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Human Gait Recognition for Virtual Environments Exploration

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Abstract— **This paper presents a novel use of sensor sytem for human gait recognition evolution to be employed in virtual environments exploration. The system allows free human motion inside a virtual environment employing human gait recognition. Experimental sessions have been organized in order to acquire acceleration data related to walking and running of several subjects. We present an algorithm that recognizes a person gait in real-time. The recognized motion can be used to enhance the presence of the user in the virtual environment. A simple scenario has been developed to assess the system functionality. The experiments carried out show that our system is suitable to classify human motion, count steps and, moreover, can be used both in virtual and augmented reality (VR) environments for an improved interaction.**

I. INTRODUCTION

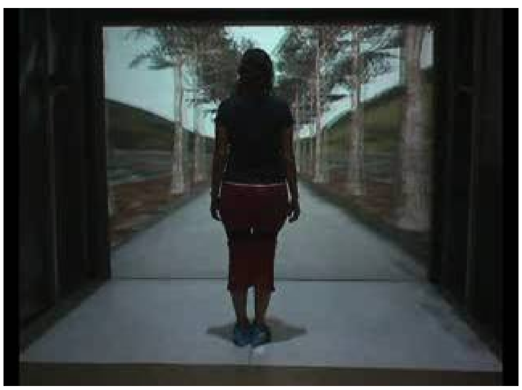

Fig. 1. *Virtual Reality Emvironment.*

Virtual Reality (VR) is one of the most futuristic, popular, and multidisciplinary areas of scientific investigation. Recently VR has started to influence society and strongly change the lifestyle of many people, especially the youngest generations, in part because of the entertainment and electronic gaming. The most common applications of VR range from entertainment and medical purposes, especially in rehabilitation, to the fields of astronomy, design, defense, cinematography, architecture, education, etc. Extreme cases are for example the virtual hair salons [6] and virtual museums. The advances in this field are evident, as we easily experience when we use a program as Google Earth. Despite these advances in the field, VR still needs more research work in order to make people confident in using the technology. The trend in VR is to simulate environments which seem increasingly real to humans. Therefore, a virtual environment simulation should be created with more sophisticated systems in order to interact with humans in natural ways. These systems should be more robust and have special emphasis on human senses, in order to provide users with a sensation of full virtual immersion. In this study, we focus on a system for motion recognition to easily augment interaction in VR environments.

Motion capturing is the first step of any motion recognition system. We distinguish between marker and markerless based approaches. The former rely generally on tracking optical markers attached to a person [10], [11], while the latter track features appearing naturally in videos [3], [8], [9]. Optical motion capture systems have the advantage of being accurate but they can be quite expensive and require users to wear markers in proper patterns. As a result, the system must be set up appropriately in advance. In this paper, we take advantage of the newest accessible electronics devices on the market, accelerometers, to develop an alternative approach for capturing human motion. Accelerometers are easy to handle and they do not need previous setup. Using this type of sensor, we propose a system that detects the speeding up or slowing down of a person during a motion and identify whether he or she is walking, running or remaining stationary. Our approach employs a real-time sensor system that could be used both in virtual and augmented reality environments. Consequently, the virtual environment changes simultaneously according to the recognized motion giving users the sensation that they are moving in a real environment.

The paper is organized as follows: Section 2 give some related works. Section 3 give a brief introduction of virtual environment exploration. Section 4 details the algorithm employed to recognize running and walking gaits in real time. The experimental results are shown in Section 5. Section 6 concludes the paper.

