Two methods for body parameter analysis using Body Sensor Networks

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***Abstract*—One of the many applications of wireless sensors, wearable computing devices, is to collect data for analyzing body parameters useful for assessing athletic performance of an individual or group of individuals. Focusing on analysis methods using parameter extraction, in this paper we will see how the cooperation between a Body Sensor Network (BSN) and a larger system (e.g. an e-health system or an e-learning system) can be exploited for the assessment and/or distance teaching of physical education skills for a movement science course or in a training college.**

Personal and body networks, wearable computing, body-area networks

I. INTRODUCTION

Recent progress in electromechanical technologies has resulted in the development of increasingly smaller sensor nodes, that can be positioned in large numbers and very close to each other thereby ensuring sensing accuracy and correct delivery of data to collector nodes [1]. This kind of sensor node, such as for instance the Aquisgrain II manufactured by Philips, has a very simple structure consisting basically of a low energy consumption RISC microprocessor, a low range IEEE 802.15.4 RF transceiver, a battery and a sensor. The latter component can vary and is able to monitor a wide variety of surrounding environmental conditions. Using a position sensor and an accelerometer we can obtain sensor nodes able to detect and send their position at each instant.

The miniature high-precision wireless sensor nodes now available prompted the idea of applying a series of sensor nodes to the human body to track and analyze movements for a variety of applications. With these devices it is possible to create a Body Sensor Network (BSN) with wearable computing. In the next sections we will describe a system for evaluating and teaching physical exercises that can be used, for example, on a movement sciences course, in a physical education training college or for distance learning and monitoring of physical exercises for therapeutic purposes. Today, in the medical world, the first steps are being taken towards diagnosis of diseases like Alzheimer's or senile dementia using movements analysis [2].

So, the basic components of the system are a BSN applied to specific parts of the body, a software for analyzing the data according to a specific logic and a platform which enables distance cooperation between therapist/teacher and patient/student.

II. THE WEARABLE NETWORK

At the basis of the system is the so-called wearable network, that is the sensor network which has to be "worn" by the student/patient so as to examine his/her movements. For this purpose let us imagine placing a series of sensor nodes at the main joints, i.e. at those points that allow to detect limb position and movements, as shown in Fig. 1:

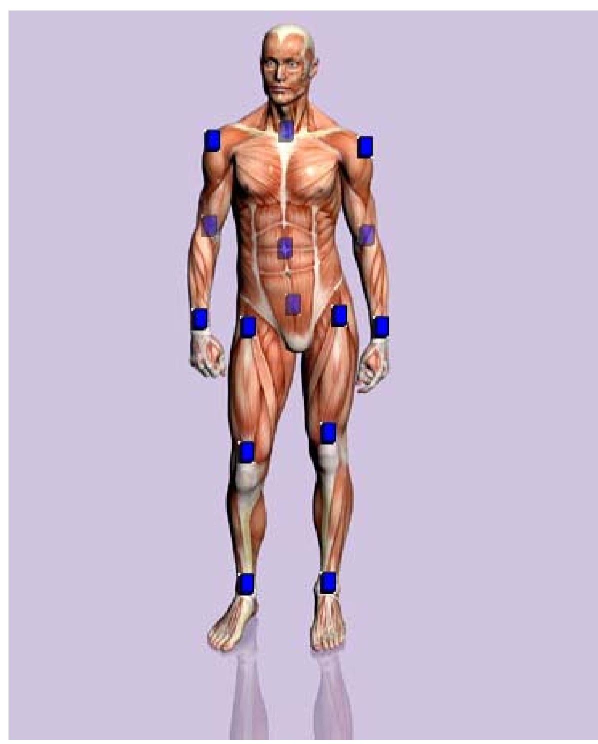

Figure 1. Position of sensors on the body

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To analyze motion and to obtain a complete picture of the athletic movement, we need to observe the body from different perspectives. So we decided to take measurements observing the sensors network from the coronal plane (frontal plane), sagittal plane and transverse plane (Fig. 2).

