# Ambient Intelligence Assistant for Running Sports Based on k-NN Classifiers

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***Abstract*—Outdoor sport practitioners can improve greatly their results if they train at the right intensity. Nevertheless, in common training systems the athletes performance use to be evaluated at the end of the exercises, and the sensed data is incomplete because only human biometrics are analyzed. These systems do not consider environmental conditions which may have direct influence on athletes performance during training. In this paper, we present the system architecture and implementation of an ambient intelligence assistant for runners. Our system is composed by a Wireless Sensor Network (WSN) deployed over a cross country running circuit, and by mobiles elements carried by the users, which monitor their heart rate. The goal is to select, for a given user, suitable tracks where the heart rate will be in the selected HR range. Decision-taking process is based on k-NN classification, and has achieved a success classification ratio of 70%.**

***Keywords*—Ambient intelligence, wireless sensor network, runner assistant, machine learning, k-NN classifier.**

## I. Introduction

WHILE performance of technologies in the area of WSN, and their processing power, are increasing rapidly, the WSN will get more embedded and more seamlessly integrated in the physical world. The environment will be sensitive and responsive to the presence of people. In fact, these advances may allow the development of context-aware personalized services.

Among the applications fields for these contextual services, the sports domain may result one of the most benefited. For instance, in outdoor sports such as cross country running and jogging, practitioners commonly use wearable computing devices, which provide useful telemetry about runner biometrics and practice related events. Among other parameters, they are able to measure heart rate (HR), track routes, measure speeds and distances, and so forth. Often the complexity of the data collected requires to be analyzed later by a human coach, sometimes with the aid of a specific software. In this scenario, the athlete is left alone during the training session, and, she/he can only take decisions *a posteriori*. For example, decrease speed when heart range has exceed some limit.

Nowadays, generation of corrective responses on the real-time runner performance, and, integration with the environment are limited in training systems. Evolution of computing and communications technologies may provide adaptive coordination between the user and the environment, modifying the system behavior as it responds to changes in the environment or the user conditions (*e.g.* temperature or runner location).

This paper presents an ambient intelligence system prototype for running sports in open areas. Our approach is depicted in Figure 1. Athletes are training in a field with a variety of tracks. Each track has different conditions (hardness and temperature), and the goal is to select, at each path fork a suitable track for the runner. In our system we aim at controlling the HR of the user. Different training ranges are possible (*e.g.* cardio-training, fat-burn, etc.). The criterion for path selection is to select a track where the heart rate will be most of the time in the wanted HR range. Notice that, in this case, training decisions are taken *a priori*. Therefore, each track must be classified as "In range" or "Out of range", and the selected track is selected at random among the suitable ("In range") tracks. The technique selected for the classification process is the k-Nearest-Neighbors (k-NN) algorithm. The relationship between HR and sport activity is affected by many factors, among others, the effect of temperature is studied in [1], or the HR [2]. Thus, the following data (*features* in k-NN terminology) have been considered for the decision-taking process:

- Current track environmental temperature.
- Next track temperature.
- Current track hardness.
- Next track hardness.
- Average HR during the current track.
- Variance of the HR during the current track.

The k-NN algorithm requires a data base with known pairs of features-classification. That is, if for a given set of features the track is either "In range" or "Out of range". Then, the k-NN classifier consist of selecting the k nearest set of features, and performing a majority vote selection with their known classes.

As training conditions can rapidly vary, the system would be expected to take real-time decisions to meet the user needs. Therefore, constant user and environmental monitoring are a requirement. Although the present work is mainly focused on developing a suitable decision engine, emphasis was also put on the development of an architecture that enables real-time data harvesting. Thus, efficient communications and localization protocols are also two key areas of this work.