II. RELATED WORK

Using accelerometers attached to the person body is a method that has been proven effective for human motion recognition. Ling Bao [17] proposed a system for activities recognition using five accelerometers worn on different parts of the body. Features such as energy, frequency-domain entropy, and correlation were computed on the acceleration data, over 6.71 s sliding windows. Several classification methods were then applied and their performance tested on 20 everyday tasks activities of daily living (walking, running, bicycling, reading, stretching, etc.). N. Ravi et

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al. [20] developed a system to recognize activities using a single accelerometer worn near the pelvic region. The authors computed features over a sliding window of 5.12 s which was sufficient to capture cycles in the different activities considered. As for the classification, they evaluated the performance of the base-level classifiers as well as the meta-level-classifiers such as boosting [23]. T. Huynh and B. Schiele [24] studied the effect of computing several features over different window lengths (0.25, 0.5, 1, 2 and 4 sec) on the recognition rates of common activities using acceleration data. The authors concluded that a better recognition occurs when selecting different window lengths for different activities. For example, the 1 second window has been chosen for the activities 'jogging' and 'walking'; the 2 and 4 second windows are more adapted for 'skipping' and 'hopping', and the 0.25 and 0.5 second lead to a better recognition rate for the activity 'standing'. Takeuchi et al. [21] investigates, between the frecuency and the time domaine, the best features parameters for human action recognition. The authors employ the acceleration information in three axes and their derivatives as the baseline method in the time domain. They use Mel-Frequency Cepstral Coefficients as feature parameters in the frequency domain. They found that the best recognition rates are obtained when the features of the axis that contained most of gravitational acceleration information were included.

Our method perform both time and frecuency domain analysis on the most gravitational acceleration information in order to recognize a person gait in real-time. The originality of the approach consists in its adaptation to real time Virtual Reality applications, where even a small delay negatively impacts the interaction. This is ensured for the careful analysis of the behavior of the human motion and the acceleration during walking, running and even of stationary persons. From this motion analysis we observed considerable differences in acceleration in both gaits and in the period between the acceleration peaks during walking and running. To verify these differences a statistical analysis of 20 subjects was done. The results from this analysis strengthen our decision to use thresholds from the maximum and minimum acceleration changes and period between acceleration peaks. As a strategy to separate walking from running gaits and identify the user moving style during VE interaction.

Knowing the acceleration behavior during walking and running, the differences between them come clear to us, which is not for a sensor system, we must enable it to separate these. For human with a simple gaze in the user motion or computed acceleration may know the user gait. The acceleration from the person thigs give information such as: when a feet is in the ground, is behind, in front, etc. It is because during a single human step each movement and acceleration have them specific features. The motion and consequently the acceleration are similar in humans. Therefore, the main strategy in our system is based on these features. Here we proposed some thresholds in acceleration changes such: the maximum and minimum acceleration and the period between acceleration peaks that are different during walking or running. These thresholds were analyzed carefully in order to develop an strategical system that does not request much computational power that could influence in delaying VR response during human interaction. Therefore, the thresholds obtained from the acceleration analysis from the 20 subjects were specified in a state machine. Which controls the acceleration features changes and identifying the gaits in which the user is moving. Send this information in real time to XVR, that would be generate a VR environment, which the user perceives and interact according to his or her motion.

III. VIRTUAL ENVIRONMENT EXPLORATION

Movement through virtual spaces is one of the simplest and most important way of interaction [Hiroo Iwata, 1999; Doug A. Bowman, 1997]. Previous studies have demonstrated that real walking in virtual environments is better than virtual walking; it is more natural and produces a higher sense of presence than other movement methods [15], [16]. Inmersive virtual enviroments (IVE) has several applications, ranging from architectural design to situational awareness training. The main problem in VE research is the continuing search for most naturals ways of human interaction (full immersion). [Hiroo Iwata, 1999; Doug A. Bowman, 1997] mentioned that locomotion through virtual spaces is the most primitive and important special case. The following three are the most commonly used alternative locomotion methods: flying, via use of a wand; normal walking, with a uniform gain applied to the output of the tracker; and normal walking without gain, but with the location and orientation of the larger virtual environment periodically adjusted relative to position of the participant in the real environment [22].

The actions and perception of the user should be in sequence with the VE, therefore even a small delay in response between the user and the VE could influence the quality of the interaction considerably.

In this study we present a novel approach for navigation in 3D virtual environments, a sensor system that can be used in augmented VR by taking advantage of new and easily accessible technologies in the market, such is the wiimote control (Figure 2). The idea is measure the acceleration of a person that moves in the VR environment and use it to identify its motion (walking or running) and thus allowing the user to control his speed within the environment.

