Position Recognition to Support Bedsores Prevention

Paolo Barsocchi
ISTI-CNR, Pisa Research Area, Via G.Moruzzi 1, 56124 Pisa, Italy {paolo.barsocchi@isti.cnr.it}

***Abstract*— A feasibility study where small wireless devices are used to classify some typical user's positions in the bed is presented. Wearable wireless low-cost commercial transceivers operating at 2.4 GHz are supposed to be widely deployed in indoor settings and on people's bodies in tomorrow's pervasive computing environments. The key idea of this work is to leverage their presence by collecting the received signal strength (RSS) measured among fixed devices, deployed in the environment, and the wearable one. The RSS measurements are used to classify a set of user's positions in the bed, monitoring the activities of patients unable to make the desirable bodily movements. The collected data are classified using both Support Vector Machine and K-Nearest Neighbour methods, in order to recognize the different user's position, and thus supporting the bedsores issue.**

***Index Terms*— Classification of user's positions in the bed, K-Nearest Neighbour (K-NN), Received Signal Strength (RSS), Support Vector Machine (SVM), bedsores prevention.**

I. Introduction

The last few years have seen research development in the field of Pervasive Systems. These researches was focused on network infrastructures (e.g. UMTS, WiFi networks), distributed software architectures (e.g. distributed middleware) as well as context information models to support pervasive computing applications in smart environments. The pervasive smart environments leveraging smart devices have the ability to support user's daily life activities through efficient context evaluation systems that support activities for different users requirements. At the same time application adaptation for these activities is also required in response to changes from the environment. Current research focused in pervasive systems has shifted towards user activity recognition based on their daily lifestyle activities that has tremendous potential to support pervasive applications, especially in the health care domain. Activity recognition is an important issue for healthcare since sufficient information about patients is vital for an effective care. Monitoring the activities of patients enables hospital staffs to provide specialized care. For example, in a pervasive hospital, a nurse can use a mobile activity monitor to provide immediate care for patients in need of assistance or in risky situations [1]. Also in home environment, due to decline in both physical and mental abilities, some elderly are not allowed to leave the bed without assistance. An elderly person may suffer problems related to falls when they are trying to get out or move from the bed without caregiver attendance. On the other hand, they are often unable to make the desirable bodily movements and repositioning that are critical for blood circulation and relieving of prolonged pressure over the body. Thus two critical conditions, namely bedsores [2] and bed-side falls [3] commonly occur among elderly persons due to lack of desirable nursing care and immediate attention. For these reasons, continuous observation of the patients is necessary in order to prevent the above mentioned adverse effects. Position recognition for elderly persons can support pressure ulcer prevention in two ways. Firstly, self-movements can be monitored in order to support risk assessment, thus it may be useful to make prognostications for bedsores. Secondly, it can help the caregiver to decide the care program of the elderly patients, since grasp the frequency of the posture changes and assess the need of the care accurately, decreases the burden of the caregiver to prevent the bed sore. In [4] the authors propose the use of pressure sensing to monitor context and behavior of subjects on the bed. In fact, the pressure evidences can assist in determining the elderly persons position. Instead, in this work we verified that the use of a generic and not specific wireless devices (such as sensors) can be exploited to infer the elderly position. Usually, the elderly person are monitored with wearable sensor devices that communicate through a Wireless Sensor Network (WSN) the medical data (such as pressure, heartbeat, etc...) to a server. We leverage the Receive Signal Strength (RSS) exchanged between the wearable sensor and the WSN to infer the patients position. Since the RSS does not require a special or a sophisticated hardware and it has become a standard feature in most of the wireless devices, the proposed technique is simple and minimally invasive. A wide variety of techniques and algorithms are found in the literature to classify measurements for posture and movement recognition. Most of them are based on traces collected using accelerometers and gyroscopes. Techniques range from feed-forward back propagation neural networks [5] to discrete wavelet transforms [6], support vector machine (SVM) techniques [7], [8] and hidden Markov models [9]. In this paper Support Vector Machine (SVM) and K-Nearest Neighbour (K-NN) classification techniques were implemented to recognize different activities, due to their success in many classification problems [7], [8]. Our purpose is not to present a finely tuned and well-engineered algorithm, but to show that standard classification methods have the potential to solve the problem with acceptable accuracy.