To perform these tasks our system is composed by a WSN deployed over a rough outdoor area. This networked system (see Figure 1) has two main elements: Infrastructure Nodes (IN), and, User Equipment (UE). The former components are

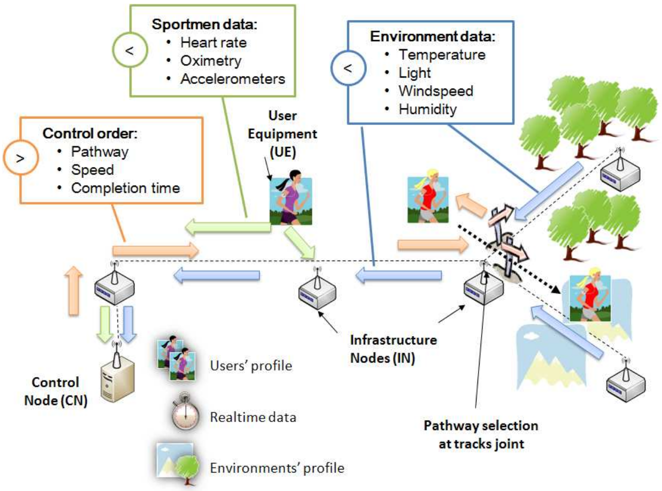



Fig. 1: Data flow of the sensed data, and, the commands flow from the CN.

static, and are used to measure environmental variables and to track the position of the runner over the course. The latter components are carried by users and, thus, are mobiles. The IN nodes includes sensing capabilities to capture the ambient temperature, and, the mobiles ones, are able to take pulse rate samples of the runner. The intelligence of our approach is in a particular fixed node (Central Node or CN) which runs the decision engine based on the k-NN classifier. This special node receives every nodes' data. The information gathered maps temperature over the training tracks, and serve to keep the runners located. As environmental conditions, the runner's HR is continuously delivered to the CN via the INs. This allow to feed the k-NN classifier with real-time feature measurements.

Our approach can be generalized to other outdoor sport fields (*e.g.* cycling or biathlon), where terrain slopes and atmospheric conditions play an important role in their practice [3].

The reminder of this paper is organized as follows. First, Section II, briefly reviews the related work in wireless mobile technologies applied to training guidance and prediction HR methods. Next, Section IV-D describes the system architecture, its components, the communication protocols, and, presents a system prototype. Later, Section III discussed the methodology used for the implementation of the decision engine. A validation experiment is analyzed in Section V. Finally, Section VI concludes the paper summarizing results and future research lines.

## II. Related Work

The use of wearable computing is, nowadays, common in athletes' training. Many of these devices are not exclusive for elite athletes, but available to the general public (e.g. heart rate monitors). In fact, the widespread use of commodity hardware (*e.g.* the Apple iPhone) has also lower the barrier to create training sports mobile applications [4].

To some extent, the availability of these devices is simply the first step towards the appearance of contextual services. Future developments will aim at expanding the range of monitored data (environmental conditions, detailed user data), and, to provide useful actions and information based on them. WSNs represent one of the enabling technologies for that evolution.

Several context-aware applications for athletes training have already been introduced. In MarathonNet [5] a WSN monitors runners in marathon events. Sensors on runners collect data about heart rate, time and location. These data are sent to a central database via base stations along the track, where they are subsequently analyzed. Base stations can communicate with the central database by means of GPRS, WLAN, or a wired network link. The sensor nodes in our work have similar functionality, but they also act as information routers.

More intelligent systems have been developed for scoring sports purposes. For example, in [6], the authors present a sensor system which intends to provide immediate feedback to alert users to incorrect movements and body positions. The prototype uses sensors attached to the human body and inserted into the boots that detect mistakes during snowboarding. In [7] authors develop a score system for golf swing motion. The golfer body motion is captured by a wireless network of inertial sensors which extracts snapshots of the orientation data of the user body throughout the golf swing. The orientation information is compared with correct motion rules, giving a measure of how well the current motion obeys the rule. The score is passed to a graphical display, and to the audio output module which provides real-time feedback about the quality of the swing. The paper [8] describes a feedback system based on sensors placed in a golf club body which capture the movements of a golf swing. The swing motion is preprocessed locally, and, then sent to a control station for further analysis. The quality of the swing motion is expressed as the amount of deviations from target line, and is computed by linear discriminant analysis technique.

To sum up, most previous systems do not sense environmental data, but only information from the athlete, and they only provide limited real-time feedback in some cases. Our proposal tries to overcome such limitations, providing useful automated feedback to runners, based on an ambient intelligent system, inferring the performance of the user under variable training conditions.