A. Parameters

By observing sensor position and movements along the three anatomic planes we can define two parameters useful for all investigations to be conducted on body movements; these two parameters are imprint and trace, defined as follows:

- Imprint: we define imprint of sensors in a given anatomical plane, the set of points given by the orthogonal projection of the sensors on that plane and the set of segments given by their conjunction.
- Trace: we define trace of a sensor in a given anatomical plane, the set of segments given by the conjunction of the imprint points left by the sensor on that plane at subsequent instants.

Thus, imprint and trace can be defined starting from a given position and from a given movement of the body at different time instants. For the athletic movement depicted in Fig. 3, the relative imprint at starting position and the trace of the full movement viewed at two subsequent time instants are shown respectively in Fig. 4 and 5.

Once we have obtained sensor positions, their movements and have derived parameters to analyze them, comparison methods are required to analyze athletic movements from different aspects. It is important to note in this respect that, to ensure high network efficiency, the activity of body-worn sensors needs to be minimized, locating in the surrounding environment a series of sensors (environmental sensors) which perform the bulk of signal processing and provide feedback to the on-body sensor nodes. In this way the computational complexity of the body-worn sensors can be reduced by up to an order of magnitude [3].

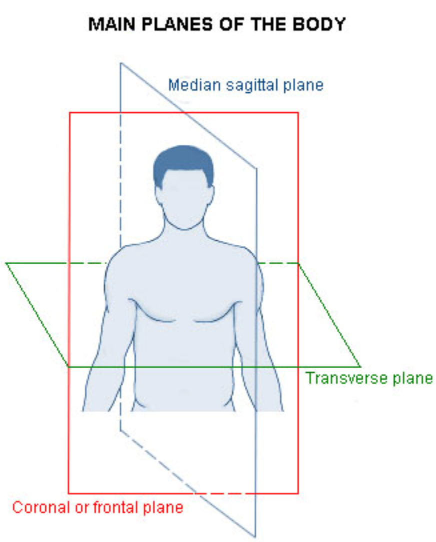

Figure 2. Anatomical planes of observation

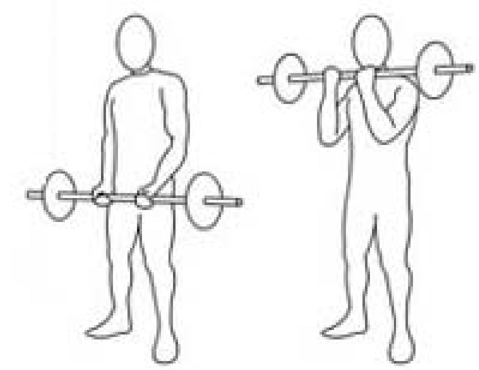

Figure 3. Example of athletic movement (arm curl)

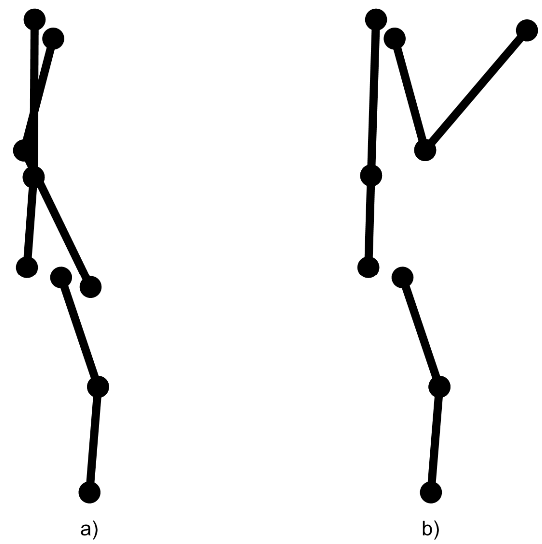

Figure 4. Imprint on median sagittal plane of the starting (a) and finishing position (b) of the athletic movement shown in Fig. 3 (right side)