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II. Motivations

Nursing home requires a caregiver that ideally observes the elderly around the clock to prevent bedsores. The caregivers have to provide an high degree of surveillance and attendance to the elderly all the time. Moreover, the knowledge and personality of caregivers affect the quality of nursing care. Lack of timely care and insufficient preventive measures taken by human caregivers leads to unfortunate consequences to be suffered by the elderly and also indirectly affects their family members. This can lead to further escalation in the already mounting healthcare costs for the government, and degradation of Quality of Life (QoL) for the elderly. The bedsores can be mainly caused due to unrelieved or constantly applied pressure over bony and bedsore-prone areas of the body. Bedsores are regarded as one of the serious diseases and take a long time to completely heal [10]. Sometimes, the damage is so huge that a surgery is needed to recovery the QoL, with the unavoidable healthcare costs for the government as well as the sufferance by the elderly and by their family members. The most widely accepted ways of preventing bedsores is to keep patients clean and dry. This means removing soiled clothing and bedding as soon as feasible and bathing patients regularly. Additionally, caregivers must actively turn the patients who have limited mobility on a regular basis (every 2 h) to avoid unrelieved pressure from forming on the body.

In this work we propose a system able to automatically assess the bedsore risk, and able to help the caregiver to decide the care program and thus increase the quality of nursing care.

III. The Proposed Solution

The goal of our work is to infer the elderly position in the bed, without using an ad-hoc or sophisticated hardware. In fact, we suppose that the elderly/patient will have on him wireless devices able to monitoring (i.e. pressure, heartbeat, etc...) and to communicate with a server medical data. We propose to leverage the Receive Signal Strength (RSS) transmitted from the wireless device to the server, in order to infer the patient bed position. By doing so, we would be able to support the bedsores prevention, alerting the caregivers if the position of the patient keeps fixed for a long time, and tailoring the interventions to the patient's current needs. In the following we will describe the equipment architecture, and the proposed system.

A. Experiment setup

In order to investigate how the RSS exchanged between wireless devices can be used to infer the elderly position in the bed, we test our systems by using a Wireless Sensor Network composed by Crossbow IRIS transceivers [11] operating at 2.4 GHz (ISM band) according to the IEEE 802.15.4 protocol [12]. The sensors include an Atmel Atmega1281 microcontroller, 128 KiB flash memory to store the executable code, 512 KiB serial (slow) flash memory to store data, 8 KiB RAM. The transceiver is powered by two AA batteries and draws 8 mA in active mode plus 17 mA in continuous Tx mode at max power (3 dBm) and 16 mA in Rx mode. The antenna is a $^1/_4$ wave monopole. Measurements were performed in a single bed by two different persons, a 1.68m height and 63 kg weight female (hereafter user A), and a 1.78m height and 95 kg weight male (hereafter user B). Finally, the environment

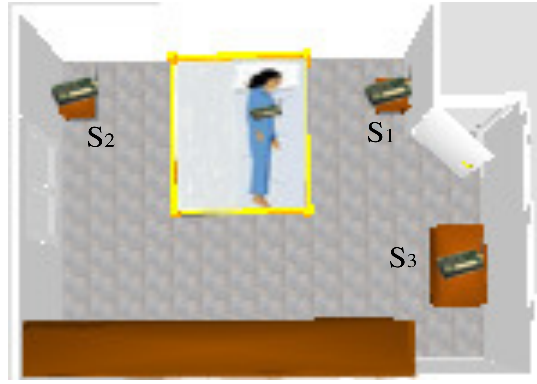


Fig. 1: Setup environment, composed by the bed, wardrobe, nightstands and a dresser.

chosen to test the proposed solution is a typically bedroom with wardrobe, nightstands and a dresser (Figure 1). Three fixed sensors are placed on the environment as highlighted in Fig. 1, two sensors were placed at about 55 cm height (S_1 and S_2), while the last one (namely S_3) was placed on the dresser at about 85 cm height. The users wear a mobile sensor that was placed on the breast.