Our system can be used to detect both *walking/running in place* and *real walking and running*, as the system has been tested in both real and virtual environments. The sensor system presented here can also be used for different purposed, for which the exploration of 3D VR enviroments is needed. In order to test the effectiveness of our sensor sytem, we designed a 3D environment, in which the user could get the sensation of moving in a park. To create this illusion, we used objects such as virtual trees, a road, blue sky and mountains. (Fig. 1).

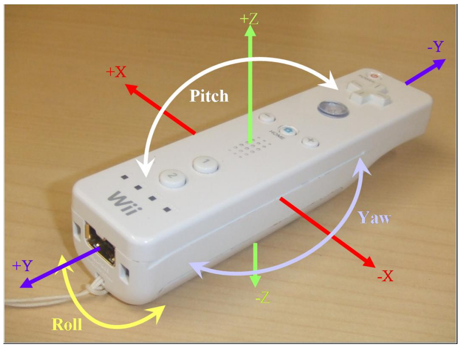


Fig. 2. *Wiimote controller device with the reference axes.*

IV. REAL-TIME HUMAN GAIT RECOGNITION

A. Humans Gait Acceleration Signal

This paragraph details how acceleration varies during walking and running. The acceleration behavior during human motion is crucial in selecting relevant features for gait recognition. When we walk or run, our movement is cyclic and our legs are constantly transitioning between two phases: stance and swing [10]. The stance phase begins when the heel initially touches the ground in front of us. The corresponding foot is then completely on the floor and the person's weight comes over it. The stance phase ends when the knee is almost straight and the other heel behind starts to rise till the toes tips barely touch the ground. The swing phase thus starts when the toes go off the ground from behind the person. The leg moves then forward in the air until its corresponding heel touches again the ground. This is the end of the swing phase [12]. Figures 3 and 4 show a typical example of the z-acceleration signals of a user walking and running. These signals are fairly repeatable over periods. Previous studies on human walking has shown that muscles act only to establish an initial position and velocity of the feet at the beginning half of the swing phase, and then remain inactive throughout the other half [1]. Thus, the swing phase is characterized by a down-up course of the acceleration, ending with the heel-strike. The latter is usually clearly visible as a negative peak. The acceleration behavior during swing phase is represented by the letters A-B-C and the stance phase by the letters C-D-E. Figures 3 and 4. In these figures a peak is marked with a circle read, it is visible that in the swing phase during running the peak is higher than during walking. On the other hand, the second half of the stance phase, when the heel is off the ground and toe still on the floor, is characterized by an increase of the equivalent acceleration. Thus, in the z-axis, there are a smooth positive peak in stance phase and some positive peaks near heel-off event [13]. For the running gait the acceleration is bigger in this phase.