Moreover, recent studies have successfully utilized the k-NN classifiers to predict a variety of heart diseases. For example, since there exists direct relation between fluctuations of oxygen saturation in blood and variations in HR, in [9], the authors use the k-NN classification method to detect obstructive sleep apnea. Also, in the paper [10] it is proposed a pruned variation of a k-NN classifier to recognize different types of arrhythmia beats.

## III. Decision engine: k-NN classification

As stated in Section I, the CN is in charge of providing the intelligence of the system. Its goal is maintaining the runners' HR in a given target range. Nevertheless, the problem of evaluating the expected HR is complex, since the mechanisms involved in cardiovascular regulation, likely interact with each other nonlinearly [11]. Thus, the HR of a runner, and, in turn,

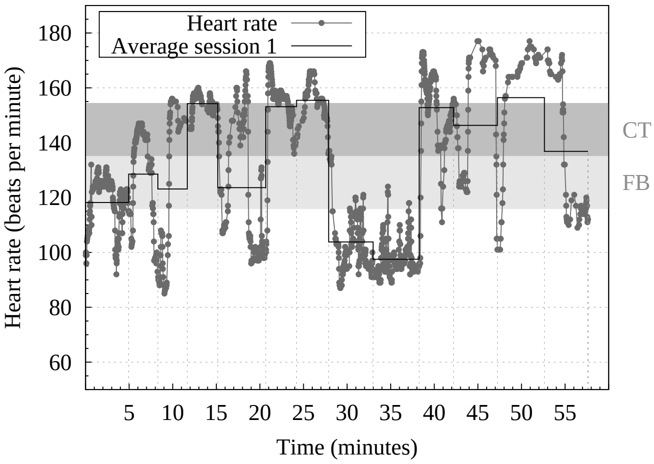



Fig. 2: HR samples of a training session.

its performance, results difficult to characterize. As an example of its difficulty, Figure 2 depicts the HR samples of a runner training session of the pilot validation (Section V-B).

The k-NN method is *memory-based*, because, in contrast to other statistical methods, requires no training, thus, no model to fit. It is included into the category of Prototype Methods. It operates on the intuitive idea that close objects are more likely to be in the same category. Thus, k-NN predictions are based on a set of prototype examples that are used to predict new (or *unseen*) data based on the majority vote (for classification tasks) and averaging (for regression) over a set of k-nearest prototypes.

The method operates as follow. Given a data set consisting of $N$ pairs $(x_1, g_1) \ldots (x_N, g_N)$ where $x_1$ is the features information and $g_i$ is its corresponding class label. Each of the $N$ pairs is called *prototype*, or *scenario*, and, every data $x_i$ belongs to the feature space of dimension $P$. In our experiment specification (see Section V) a feature space of dimension 6 is considered, consisting in, next and current environmental variables (temperature and track hardness), and, current average and variance of the HR. Besides, two classes are possible ("In range" or "Out of range") corresponding to a track where the HR is in the objective range or outside, respectively. Thus, the classification problem consists in, given a query point $x_0$, find the $k$ training points $x_{(r)}, r = 1, \ldots, k$ closest in distance to $x_0$, and then classify it, (*i.e.* assign a class label) using majority vote among the $k$ neighbors. If vote results a tie then it would be resolved at random. In our study, it is assumed that the features are real-valued, and, Euclidean distance is be used in the feature space:

$$d_{(i)} = \|x_{(i)} - x_0\|_2 \tag{1}$$

Commonly, before of calculating these distances each feature was standardized to have mean zero and variance 1, since they can be measured in different units. This approach was followed in our work.

# IV. System prototype

A prototype system has been implemented using standard WSN hardware (MICAz and IMOTE2 motes from Crossbow Technology). This section describes these elements in depth, and the communication protocols used.

## A. IN node implementation

The IN requires sensing, processing, and communicating capabilities. IN nodes were implemented using MICAz devices, and are composed by a processing unit, a wireless interface including directional communication antennas, and a power supply. IN nodes operates in the 2.4 GHz band, and are compliant with the low power Zigbee/IEEE 802.15.4 physical interface. Environmental sensing is carried out by a MTS400 sensor board, which measures light, temperature, humidity, and barometric pressure, although in our testbeds (Section V) only temperature sensing has been activated.