B. Bed positions

The proposed system is composed by a sensor node placed on the breast of the patient and by a fixed off-body motes connected to a server. The on-body mote emulates a more general wireless monitoring device that periodically transmit the sampled health data to a server with a fixed power. The receiving motes sample the received beacon, estimate the RSS and send it to the server, that processes the measures. The bed position in the bed has been inferred through a classification procedure, that assigns a given object to a given number of classes. The bed positions we take into account in this work are summarized in Table I. We conducted a series of experiments (fifty) that consist on cyclical repeat all the bed positions in Table I. The single bed position are held at least 10 seconds, and the fifty repetitions, for both volunteers, were performed in different days to verify the experiment repeatability. The sampling frequency should be chosen considering on one hand the computing constraints and networking overhead, which are both directly responsible for power consumption in the sensors, and on the other hand RSS waveform reconstruction accuracy. Given the relatively slow motion, it was possible to set the sampling rate to a no compromise value of 8 Hz.

C. Classification methods

Classification is a procedure that assigns a given object to a given number of classes. A classifier is trained using a training dataset where the class of each object is known. After training, the classifier should be able to assign a new object to its right class: in the testing phase the classifier is applied to a testing dataset. By comparing the classifications made on the testing dataset, the performance of the classifier is evaluated. In our case, each bedside position (a class) produced three traces (one for each receiver, S_1, S_2, and S_3), each

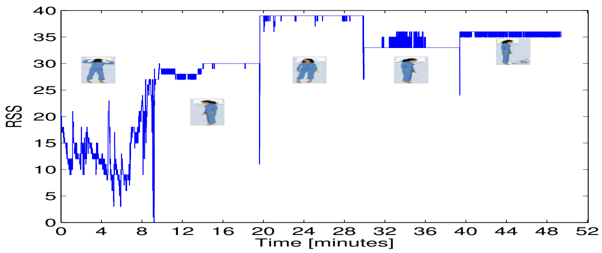
TABLE I: Schematic representation of the considered positions

Prone - Position 1	**Left Lateral - Position 2**	**Supine - Position 3**	**Right Lateral - Position 4**	**30°Lateral - Position 5**
				
lie on their bellies with head turned to the side	sleep on left side with both arms down	lie on their backs with arms up or down	sleep on right side with both arms down	the body is placed in a 30-degree laterally inclined position

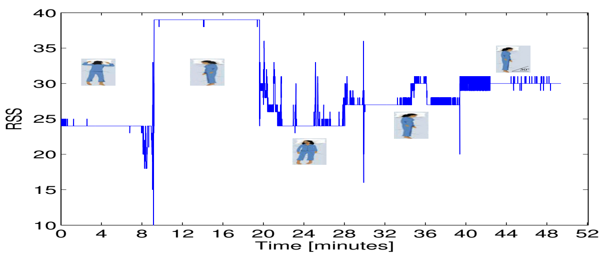
composed of 80 RSS samples. Each triple-traces is an object to be classified. Most classifiers work in a feature space, which is a multidimensional space where each object is represented by a point. In the feature space, the coordinates of the point are the values of the object's features. A feature can be any quantity that is significant for the object. Usually, features are normalized, so that all points lie in the unity hypercube of the feature space. The most important step in classification problems is the choice of relevant features. The number of features should be as low as possible to avoid overfitting and reduce computational complexity. Their number should be sufficient to distinguish the objects, namely to assign each position to the right class. In our case, each object (a triple of RSS traces) was identified by up to four features, as described in the next section. The specific features extracted from the RSS traces were chosen using Weka, a collection of tools for data pre-processing, classification, clustering and more [13]. Weka was also used to compare the performance of two different classifiers working in the same feature space; K-Nearest Neighbour (K-NN) and Support Vector Machine (SVM). The first is a supervised learning algorithm where new objects are classified based on a voting criteria: the K nearest objects from the training set are considered, and the new object is assigned the class of the majority of those. The training phase of the K-NN algorithm consists in storing the features and the class label of the training objects. In the classification phase, an unlabelled object is classified by assigning the most frequent label among those of the K training samples nearest to it. Various distance metrics can be used, the Euclidean distance being the most common. In this work we used the most basic settings for the algorithm: Euclidean distance and K set to 1. This means that the class label chosen was the same as the one of the closest training object. The latter is a sophisticated learning technique that can deliver good detection and classification performance. In its basic form SVM is a binary linear classifier, meaning that it assumes linear separability of two classes of data and attempts to find a hyperplane in the feature space separating the data points of the two classes. The optimum separation is achieved by the hyperplane that maximizes its distance from the marginal data points on each side (the support vectors), that is the maximum-margin hyperplane. Computation of the hyperplane can be made using quadratic programming, a computationally efficient optimization technique. The first improvement on the basic form of the SVM is to account for data sets that can not be clearly separated by a hyperplane, by using soft margins. This means that the algorithm chooses a trade-off between a large margin and the possibility of some points being misclassified. The second improvement, which makes the method so powerful, is to map the non linearly separable classes into a high dimensional feature space where the classes become linearly separable using a non-linear kernel function [14], [15]. What makes this technique computationally efficient is that, by choosing an appropriate kernel function, quadratic programming can still be applied [14], [15]. In this work, the classical Pearson kernel function was chosen as one of the best performers. Binary classifiers can be combined to solve multiclass problems. An one-against-one approach was used to tackle the multiclass classification problem. The classification is made by a max-wins voting strategy. A specific classifier is trained for every pair of classes (in our case a class was associated to a specific position). For a test sequence, each classifier assigns one vote, and the object is assigned to the class with the highest number of votes. For both classification methods, classification performance was computed by using a 10-fold cross-validation technique. An object set (a triplet of traces, for each position) was randomly subdivided into 10 equal-sized partitions: 9 of them were used as the training dataset and the last one was used as the testing dataset. The same procedure was repeated 10 times, until each partition was used for testing. In this way, each object was used exactly once for testing. The performance results will be evaluated measuring the error rate i.e., the number of misclassifications divided by the total number of trials, and the true positive (TP), and the false positive (FP) rates. As highlighted in table II, for a given Position P, true positive rate is the correct classifications with respect to the total number of objects (i.e., the sensitivity), while false positive rate is the erroneous position classification with respect to the number of times the algorithm chooses P (i.e., one minus the positive predictive value).