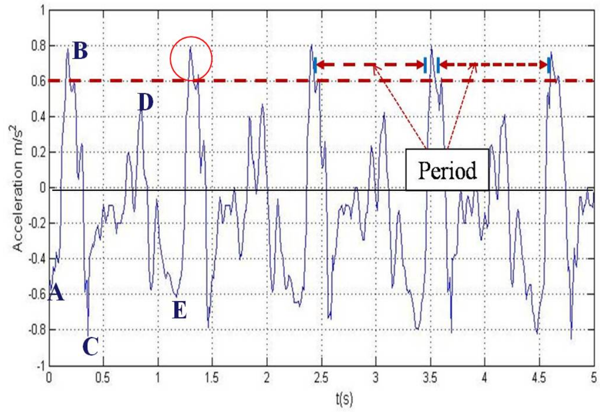


Fig. 3. *Vertical acceleration of the walking gait over time.*

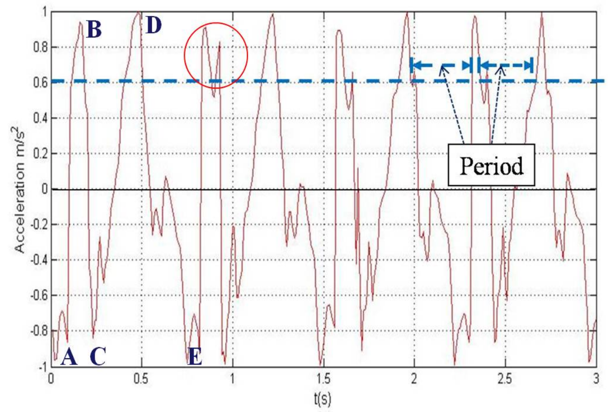


Fig. 4. *Vertical acceleration of the running gait over time.*

B. Feature Extraction

This paragraph details the experiment conducted in order to extract relevant features from the acceleration signal permitting to differentiate between walking and running gaits. We have asked 20 healthy subjects, aging between 23 and 35 years, to walk and run in a straight line at their corresponding natural pace (not too slow, nor too fast). The acceleration data acquired from the wiimote was then sent to a PC via Bluetooth and analyzed in a Matlab/Simulink environment. Not noise filtering was carried out in the data, since we observed that is not need and the use of a filter could influence the delay of the recognition system.

This evaluation shows that the acceleration varies from one person to another according to several parameters, such as legs length (from the pelvis to the end of the heels), thigh

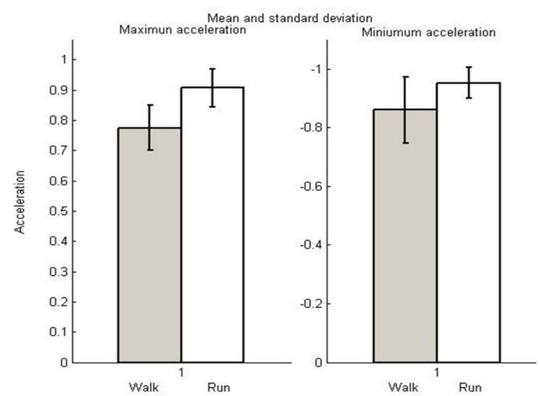
No.	Height [m]	Legs [m]	Thigh [m]	Min Acc $[m/s^2]$	Max Acc $[m/s^2]$	Period [s]
1	1.65	0.84	0.43	-0.8661	0.7120	1.000
2	1.75	0.97	0.50	-0.8719	0.7728	1.1343
3	1.60	0.90	0.44	-0.9866	0.6505	0.9491
4	1.70	0.92	0.50	-0.8927	0.8080	0.9560
5	1.91	1.02	0.51	-0.9703	0.7555	0.9000
6	1.83	1.03	0.52	-0.8226	0.8100	1.0286
7	1.80	1.03	0.52	-0.9920	0.8806	1.0440
8	1.73	0.92	0.49	-0.5140	0.7325	1.0056
9	1.89	1.10	0.55	-0.8436	0.7380	0.9750
10	1.76	1.05	0.47	-0.8891	0.8167	0.9420

Fig. 5. *Walking style: the first three columns represent the person's height, length of the legs and length of the thigh. The last three columns shows the average minimum and maximum acceleration as well as the average acceleration period for each person.*

No.	Height [m]	Legs [m]	Thigh [m]	Min Acc $[m/s^2]$	Max Acc $[m/s^2]$	Period [s]
1	1.65	0.84	0.43	-0.9768	0.9121	0.2867
2	1.75	0.97	0.50	-0.9472	0.9635	0.3061
3	1.60	0.90	0.44	-0.8613	0.8064	0.3406
4	1.70	0.92	0.50	-0.9370	0.8158	0.3090
5	1.91	1.02	0.51	-0.9472	0.9358	0.24
6	1.83	1.03	0.52	-0.9803	0.9055	0.2992
7	1.80	1.03	0.52	-0.9888	0.8627	0.3304
8	1.73	0.92	0.49	-0.9712	0.9267	0.3205
9	1.89	1.10	0.55	-0.9620	0.9387	0.2550
10	1.76	1.05	0.47	-0.9838	0.9886	0.2905