In addition, each MICAz is equipped with two panel antennas (a 2.4 GHz Stella Doradus 24-8080 planar antenna) to increase communication range. The reason is twofold. First, the natural obstacles (*e.g.* knolls or woodlands) may worsen communication among IN nodes. Second reason is the increase of communication range between the stations, allowing a lower density of IN nodes, and, therefore, reducing installation and operation costs. In actual deployments, it was verified that communication range may reach up to 180 meters, although the IN nodes were installed with a maximal distance of 150 meters in between, as a security margin and to increase the precision of the location algorithm. Notice that, with the default antennas that are embedded in the MICAz motes, the typical range is less than 100 meters. The Figure 3(a) shows two deployed INs.

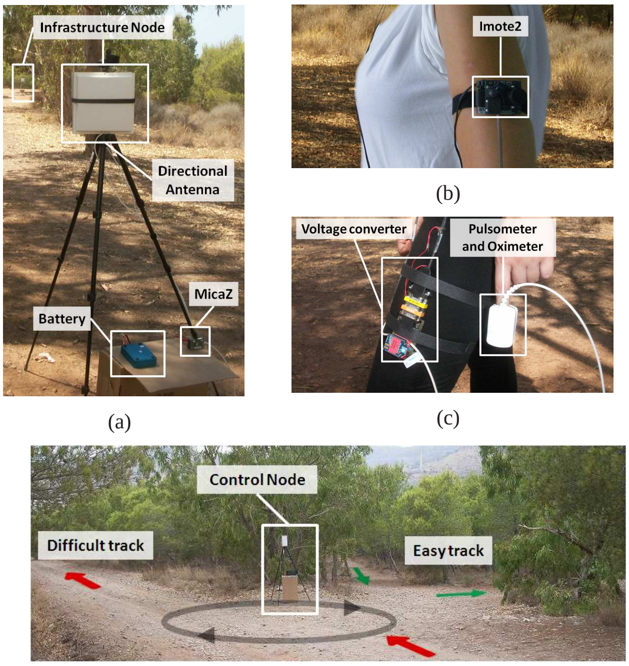
## B. CN node implementation

The CN has the same IN's sensing and data transmission capabilities, and, thus, can be considered a special IN node. The CN also provides the intelligence of the system. The decision engine in the CN selects tracks and informs the users. The location of the CN in our network deployment is shown in Figure 3(d).

## C. UE implementation

Similarly to the IN node, the UE combines sensing and communications functionalities. Nevertheless, the UE is designed to sense human biometrics (HR in our implementation). Instead of environmental parameters, human biometrics variables usually change faster than environmental ones. Therefore, sample frequencies must be higher. The UE is also the interface between the system and the user: it delivers training orders to the athletes.

To perform these operations, the UE is composed by several modules, as shown in Figures 3(b) and 3(c). The main module is the Crossbow IMOTE2 IPR2400, a wireless sensor network platform, which can be expanded with extension boards, allowing system adaptation to a specific application. IMOTE2 also includes an 802.15.4 radio (CC2420) with a built-in 2.4




(a) (b) (c) (d)

Fig. 3: Deployed hardware. 3(a) Infrastructure node. 3(b) Upper User Equipment. 3(c) Lower User Equipment. 3(d) Crossroad.

GHz antenna for IN-UE data communications. A IMB400 multimedia board is used with the IMOTE2, it includes an audio output to play the speech messages (there is one message recorded per every command).

For human biometrics sensing, an integrated pulse oximetry device (iPOD model 3211, from Nonin Medical company) was used. This sensing device takes measures of pulse rate and oxygen saturation with a low power consumption. The iPOD was chosen due to its lightness, size, and easy integration in the UE (via a RS-232 interface). A specific driver in TinyOS for connectivity and iPOD control was also developed.

