected periods. The detection result is listed in Table VI.4.

Table VI-4 Performance of the proposed method

Method	Situation	TP	FN	FP	SE (%)	PPV (%)	DER (%)
ECG-TMSA	Walking periods	13	04	02	76	86	89
	Stress periods	08	04	02	66	80	85
	Moving on site periods	11	03	02	78	84	87
HR	Walking periods	16	01	11	94	59	60
	Stress periods	02	10	00	16	100	100
	Moving on site periods	01	13	00	07	100	100

The proposed algorithm combined with HR produces 76% as SE, 86% as PPV and 89% as DER when walking, this result is much better than the HR alone where we have 94% as SE but 59 % as PPV and 60 % as DER. For the stressful situations, the PPV and the DER are the maximum but as we can see the SE is very low, this is because when the HR increases, the HR method can't differentiate between the increases due to physical or mental activity. With the proposed algorithm we are able to do that. In addition, the HR method cannot distinguish between movements on site and walking slowly, this is because both increases HR. The proposed method is also able to distinguish between these two movements. Similarly, using the developed method, we are able to evaluate the specific occupations whose energy expenditure is close to the expenditure at rest, such as watching television or videos, computer work, reading ... etc. Also to estimate the time spent in front of a screen(TV, video, video games, computer...) with more accuracy, and so we can diagnostic if the subject has a sedentary lifestyle or not with higher accuracy than the existing methods.

9. Conclusion And Future Works

In order to further explore the relationship between PA and health, a new approach, using trunk muscles electrical activity to estimate PA, was investigated. The starting point was to use an existed and well spread device, to modify its software and improve the accuracy of the measure of PA. We found that HR method is the most used for PA measurement. However it exist many methods to measure HR, we also have found that ECG device is the most used method to measure HR, the ECG chest strap device more precisely. After some tests using a treadmill with different velocities, we noted a well-known statement, which is the presence of noise when subject is moving. However, we know that the ECG signal is corrupted with different kinds of noises when the individual is moving. We decided to go further and study which noise is the most correlated with the intensity of the movement. We found that the electrical activity of trunk muscles, superimposed on the ECG signal, is the most correlated. Then, we wanted to investigate if the electrical activity can be used to estimate PA level. In order to do this, a comparison with a gold standard or objective methods is needed. In this thesis, the ECG-TMSA was compared to HR changes since HR is a valid method to quantify PA when mental stress influence is removed. After the study of the advantageous and disadvantageous of the existing methods and after a theoretical research about the relation between ECG-TMSA, HR and PA, three experiments were performed. The result of the first experiment showed that a clear linear relationship exists between HR and ECG-TMSA when walking and running on treadmill with different studies. With that first result, we could say that the ECG-TMSA can be used to estimate PA when walking on treadmill. However, it is essential to investigate if the ECG-TMSA is influenced by mental stress. The second experiment was performed for that purpose and results was encouraging since the ECG-TMSA was not affected by mental activities. A last experiment studied if the ECG-TMSA will change during a certain period on real life. Here also, results were positive since the values of the ECG-TMSA did not change considerably. With all these results, we can conclude that ECG-TMSA can be used to estimate PA when walking on a treadmill and on real life in specific periods with a specific movement. The perspectives are to study the correlation of not only trunk muscles but also all the body muscles and investigate how we can improve again the accuracy of the measure with other types of movement. In addition, a comparison between ECG-TMSA with a gold standard and other objectives methods is essential. This will be carried out in the near future.

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