Fig. 6. *Running style: the first three columns represent the person's height, length of the legs and length of the thigh. The last three columns shows the average minimum and maximum acceleration as well a s the average acceleration period for each person.*

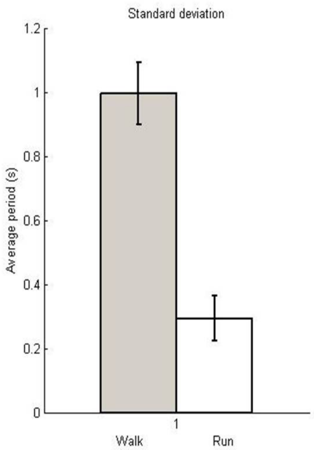
length (form the pelvis to the end of the knee joint) and person's height. Figures (5, 6) show these parameters as well as the corresponding acceleration minimum and maximum values for several persons while running or walking. The ideal situation is that the user walks and runs in a regular pattern which would lead to equal gait cycles. However, during a natural walk or run, a person gait cycles may be of different lengths. Thus, the values presented in figures (5, 6) correspond to the average ones computed for each person. In a second time, the average values for the 20 subjects were computed: Fig. (7) illustrates the minimum and maximum acceleration values, as well as the standard deviations for the two gaits. It is clear that the acceleration values are not enough to distinguish between the gaits. Thus, another criterion is needed. We have shown previously that the z-acceleration signal of each gait over time is fairly periodic (Fig. 3, 4). The corresponding cycles are detected from this signal by: (1) determining the swing peaks and (2) measuring time between two successive peaks. For locating acceleration swing peaks, and since the acceleration values are similar for running/walking, the same threshold of $0.60m/s^2$ is used for the two gaits. This threshold is derived empirically after studying the acceleration changes over time in several subjects. The threshold is shown in (Fig. 3) as a red dashed line for the walking style and a blue dashed line for the running gait in (Fig. 4). The time period in (Fig. 5, 6) is the average period computed for each person. Figure (8) shows the average period and its corresponding standard deviation



		Walk	Run
Max $[m/s^2]$	Mean	0.7750	0.9067
	Std	0.0743	0.0631
Min $[m/s^2]$	Mean	-0.8602	-0.9519
	Std	0.1128	0.0523

Fig. 7. *Maximum and minimum accelerations of walking and running gaits. The bars, stand for the acceleration average, the lines represent the standard deviation.*

for the 20 persons. This shows that one can easily distinguish between the periods of two styles. Thus this criterion can be used to recognize running/walking behavior.



Gait	Mean	Std [s]	Max [s]	Min [s]
Walk	0.9977	0.0959	1.2600	0.6300
Run	0.2934	0.0701	0.48	0.1200

Fig. 8. *Mean and standard deviation of the period between acceleration peaks (walking and running gaits).*

C. Gait Recognition Algorithm

To identify the acceleration peaks, as well as the transition from one gait to another, we used a state machine. Using an acceleration threshold, it was able to perform automatic recognition of the acceleration peaks. The distance between the peaks are then used to define the step period, which is used for the recognition of the gait in a moving person.

1) Selection of periods: A statistical analysis aids us in the choice of thresholds for the time intervals. The minimum and maximum step period for the users were $0.6300s$ and $1.2600s$ during walking. On the other hand, the intrasubject variability was low. For our state machine we used period thresholds of *walking (t)* should be (*0.5560s, 1.2854s*), the former was estimated from the average between the minimum period of walking and the maximum period from running stile, and the latter is the mean period from the 20 subjects plus three times the standard deviation, these threshold represents an interval well covering the measured variability of all subjects. Opposite, during running the minimum and maximum step period for the users were $0.1200s$ and $0.48s$. For our state machine we used period thresholds of *running (t)* should be (*0.1200s, 0.5550s*), the former is the minimum period during running and the latter is average between the minimum period of walking and the maximum period from running stile that is also close to the mean period of running plus three times the standard deviation that is $0.5037s$. The statistics is shown in Figure 8. Note that there is a gap between the periods of running and walking. This is needed to account for the fact that we often get artifacts mid-step from the shock as the foot hits the ground.