TABLE II: Relationships among terms

		Condition		
		P_x	Other Positions	
Test Outcome	P_x	True Positive	False Positive	FP rate = $1 - \frac{\sum TP}{\sum TP + \sum FP}$
	Other Positions	False Negative	True Negative	
		TP rate = $\frac{\sum TP}{\sum TP + \sum FN}$		



(a)



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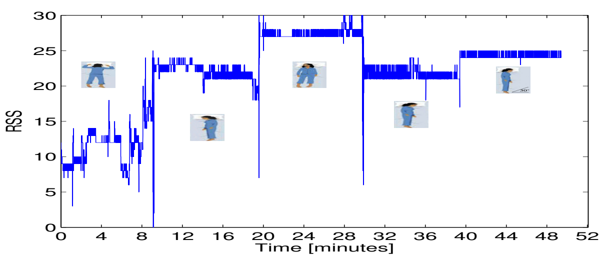

(c)

Fig. 2: Samples of RSS traces of the five different bed position estimated from sensors a) S_1, b) S_2, and c) S_3.

IV. Results and Discussions

A. Preliminary RSS traces analysis

Figure 2 presents an example of typical RSS 40 minutes-registrations for the bed positions. The variations between RSS traces relevant to different user position are clearly apparent. In particular, the RSS values when S_3 is used for the left and right lateral positions are quite similar, as well as the prone and supine position for S_2. For this reason, exploiting more sensors and/or more RSS features we can increase the classification performance, distinguishing the different user positions. In the following, we will describe the features extracted from the RSS traces in order to classify the user position and we will show the obtained performance.