### D. Communication protocols

The previous elements communicate using a communication protocol stack composed by different protocols. Since nodes have to run unattended, power save was an important requisite for protocol design/selection. Therefore, signaling messages are minimal. For routing task a simple tree topology was selected. Notice that information flows are from the IN nodes to the CN, or vice versa. This suggest the *tree-form* network topology, with the CN as a root. This topology decrease the burden introduced due to signaling, and, also, simplifies routing task. At network startup, a reduced version of Level Discovery Protocol (LDP) has been implemented, that updates topology every hour, using the CN as the coordinator and as the root node of the tree.

The Medium Access Control (MAC) protocol used is a variation of B-MAC which provides unicast and broadcast transmissions. B-MAC is focused on energy consumption minimization, which is mandatory. Unicast transmissions include

| Parameter | Value |
|---|---|
| $N_{QUERY}$ | 4 |
| $T_{QUERY}$ | 10 s |
| $T_{CN}$ | 60 s |
| $T_{IN_{DATA}}$ | 120 s |
| $T_{UE_{DATA}}$ | 1 s |

TABLE I: Protocol parameter selection

an Automatic Repeat reQuest (ARQ) mechanism that guarantees packet delivery in case of wrong packet transmissions.

*1) Data exchange:* Data is gathered, periodically, by the IN and UE nodes (every $T_{IN_{DATA}}$ and $T_{UE_{DATA}}$ seconds respectively). Once the data are collected, the IN nodes send them to their parent nodes (see Figure 1), which backward them again until they eventually reach the CN. The UE records the sensed data collected in a buffer, and, group them in a packet when ready. These packets, with the sensed data, are delivered to the CN via the IN nodes, when the UE responds to a location update query.

The CN also issues orders for specific UEs by means of command packets (see Figure 1). These commands are delivered when the athlete must select another track. The CN delivers the orders by transmitting the command to a specific IN, which, in turn, handles its transmission to the UE. The specific IN is selected according to the UE position and its movement direction. Both informations are provided by the location procedure.

*2) Localization procedure:* The CN periodically (each $T_{CN}$ seconds) starts a UE search by sending a location request message, including the identity of the nodes it looks for, or, a special value indicating that all nodes must respond. Immediately, the IN nodes forward this query to all their leaf nodes using broadcast packets. If one, or more, of the sought UEs receive this packet, they answer to the transmitting IN with an unicast packet, which also includes the last runners' sensed data. Then, the IN backwards the packet to the CN. Each IN retransmits the broadcast query packet every $T_{QUERY}$ seconds for $N_{QUERY}$ times, since the broadcast packet can be lost. Finally, the CN receives the information from the IN nodes covering the runner.

The runners's direction may also be computed by the CN from the previous location records.

## V. Pilot Experiment

A pilot experiment was deployed in a cross country training circuit using the configuration parameters summarized in Table IV-D2. The goal was to keep a planned activity level for athletes. Among the different levels of activity [12], for our experiment, *cardio training* was the selected target. In cardio training activity, the athletes' HR shall be between 70% and 80% of her/his maximum value [12], which, for a healthy male person it follows the following relationship: $HR_{max} = 220 - age$.

As stated in the introduction, the following features are considered in our decision engine implementation:

- F1: Current track environmental temperature, which is considered to be divided in two ranges: "hot" (1) if

average temperature in the track is over 25 Celsius degrees or “cold” (0) for lower ones.
- F2: Next track temperature: Hot (1) or cold (0).
- F3: Current track hardness: Difficult (1) or Easy (0) tracks.
- F4: Next track hardness: Difficult (1) or Easy (0).
- F5: Average heart rate during the current track (in beats per minute, bpm).
- F6: Variance of the heart rate during the current track (in $\text{bpm}^2$).

As stated in Section III, feature values have been scaled, such that the arithmetic mean for each feature is $0$ and its standard deviation is $1$.