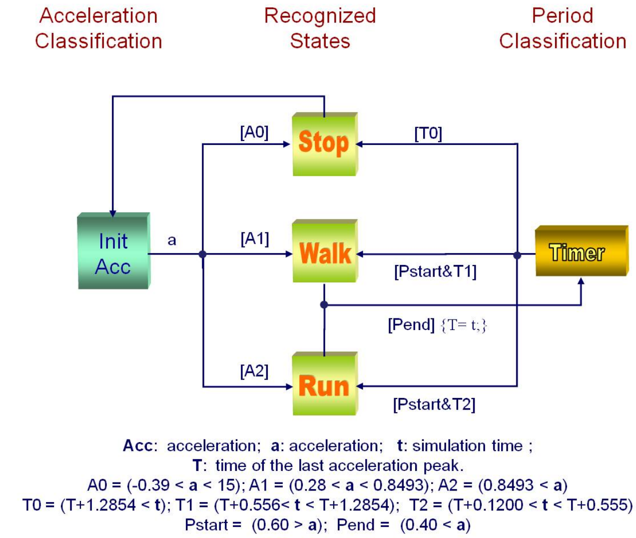


Fig. 9. *State flow algorithm of the main solution, Pstart represents the beginning of acceleration peak and Pend represents the end of the acceleration peak see figures 3 and 4.*

2) Initial recognition: In order to avoid delay at the beginning of the gait recognition process, before the second step and consequential time interval has been measured, we decided to give the system the option to recognize gaits using only the maximum acceleration for the first step. Even if this, as discussed in paragraph 3.2, doesn't result in reliable classification in a moving person, it is considerable more robust in classification of the first step. By using this additional method we allow a more responsive virtual environment. After the second step has been completed, the system switches to the time-based recognition process.

3) Acceleration thresholds: The acceleration thresholds for the walking gait were set to $(0.28m/s^2, 0.8493m/s^2)$, while the threshold for the running gait is $(0.8493m/s^2 \leq acceleration)$, both of these threshold would be used for the steps counting. A single step is consider when it finish a cycle that it start with the feet touch the ground and end in the same position. The threshold separating walking and stationary may be adjusted depending on the expected stationary movement in the virtual environment. The threshold between walking and running is placed an equal number of standard deviations from each mean, in order to maximize the classification ability. They are set apart by 0.7750 standard deviations, theoretically resulting in a successful recognition of about 80 percent of all steps. The statistical analysis results for maximum and minimum acceleration can be found in Figure 7. The state flow algorithm of the solution is shown in Figure 9. All calculations used a time resolution of 10 ms.

D. Model of the solution

The model of the solution was developed in a Simulink environment it is shown in the figure 10. The wiimote control function is represented by the two blue squares placed in the left side of the figure. In order to enable the PC to handle more than one wiimote control, the Wiiuse library was used [4]. The acceleration data information is sent in this process to the state flow, represented by the grey block, which handles the classification of the human motion explained before(Fig. 9). Once the gait is identified it sends the information to the virtual environment by a UDP protocol. The virtual reality process is represented by a smaller light blue square and the first output is the one to send the style. The second scope display the moving styles (1: stop, 2: walking, 3: run) and the last scope display the number of steps of the user during interaction. We added this last procedure to count the user steps as an extra of our system. The Simulink setup provides a flexible framework for handling the recognition in real-time. This let the programer to specifcate the simulation time acording to the requestment of the system; it is reprecented in the schema by the green square. The models used in the VR environment were designed in 3D Studio Max. The virtual reality application was developed in XVR, which provides extensive libraries for controlling virtual reality devices [14]. Therefore, the velocity of the moving environment mirrors the gait of the user (walking, running or remaining stationary).