B. Feature extraction

The first step of the classification procedure was to identify a limited number of features that act as the "fingerprint" of a trace. An initial large set of possible features was defined, from which the best performers were chosen using the feature selection tools provided by Weka. In the set of possible features we considered both time-independent and time-series based statistics. As far as time-independent statistics are concerned, the ones involving only one transceiver (either S_1, S_2 or S_3) were: mean value μ, standard deviation σ, skewness, kurtosis. The one involving two transceivers (chosen among S_1, S_2 and S_3) was the cross-correlation ρ. As far as time-series based statistics are concerned, we considered the level crossing rate (LCR) at four different thresholds, firstly computed on each devices separately, and secondly on the difference of the devices' RSS measurements. The LCR is a statistical parameter that quantifies how often the signal crosses a given threshold in the positive-going direction. The four thresholds considered in this work were LCR1 at $\mu - 0.5\sigma$, LCR2 at $\mu+0.5\sigma$, LCR3 at $\mu-\sigma$ and LCR4 at $\mu+\sigma$. A features short list was selected from the initial large set data in order to optimize classification performance. If two of the three transceivers are used, the list of features includes two mean values among μ_1, μ_2, or μ_3, and two standard deviations σ_1, σ_2, or σ_3. If only one sensor is used, the feature list includes the mean value μ, the standard deviation σ, LCR2 and LCR4. An example of how some features are distributed, changing the number of exploited sensors, is shown in Fig. 3. As shown in Fig. 3a, exploiting only one sensor and hence LCR1, μ, and σ, the Position 1, and 3 are well separated from Position 2 and 4, which means that Positions 1 and 3 can be well recognized. Whereas Position 2 and 4 are more difficult to identify and may be confused each other. Instead, when we chose to exploit all the three sensors and μ_1, μ_2, and μ_3, Fig. 3b shows that all the Positions can be easily recognized since the features are well distributed.

C. Experimental results

Performance of the proposed system is measured in terms of error rate or, equivalently, of matching rate (i.e., its complementary) and in terms of TP and FP rates.

Classification. Figure 4a shows the error rate using only sensor S_3 as a function of the number of features, for both persons (users A and B) and both SVM and K-NN algorithms. We chose the sensor S_3 since it did not get neither the best nor worst performances. Firstly, one feature was considered (μ_3) achieving about 80% of matching rate for both users and both algorithms. The matching rate increases with the number of features, as expected. In fact, when using four features (μ_3, σ_3, LCR2, and LCR4) 90% matching rates were achieved. In this case the use of LCR4 does not significantly improve the performance. Performance in terms of error rate shown in Fig. 4a is better when used K-NN algorithms instead of SVN one. Fig. 4b shows the TP and the FP rates, considering sensor S_3, user A, both algorithms, and only one features (μ_3). Position 1 exhibited 100% TP and 0% FP, Position 2 was classified with 61% TP and 11% FP, Position 3 was classified with 100% TP and 0% FP, Position 4 was classified with 52% TP and 10% FP, and finally Position 5 was classified with 98% TP and 1% FP ,when the K-NN algorithm was chosen. Position 2 (left lateral) together with Position 4 (right lateral) presented the highest value of FP, which means that it was the most often misclassified one. In fact, as we will see later these two position are misclassified each other, i.e. the Position 4 is classified as 2 and vice-versa. Moreover, Position 1 (prone) and Position 3 (supine) had the highest value of

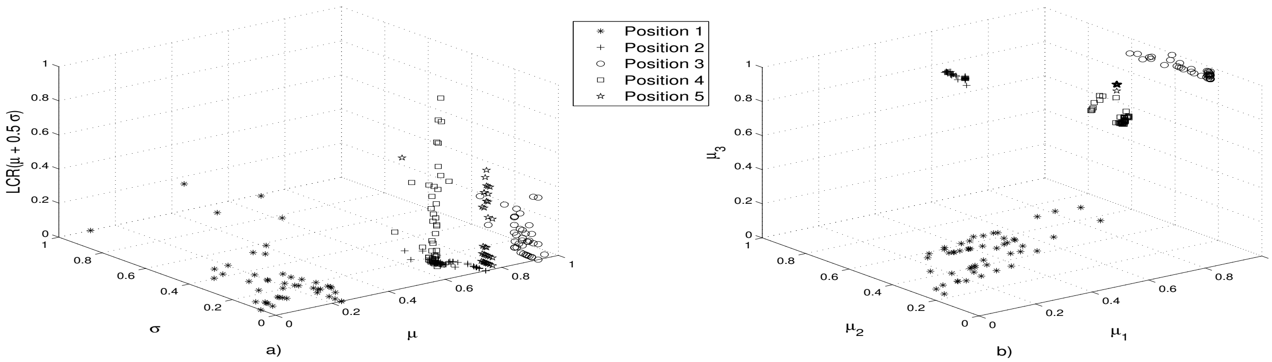

Fig. 3: Two examples representing objects in their feature space (a) using S_3 and hence μ_3, σ_3 and LCR2 and (b) using three sensor and μ_1, μ_2, or μ_3.