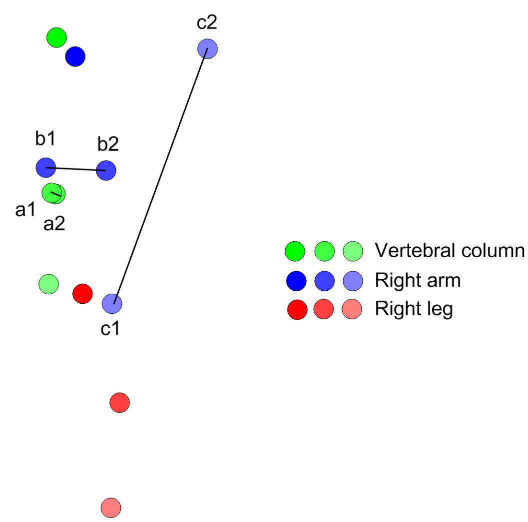

Figure 5. Trace on median sagittal plane of the athletic movement shown in Fig. 3

For this work we opted essentially for two kinds of analysis, namely the assessment of an execution according to predetermined models and the search for the best execution according to predetermined parameters and constraints. In the following sections we will see how these methods have been implemented also in the light of the tests conducted.

III. ANALYSIS METHODS

Data obtained from sensors used in a BSN are typically (multidimensional) spatio-temporal data and their analysis and recognition is an important area in data mining for identifying structural and temporal relationships or hidden dependencies in BSNs [4]. More generally, this kind of data is defined as movement data, basically characterized by trajectory, space and time [5]. Disregarding the definitions of space and time, we can formally define a trajectory as the continuous mapping from the set of time instants $\mathrm{I} \subseteq \Re$ to the plane points set $\Re^2$:

$$\mathrm{I} \subseteq \Re \rightarrow \Re^2 : t \mapsto \alpha(t) = (\alpha_x(t), \alpha_y(t)). \quad (1)$$

Then the trajectory is a triad consisting of:

$$\mathrm{T} = \{(\alpha_x(t), \alpha_y(t), t) | t \in \mathrm{I}\} \subset \Re^2 \times \Re. \quad (2)$$

Viewed from this perspective, the definition of trajectory is comparable with the definition of trace given in the previous section; but for evaluating execution we only used a sequence of imprints starting from the initial position of the athletic movement up to its complete execution. Thus, trace and trajectory are of marginal importance in the execution assessment and only play a role with respect to the resolution used to analyze the movement, i.e. to the sampling frequency used to extract the imprints; anyway, they are at the base of the best execution method.

A. *Execution assessment*

The procedure for evaluating athletic skills is based on capturing and comparing successive imprints, obtained for a sampling frequency directly proportional to the rhythm with which the exercise has to be performed. Once the imprints are obtained, they are compared with those taken as reference and then evaluated [6]. Obviously, the reference movements are sampled with the same frequency and the final result of the evaluation takes into account the scores recorded at each instant. Comparisons are made on the three anatomical planes.

First of all, imprint dimensions need to be standardized with respect to those of the reference imprints. Hence, the imprint is translated such that the position of the sensor placed in the lumbosacral area coincides with its counterpart in the reference imprint. The imprint is then scaled and rotated so that it too coincides with the sensor positioned in the nape of the neck. By so doing, the segment representing the vertebral column is made to coincide to the greatest extent possible.

1) The algorithm: Imprints are black and white images and thus they can be compared simply by pixel subtraction. Since they are a set of points (the sensors) and segments (scaled in order to obtain lengths as equal as possible, in line with differences in body proportions) no special pre-processing of the images, like edge thinning or thresholding, often used in this kind of application on grayscale images, is required. In simulations and tests, we calculated distance between imprints as absolute value distance and quadratic distance, the latter yielding better results. The value of the distance provides a score index for the evaluation of single imprints and thus of the athletic movement as a whole.