E. System Setup

Two commercially wiimote controllers were used to register the acceleration signals [2]. These devices can sense both rotational and translational accelerations by the triple-axis accelerometer (ADXL330) embedded in the controller: backward-forward (x-axis), lateral (y-axis), and vertical (z-axis) (Fig. 2). Thus, data corresponding to the z axis reflect the acceleration provided by the rising and lowering of the body. The x axis's data register the sideways action of the body. Finally, the y axis data register the acceleration when the user moves sideways. The accelerometer has a measurement range of ± 3g (where g is the gravitational acceleration) and outputs analog voltage signals proportional to the acceleration. The portable devices were attached to the user's legs: one to each of the right and left thighs (Figure 11), close to the knee joint, which performs most of the work during walking and running gaits [5], moreover, the acceleration of the thigh is the most useful single sensor location for discriminating activities [17]. These devices communicate with the computer via a Bluetooth adapter, which provides a suitable operating range. Depending on the device class, it covers from 1 to 100 meters from the receiver. Four stereoscopic video projectors were used to project the images of the 3D Virtual environment. The projectors are connected to the PC by a VICON MX ULTRANET system which provides power, synchronization and comunication with each projector through a single cable connector [7]. The two images use different polarizations of the light and are projected on the screen. The VR glasses filters the polarizatio, so that each eye sees only one of the projections. The difference between the two images gives the user an illusion of depth in the image.

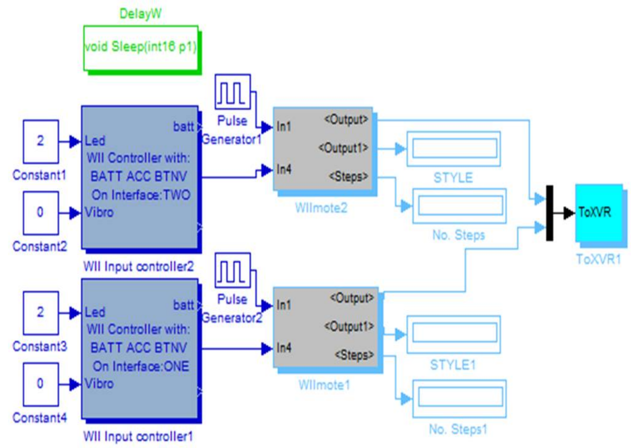


Fig. 10. *Simulink model of the solution. The first output is the one that send the style to XVR, the second scope display the styles (1: stop, 2: walking, 3: run) and the last scope display the number of steps of the user during interaction.*

V. EXPERIMENTAL RESULTS

In order to test our system, we validated the state machine on a separate group 8 healthy subjects, aging between 23 and 35 years, which were not used in development of the state machine.

1) Motion in real environment: We test the functionality of the system in real environment, the experiments were performed outside of the Perceptual Robots Laboratory in the sidewalk in which we have asked the subjects to walk and run in a straight line at their corresponding natural pace (not too slow, not too fast), without stopping. We reliesed

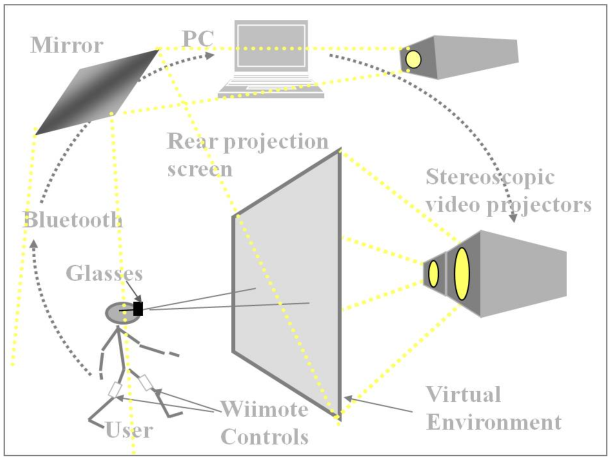


Fig. 11. *The full system setup*

TABLE I
CONFUSION TABLE FOR GAIT RECOGNITION IN NORMAL ENVIRONMENT.