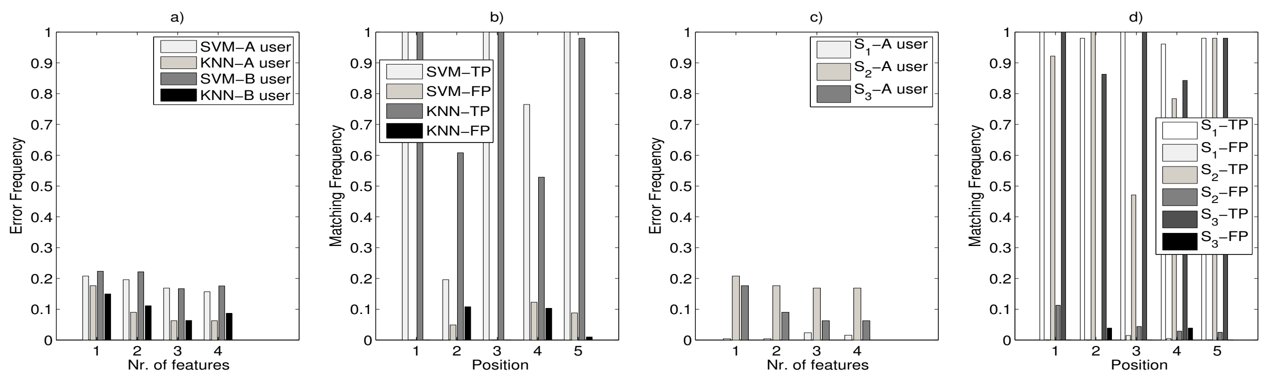

Fig. 4: Classification performance using SVM and K-NN for the bed positions: a) shows the error rate as a function of the number of features of sensor S_3, evaluated for both users A and B; the features considered were μ_3, σ_3, LCR2, and LCR4, b) shows True Positive and False Positive Rates for each bed position, user A, one feature of the sensor S_3 (μ_3), c) shows the error rate as a function of the number of features using the K-NN algorithm for each sensor, user A, d) shows True Positive and False Positive Rates for each bed position using K-NN algorithm for each sensor, user A, four features (μ, σ, $LCR1$, and $LCR4$).

TP, making them the most correctly recognized movements. When the SVM algorithm was used, Positions 1, 3, and 5 were the most correctly recognized movement, while Position 2 was the most often misclassified one. In order to evaluate which transceiver performs better, the performance of the K-NN algorithm for the A user is shown (SVM performance being similar for both users). Fig. 4c shows the classification error rate for A user, for each sensor S_1, S_2, and S_3 as a function of the number of features. The features considered were μ, σ, LCR1, and LCR4 for each sensor. Sensor S_1 exhibits better performance, probably since it experienced greater RSS variations with respect to the other sensors, and hence the algorithm is able to better distinguishes the various positions. Fig. 4d shows TP and FP rates for user A using four features (μ, σ, LCR1 and LCR4) of sensor S_1, S_2, and S_3, using K-NN classification algorithm. Positions 1 and 3 were always recognized when using K-NN (100% TP) and was rarely confused with other positions (about 2% FP regarding the Position 3) by leveraging the RSS from S_1 or S_3. Position 2 shows 100% TP and 0% FP when using S_2, while Position 4 was classified with 84% and 96% TP, 4% and 0.5% FP by using S_3 and S_1, respectively. Concluding, using only one sensor device, the better performance are achieved by using the sensor S_1, probably because is more in Line of Sight region (LOS) with respect to the other cases and it is more close to the mobile device. In this case 3 features (μ_1, σ_1, and $LCR1_1$) is sufficient, and the choice of the classification algorithms is not critical. If we want to reach a 100% of matching rate for all the considered positions, the conducted experiments show that at least two of three sensors should be selected.