The Figure 4 shows operation of the decision engine. The input data is used in the *distance computing* and *majority selection* blocks. At each decisions instant ($t_{i-1}$, $t_i$, ...) the classifier compounds L *query* points, one for each one of the L possible track alternatives, from current environmental variables (temperature and track hardness) and from athlete’s HR statistics (which are calculated in the *HR average and variance* box in Figure 4 from HR samples). Then, for each query point, the *distance computing* block calculates the distance from this query point to every point in the input data table, sort them, count the label classes of the $k$ closest neighbors, and assign the most frequent class to the query point.

| Next | | Current | | | | Measured |
|---|---|---|---|---|---|---|
| Hardness ($x_1$) | Temperature ($x_2$) | Hardness ($x_3$) | Temperature ($x_4$) | Average HR ($x_5$) | Variance ($x_6$) | Class |
| 0 | 0 | 0 | 0 | 124.06 | 200.57 | 0 |
| 0 | 0 | 0 | 0 | 131.52 | 738.09 | 1 |
| 1 | 0 | 1 | 0 | 108.78 | 323.5 | 0 |
| 0 | 0 | 0 | 0 | 131.29 | 200.93 | 0 |
| 0 | 0 | 1 | 0 | 127.59 | 635.41 | 1 |
| 0 | 0 | 0 | 0 | 148.76 | 183.11 | 1 |
| 0 | 0 | 0 | 0 | 128.55 | 312.67 | 0 |
| 0 | 0 | 0 | 0 | 153.13 | 165.6 | 0 |
| | | ⋮ | | | | ⋮ |
| 0 | 1 | 1 | 1 | 81.19 | 455.38 | 1 |
| 0 | 1 | 0 | 1 | 150.49 | 297.94 | 1 |
| 0 | 1 | 1 | 1 | 90.66 | 83.74 | 1 |
| 0 | 1 | 0 | 1 | 137.45 | 11.89 | 1 |
| 0 | 1 | 1 | 1 | 120.3 | 96.18 | 1 |
| 0 | 1 | 1 | 1 | 154.56 | 12.41 | 1 |

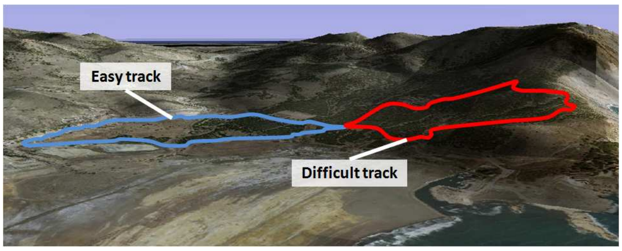
TABLE II: Data-set example

Table II contains an input data sample extracted from our experiment. Class label $1$ means “In range”, and, label $0$ “Out of range”. “In range” class corresponds with a track were at least 50% of the HR samples are in the target range. Otherwise, it is considered “Out of range”.

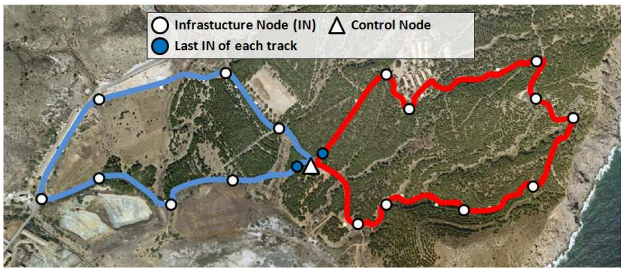
### A. Deployment

The prototype has been validated by means of a cross-country area located close to Cartagena (Spain), (Figure 5). It consists of two interconnected loops (red and blue) with different hardness and environmental conditions due to:

- Closeness to the coast in some areas of the circuit, since training by the coast is characterized by constant winds.




(a)




(b)

Fig. 5: Aerial sights of the training circuit. 5(a) Cross training circuit. 5(b) Deployed infrastructure

- Different terrain slopes, since part of the circuit is on a hill whose height is $97$ meters over sea surface, with some slopes of $14\%$.
- Shadow, depending on training hours, and the trees along the circuit (as can be observed in the red circuit in Figure 5(a)). It has influence on temperature.
- Different lengths: $1.1$ and $0.9$ kilometers for the red and blue tracks, respectively.

The *red* track is considered *difficult* due to of its length and more pronounced slope. The blue track is tagged as *easy*. We have deployed ten INs in the difficult sector of the training area and eight in the easy one, as shown in Figure 5(b). The CN is placed in the junction of both loops. The network was configured with the protocol parameters that are summarized in Table IV-D2.