The imprint to be analyzed can be compared with a single imprint, extracted from a reference physical exercise whose execution is considered ideal, or with a set of reference imprints. In the second case we obtain a kind of reference training set to which classification algorithms can be applied as in a recognition problem. In this case, the aim is not to perform a recognition but to evaluate the distance from a set of samples already classified, evaluated and considered as reference models: using the K-Nearest Neighbour algorithm we obtain a classification in ascending order of distance from samples to which a score index is associated (perfection of the execution). An example (from simulation results) is given in table 1.

Starting from this kind of classification, different possibilities exist for calculating the score of an imprint [7]. The first is to decide a K value for the K-NN algorithm, keeping the similarity percentage or the score index as score of the imprint to be analysed.

Using this method, the best choice in tests was found to be a K value equal to one and to use the score index as evaluation score: the results obtained proved to be the most consistent with the assessment of a hypothetical board of examiners.

As an alternative we can calculate the average percentage of similarity and average score index for the first K samples of the classification and use these values for assigning the score. In this way we obtain an evaluation that accounts for the different reference samples as far as similarity percentage is concerned and are not dependent upon possible errors in samples index score assigning.

2) Assessment correctness: In order to verify the correctness of the evaluation computation, we performed a classification procedure of the imprints to evaluate using reference samples as training set.

TABLE I. EVALUATION CLASSIFICATION OF AN IMPRINT

Position	**Similarity**	**Reference sample**	**Score index**
01	93.9131%	n. 12	96/100
02	93.8016%	n. 05	94/100
03	93.5187%	n. 09	98/100
04	93.2145%	n. 17	91/100
05	92.9734%	n. 03	89/100
05	92.7559%	n. 21	92/100
07	92.4589%	n. 25	88/100
08	91.6753%	n. 10	90/100
09	91.1267%	n. 07	86/100
10	90.3426%	n. 16	87/100

As usual, we used the K-NN algorithm and the best value of K proved to be 1. The results obtained using this procedure proved to be the larger training set dimension the more accurate, and they allowed to establish whether a certain imprint (already classified and evaluated) was classified as a training set imprint of the same class and the same score. For small training sets (less than 100 samples) correct classification was over 80%, reaching maximum values (over 98 %) for about 1000 samples.

B. Best execution

The second kind of analysis we implemented on data collected by sensors was the search for and evaluation of the "best execution" starting from given parameters and constraints. This method can be applied not only to the final evaluation of athletic skills but also for correction and preparation in training. This kind of analysis can be useful and can replace the first type insomuch as it is not always possible to correctly compare sensor movements and their relative positions, because proportions of bodies on which sensors are worn can differ, even after scaling and rotation of the imprints. These differences can result in disadvantages already in the starting and finishing positions of the athletic movement.

To solve this problem, the analysis method calculates the best execution for a given person based on the starting and finishing positions of the athletic movement (made as similar as possible to the positions of an ideal execution) and a set of constraints to be observed during execution. The computation results are compared with the execution examined which can be evaluated in its entirety and independently of possible physical limits. The best execution has been computed as a minimization problem that finds the shortest path to reach a given position, optimizing execution speed and relative power consumption. Of course in the computation we have to observe constraints imposed by execution specifications or physical constraints imposed by the impossibility to perform certain movements. An example of a physical constraint is shown in Figure 6.

In the computation this kind of constraint has been imposed by verifying relative positions between sensors (in the case of Fig. 6, which shows an imprint on the median sagittal plane, the sensor placed on the wrist cannot lie to the right of the segment representing the upper arm), and by imposing that at given instants given sensors lie in specific positions of the plane and by verifying that the distance between adjacent sensors (that can represent the length of a certain limb) do not change during the execution [8].