Finally, confusion matrices for the analyzed classification problem are presented in Fig. 5. Confusion matrices are a compact graphical representation where each row of the matrix corresponds to the position assigned by the classifier (predicted class), while each column represents the position performed (actual class). A classification method with ideal performance will only have bars on the main diagonal of the matrix. The more bars on the non-diagonal cells are high, the worst the classification performance. As far as the SVM algorithm is concerned, and only one feature case (μ_3) there was moderate confusion between Position 2 and Position 4. In fact, 49% Position 2 (left lateral) was misclassified as Position 4 (right lateral), and 31% as position 5, while 20% Position 4 was misclassified as Position 2. On the other hand, Position 1, 3,

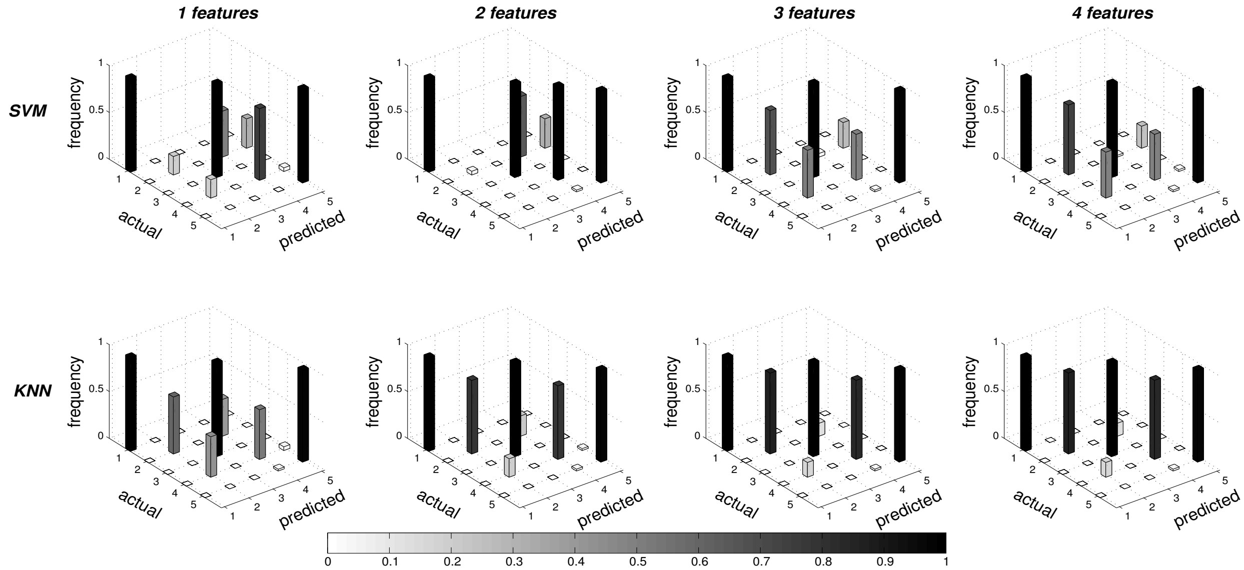

Fig. 5: Confusion matrices for the bed positions. The two axes on the base of each graph represent the actual position class and the class predicted by the algorithm, respectively. The performance is given in a matrix fashion; two rows (one for each classification method) and four columns (for each selected features) of the sensor S_3 (μ, σ, $LCR1$, and $LCR4$). The smaller the bars outside of the main diagonal, the better the performance.

and 5 were well recognized (100% of matching rate) even with one features only. As expected, the greater the number of features, the less the error rate, except for the Position 4 that also using four features was misclassified in the 50% of cases with Position 2. The K-NN algorithm performs better, in fact only 15% of cases was misclassified with the Position 2 (left lateral). This means that the sensor 3 didn't recognize the right position with respect to the left position. This behavior is due to the location of sensor 3 that was near to the right corner of the room at the end of the bed. Sensor 1 performs better with respect the other sensors, in fact by leveraging 2 features it achieved the 100% matching rate (Fig. 4c).

Movement detection. As shown by the previous analysis, passing from a LOS to a non-LOS condition (between fixed and mobile sensor) is beneficial, as it has the potential of amplifying the RSS variations during the movement. Moreover, complete lack of LOS, due to the user position, may be detrimental, because it has potential for lowering the overall strength of received signal and its information content. These considerations, however, help us on recognizing not only the users position, but also to correctly identify if the user change its position (as required to support risk assessment and to plan the caregivers interventions). Figure 6a shows the error rate on recognizing if the user moves from one position to an other, as a function of the number of features (μ, σ, $LCR1$, and $LCR4$). As expected from the previous analysis, S_1 performs better (100% of matching rate with one or two features exploited) with respect to the other sensors due to its vicinity and LOS condition with the mobile sensor. Moreover, the K-NN algorithm performs about 10% better than the SVM one. In order to support risk assessment, the FP analysis is essential. In fact, if the system recognize the immobility of the user while the user has moved, the number of the needed caregiver interventions will be overestimated. On the contrary, i.e., the system recognize a motion of the patient while he/she was motionless, the number of the needed caregiver interventions will be underestimated. Figure 6a shows this analysis reporting the false positive rates as a function of the number of exploited features when the K-NN algorithm, the A user, and the sensor S_3 is used. Leveraging three features the proposed method reaches only 2% FP when the motion is considered, while 8% FP for the motionless case.