TABLE III: Course profile of a training session.

| Loop | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hardness | WU | E | E | E | D | E | E | D | D | E | D | D | D |

In deployment phase, connectivity was extensively tested, with correct performance in all the tests. The ARQ algorithm in the MAC layer cope with retransmission errors (mainly produced when the UE nodes were in a shadow area), and, automatic retransmissions of broadcast packets solves concerns with location protocol messages diffusion. Simultaneous tests were carried out with three runners, and protocols operation were again correct. In this case the CN orders a general location (all UE nodes must respond) with location request messages. The tests were limited to three users since this is the number of IMOTE2 available. Similar performance would be expected with more users. However, additional test should be performed to confirm this hypothesis.

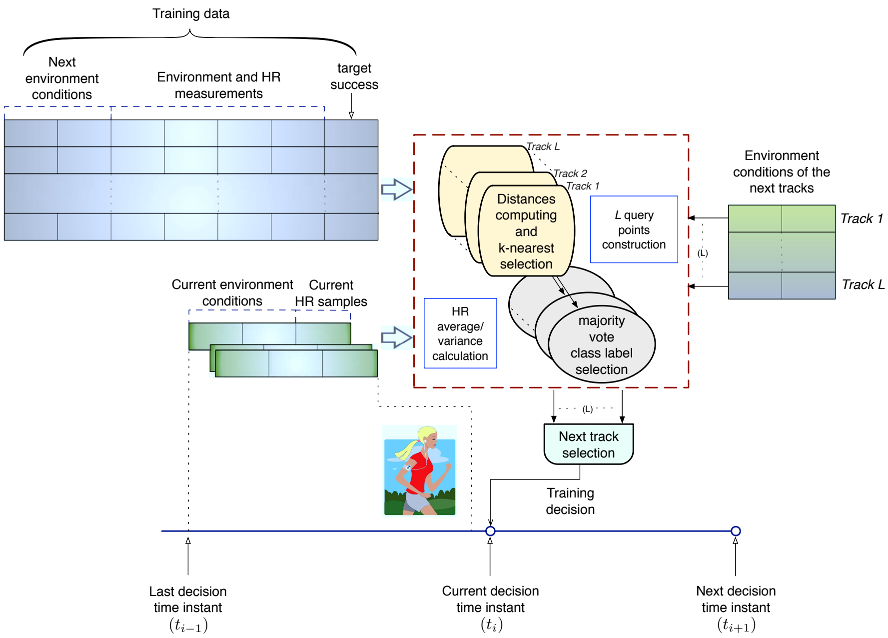



Fig. 4: Decision engine functional scheme

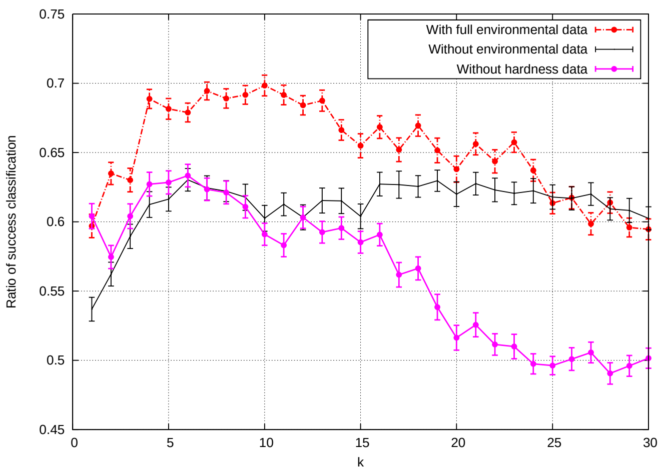



Fig. 6: Ratio of decision engine success

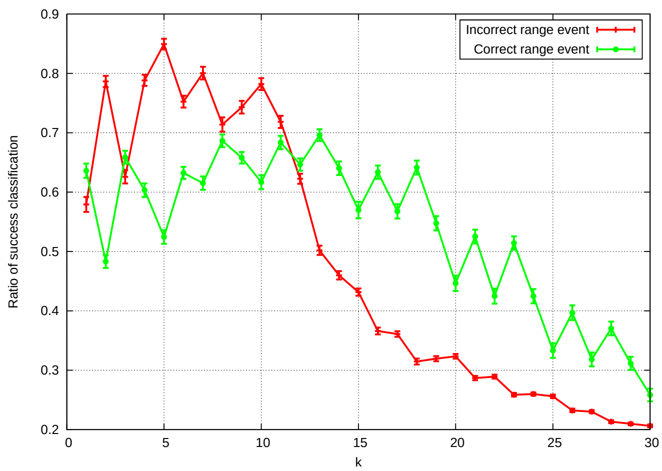



Fig. 7: Ratio of decision engine success

In addition, some parameters were measured in our test, as a reference of the protocol operation: The round trip time of a message from the CN to a particular UE (or vice versa) was less than $5$ ms per hop for a packet length of $100$ bytes including headers (the length of a packet of samples). The average location delay was $5.73$ s. (the procedure may suffer temporary fading of the communications due to shadow areas). And, finally, in the location procedure, an average number of $1.3$ nodes were detected by each UE node (note that more than one node can receive replies from the same UE).

### *B. Results*

The Figure 6 shows the classification success ratio of the k-NN decision engine implementation for a range of $k \in [1, 30]$. These results are obtained using a data base of 86 points (50% of "In range" class versus 50% of "Out of range" class), from the same athlete, that were captured over a training period of 10 days. Query points were selected extracting at random a 15% of these samples. A point is classified correctly if the real classification (notice that this is already known) matches the outcome from the k-NN classification. Besides, k-NN uses the remainder 85% points as the input data. In Figure 6 the average success ratio is depicted with its corresponding confidence interval for a 90% confidence level. It can be observed that the best results appears using a value of $k = 10$, with $70\%$ of success. This classification process was run using the same number of points for each class. Other experiments were performed using a large number of samples with unbalanced classes (20% of "In range" class points versus 80% of "Out of range" class points), but the ratio of success classifications were close to 50% (notice that a random classification achieves this level). In addition, for another athlete, with few input registers (only 7 "In range" points) the outcome of the k-NN also resembles a random classification. Therefore, we conclude that the method proposed required a balanced and large number of points of both classes.