Once all constraints are satisfied, the computation of the best execution is simply a problem of minimization on graphs (traces and trajectory previously defined) and the result can be easily compared with others. In order to render the trajectory defined by the computation as natural as possible and to compare it with the trajectory of a real athletic movement, the sampling frequency needs to be sufficiently high to delineate a trace using linear interpolation. Alternatively, to reduce sampling frequency, some constraints can be established that enable trajectories to be defined with the Bézier curve interpolation.

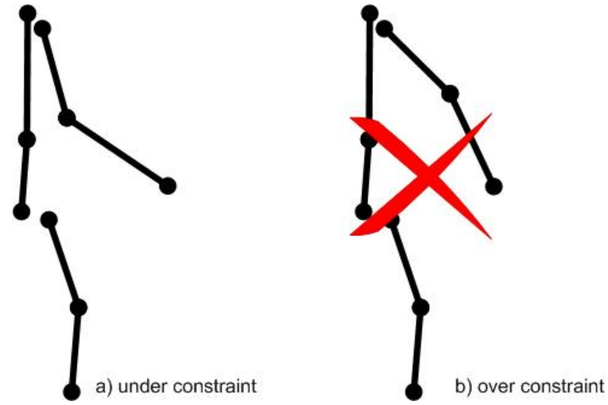

Figure 6. Physical constraint in the computation of best execution

IV. CONCLUSIONS

Simulations and tests produced optimum results for the hypothetical use of a system like the one described here. The strong point lies in the possibility of always obtaining accurate measurements and data on which to perform objective and error- free evaluations: in this kind of application, in fact, visual interaction alone can be restricted by the quality of the images and by the difficulties in evaluating them, that is by the lack of an objective measurement of athletic skills. This is the main reason for using a BSN in this kind of application, apart from the possibility of obtaining important data sets useful for improving the application itself. Furthermore, these innovative sensors open the door to a variety of applications similar to the one proposed here, such as their use for medical purposes, in industry, on construction sites and again in the sports sector, for improving athletic performance.

Finally it should be recalled that further research in this direction, using the methods described here, opens up paths for developing the concept of dynamic improvement of athletic skills including the ergonomic improvement of the equipment used by athletes.

REFERENCES

[1] R. Aylward and J.A. Paradiso, "A compact, high-speed, wearable sensor network for biomotion capture and interactive media", Proceedings of the 6th international conference on Information processing in sensor networks, Cambridge, April 2007.

[2] J. Barnes and R. Jafari, "Locomotion monitoring using body sensor networks", Proceedings of the 1st international conference on PErvasive Technologies Related to Assistive Environments (PETRA 08), Athens, July 2008.

[3] A. Vehkaoja, S. Iyengar, M. Zakrzewski, R. Jafari, R. Bajcsy, S. Glaser, J. Lekkala and S. Sastry, "A resource optimized physical movement monitoring scheme for environmental and on-body sensor networks", Proceedings of the 1st ACM SIGMOBILE international workshop on Systems and networking support for healthcare and assisted living environments, San Juan, June 2007, pp. 64-66.

[4] G. N. Pradhan and B. Prabhakaran, "Storage, retrieval, and communication of body sensor network data", Proceedings of the 16th ACM international conference on Multimedia, Vancouver, October 2008, pp. 1161-1162.

[5] F. Giannotti and D. Pedreschi, Mobility, Data Mining and Privacy, Geographic Knowledge Discovery, Berlin Heidelberg: Springer-Verlag, 2008.

[6] G. N. Pradhan and B. Prabhakaran, “Quantifying human performance by analyzing multi-dimensional streams”, Bodynets 2008, Phoenix, March 2008.

[7] H. Lakany, “Extracting a diagnostic gait signature”, Pattern Recognition 41, May 2008, pp. 1627-1637.

[8] R. Ramachandran, L. Ramanna, G. Hassan, G. Pradhan, R. Jafari and B. Prabhakaran, “Body Sensor Networks to Evaluate Standing Balance: Interpreting Muscular Activities Based on Inertial Sensors”, HealthNet 2008, Boulder, June 2008.