V. Practical Usage

Objective of this work is to identify the elderly position in order to support pressure ulcer prevention. The proposed system reaches this goal in two ways; i) analyzing the self-movements in order to make prognostications for bedsores and plan the caregivers interventions, and ii) decreasing the burden of the caregiver to prevent the bedsore. We reach this goal by only leveraging the RSS measurements already available on small wireless communication devices. We envision that these devices are going to be extensively deployed in indoor environments in the near future, for communication and control purposes. The idea is to exploit the ubiquity of wireless sensors to obtain measurements "for free". The outcome of this feasibility study is twofold. Firstly, it is possible to recognize movements without the need of ad hoc sensors, provided that wireless transceivers are already installed on the human body for medical purposes. Secondly, if dedicated sensors are already installed for this purpose, their results can be complemented with RSS measurements, thus potentially improving accuracy and reliability.

Although this study has been conducted on only two healthy persons, the results can be generalized to sick elderly patients. In fact, we proposed a system that needs a training phase, this

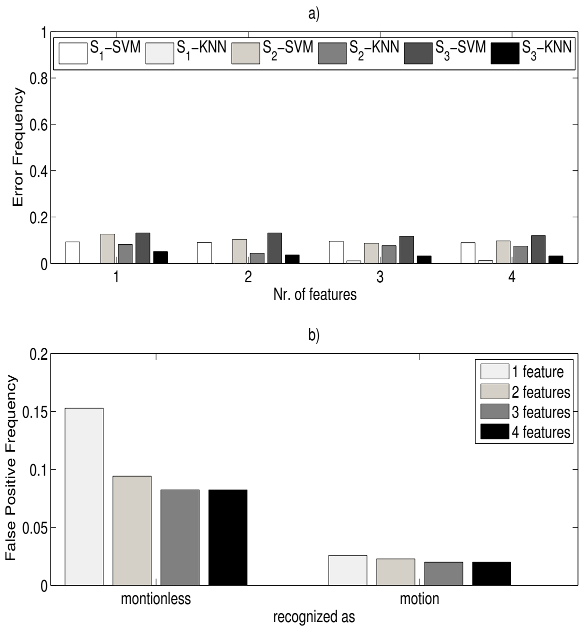

Fig. 6: Movement detection (motion or motionless) using SVM and K-NN: a) shows the error rate as a function of the number of features using the both algorithms for each sensor, user A, b) shows the false positive rates for each position as a function of the number of the exploited features, using K-NN algorithm, S_3, and user A.

means that the system dynamically adapts to the environments and to the characteristics of the patients. Moreover, this work shows a clear difference among RSS behaviors for each bed position (Fig. 2 and 3), hence classification techniques are suitable in this context.

Like all the systems that use classification methods, the performance depend on the number of classes (i.e. the number of positions to recognize). Generally speaking, increasing the number of classes, the matching rate decreases. This effect can be overcome increasing the number of the deployed sensors. In fact, in this work we showed that using together features coming from two different devices, the 100% of matching rate is reached.

VI. Conclusions

The automatic recognition of the patient's position, is essential to support the bedsores prevention: measurements showed that it is possible to use low-cost transceivers to classify the patient's positions. Good classification performance can be achieved by using only the received signal strength measurements relevant to two wireless sensors (a wearable and a fixed one). Moreover, the performance increases if, as required by the proposed system, we concentrate only on the movement's detection instead of on its classification. A simple K-NN classifier performs better than a more sophisticated SVM classifier. The features considered for classification are computationally inexpensive and only a few (three to four) were sufficient to obtain a good identification accuracy, even for relatively similar positions. Our analysis suggests to place a fixed sensor close to the patient (as on the nightstand) in order to guarantee the LOS condition and obtain 100% of matching rate.

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