Style Identified	Stop [%]	Walk [%]	Run [%]
Stop	100	0	0
Walk	5.68	94.32	0
Run	0	1.19	98.81

TABLE II
CONFUSE TABLE FOR GAIT RECOGNITION IN MOVING IN PLACE USING VE.

Style Identified	Stop [%]	Walk [%]	Run [%]
Stop	100	0	0
Walk	11.5	88.5	0
Run	3.3	0.45	96.25

from some experiments using the walking machine that the used velocities for each gait were 4 and 8 Km/h approx. and the travel distance was 20 meters approx. In order to test the stationary gait recognition grade we asked the subjects to walk and a run for a small period and after stop for 10 seconds. To verify the system by ourself we performed real moving experiments in which the subjects moved around freely using different styles while we observe the recognition in the computer.

2) Motion in VE: In order to proved the system in VE we performed an experiment in where we have asked to the subjects to walking and running-in-place it mean walking or running without real gain but the sentation of moving should be given by the screen, wich the user may looks while is moving. For this experiments we used the previous mentioned VE application. Performed these experiments we approached the referents of perception and action during motion in an VE exploration.

3) Results: To measure the confusion matrix, we compared the output each time the state machine entered one of the three recognition states (stop, walk run in the diagram) with the actual gait being performed in the experiment. In the tables we present an average of the recognition from the two wiimotes placed in the user thighs. The experiments to identify gait in natural environment shows us that the recognition in the running style the model give us some how good results. There was some confusion of the walking gait as well with the stopping gait, but overall performance was well above 90 %. Opposite in the moving in place using VE the more confuse was with walking and stopping an 11%, we have observed that some of the participants here sometimes were relaxing the way of moving the legs during walking, therefore the system confused this style with stopping. For the option of counting steps we just verified with the number of steps of the user with the ones specified in the display it was accurate as is in relation with the average of recognition system, since this option depends also of the acceleration. The experiments show that, our algorithm is able to detect the changes in acceleration and identify whether a person is in motion or stationary as well as classify the motion as either walking or running in both natural and VE environments.

The experiments carried out show that, given the acceleration data information over time, it is possible to identify in natual moving whether a person is walking with an accuracy of 94%, running at 98%, and stationary person at 100%. For the recognition un moving in place in VE the accuracy for walkin was 88%, we belive that this recognition could be impruve just to explaining the user how to work and trying to avoid delays that these not happen in a normal walking. For running in place we got an accuracy of 96% little bit bgger than a normal run.

VI. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

We presented a methodology for human gait recognition, to be employed in virtual reality environments exploration. After capturing the acceleration data using two wiimote devices attached to the user thighs , we developed a state machine permitting to detect the user gait based on the acceleration and period between acceleration peaks. Both of them were subject of a careful statistical analysis that lead to a threshold outputted recognition algorithm. Once that the user start walking or running the system immediately detects the changes in acceleration and identified these by the specified threshold in accelerations and period between peaks using as referents, outputting the detected gait in real time. The originality of the approach consisted in its adaptation to real time Virtual Reality applications, where even a small delay negatively impacts the quality of the interaction. Evenmore, the system presented here dose not take much computational power that could influence in delaying the time of recognition. We tested our strategy in both real and virtual environments. Our system was able to detect acceleration changes in real-time and classified it into the gait of walking, running and stationary. The corresponding recognition rates were of 94%, 98% and 100% respectively in the real environment and of 96% , 88% and 100% in the virtual one.

B. Future Works

A possible future extension of the model would be to make a more detailed description of the movements speed using a combination of acceleration periods and biometric data from the user. Another possibility would be to estimate the two-dimensional displacement of the users after a horizontal movement, e.g. a short run. However, the wiimote controller requires high frequencies of sampling to be accurate in a position system and in addition there will be a high level of noise if the accelerometer is not used in a vibration diminishing platform. For these reasons, initial studies of measuring walking/running using accelerometers focus on motion recognition and not in position estimation. On the other hand, we plan position estimation to be part of our future research.

VII. ACKNOWLEDGMENTS

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