In addition, the influence of environmental data on the success ratio was measured. Figure 6 shows the results if no environmental data (neither temperature nor track hardness is used) and if no track hardness is used. As can be clearly seen, both results are worse than the outcome if all the environmental data is used. We conclude that if decision is taken from only HR statistics, success percentage is 10% inferior in the considered range of $k$. Surprisingly, for large values of k ($k > 15$) system classification ratio increases if all environmental data is eliminated.

Finally, Figure 7 shows the ratio of classification for the different classes. That is, the probability of successful classification if the data point actually belongs to the "In range" class, or to the "Out of range" class, respectively. It can be observed that both curves decrease as $k$ increases, with a sharper decrease in the case of incorrect classification event. Moreover, notice that two types of errors are possible in the classification:

- Error I: Do not select an "In range" track.
- Error II: Select an "Out of range" track.

For the selected value of $k = 10$, the Error-I type is more likely than Error-II (37% of probability versus 23%), and this is beneficial for our problem: Error-II consequence is that user will be outside the selected HR range, and this situation must be avoided. However, if another tracks are suitable, Error-I has no consequence (since the user do not exceeds the selected HR). This observation also suggest that $k = 5$ may be a good option (16% of Error-II probability versus 46% of Error-I probability). However, in this case, the number of possible track selections must be enough to guarantee that a path is selected as suitable.

## VI. Conclusion

This work demonstrates the feasibility and the benefits of an ambient intelligence system applied to the practice of outdoor running sports. Personalized real-time feedback to sport practitioner is provided, considering runners performance, temperature and track conditions.

In addition, a prominent outcome of this study is the decision method developed by means of a k-NN classifier, which features a success ratio up to $70\%$. These results could be improved with the increase of input data points. Results demonstrate that if environmental information is not taken into account to derive training orders, the success rate is reduced notably.

Future developments aim at improving success ratio by means of performing new experiments extending classification features, for example, including environment humidity or information of the time elapsed in the circuit by the athlethe. The use of other classification methods, such as support vector machine, should be also tested.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