Estimating Hospital Work Activities in Context-Aware Healthcare Applications

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Abstract—Hospitals are convenient settings for the deployment of context-aware applications. The information needs of hospital workers are highly dependent on contextual variables, such as location, role and activity. While some of these parameters can be easily determined, others, such as activity are much more complex to estimate. This paper describes an approach to estimate the activity being performed by hospital workers. The approach is based on information gathered from a work study conducted in a hospital, in which 196 hours of detailed observation of hospital workers was recorded. This data is used to train a back propagation neural network to estimate user activity based on contextual variables such as location, artifacts being used, the presence of colleagues and the subjects’ activity. The results indicate that the user activity can be estimated with 75% of accuracy (on average) which could be sufficient for some applications. We discuss how these results can be used in the design of activity-aware hospital information systems.

Index Terms—Activity estimation, Context-aware computing, Hospital activities, Neural networks.

I. INTRODUCTION

Hospitals are good candidates for the introduction of ubiquitous computing technology [2, 4]. These are working environments filled with increasingly complex technology, including computers and sensors, where patient care requires coordination and collaboration among specialists; and the working staff is highly mobile and technology savvy. Indeed, some elements of ubicomp are gradually being introduced in hospitals. These range from wireless networks, PDAs [6], RFID tags for patient tracking [20], voice-activated communication devices [24], and sensors for patient monitoring [21].

One of the challenges of hospital work is the management of large amounts of information, including patient records, medical guides, and scientific papers used for evidence-based medicine [15]. The information needs of hospital workers are highly dependent on contextual information such as location, role, time of day, and activity. For instance, the document more relevant to a nurse attending a patient might be that patient’s chart, while for a physician might be the patient’s health record.

This has motivated the development of context-aware applications that adapt to changes in the environment to better assist hospital workers [1, 19]. These applications focus mostly on supporting intra-hospital communication and information access based on user location and role. In this regard, considerable work has been done in the development of robust approaches to location estimation for in-door working environments [13]. Although, other contextual variables such as role and time of day can be easily determined, estimating the activity being performed is not an easy task.

In this work we present an approach for the automatic estimation of the activity being performed by a hospital worker. This approach is based on the use of a neural network trained to map contextual information such as location or artifact used with user activity. The classifier is trained and evaluated with data captured from close to 200 hours of detailed observation and documentation of hospital workers.

Activity information could be relevant for a number of hospital applications, such as deciding whom to call for help or facilitating access to relevant patient information. For instance, the Vocera communication system uses a voice-controlled badge to enable mobile users to communicate over the wireless network currently being used in some hospitals [24]. This system enables a physician to place a call to “a nurse in the emergency unit”. If the user’s activity could be accurately estimated, a system such as this one might be able to decide which of the nurses to call based on their perceived availability.

We can consider as an additional example of an activity-aware nurse chart. Hospital workers, nurses in particular, spend a considerable amount of time documenting their work. If the system is aware of the nurse’s activity, for instance the fact that she is administering medication to the patient in bed 109, this information could be automatically recorded, or at least present to the nurse, in her PDA or tabletPC the record where this information will be registered.

The rest of the paper is organized as follows: In Section II we describe a user study conducted in a hospital to determine the activities performed by hospital staff as well as to gather the data used to train and evaluate the activity classifier. Section III describes the architecture and training of the neural network that estimates user activity, as well as the contextual variables used as input to the classifier. The results obtained are presented and discussed in Section IV. In Section V, we present some implications for the design of activity-aware applications for hospital work. Section VI describes the previous work related to activity estimation and how it compares with the approach being proposed. Finally, Section VII presents our conclusions and directions for future work.
II. ACTIVITIES PERFORMED BY HOSPITAL STAFF

We conducted a series of workplace studies in a mid-size public hospital in the city of Ensenada, Mexico. We studied the Internal Medicine area where more than 70 percent of the patients are attended. A preliminary study, was conducted in this area, aimed at revealing the time hospital workers spend performing different activities; the distance they move, the places they move to and the reason of doing it; the people with whom they collaborate more often and the artifacts they use in support of their work [18]. The main contribution of this study consists of the characterization of mobile work and the information usage practices that hospital workers engage in. Then we conducted a more detailed study to gather additional data. In particular, we recorded the user’s location, time of day, artifacts being used and the presence of collaborators. This information can be used to estimate the user’s activity (which we recorded as well) if one is familiar with the hospital’s rhythms of work. Temporal patterns or “rhythms” are used by hospital workers to coordinate their activities and contribute to the regular temporal organization of work in the hospital [23]. These rhythms are often used by hospital workers to infer the activity conducted by colleagues. For instance, one can infer that a physician is in a ward round from being in a patient room, with medical interns at 11am.

The study was conducted for a period of eight months, where five medical interns, five nurses and five physicians were shadowed for two complete working shifts and interviewed by a several researchers. These roles were selected because they experiment frequent task switching and are responsible for patient care. Each subject was introduced to the study, and was asked to participate voluntarily. Figure 1, shows pictures of the subjects while working during a day of observation.

The following lines provide a general description of the activities performed by these three roles:

1) Nurses. The internal medicine nursing staff includes five nurses who are responsible for the care of five or six patients depending of the number of patients per area. They provide most of the hours of patient care in the unit and they are constantly changing their activity. Some of the activities performed by nurses in a work shift include: shift connection, patient care, coordination, and paper work.

2) Physicians. There are two attending physicians in charge of each area of the hospital per shift, with fifteen to twenty patients per area. The activities performed by physicians during a work shift include: exchange with colleagues information related to events that arose in their absence, conduct exploratory and interrogatory evaluations of patients, update medical notes with tailored treatments and diagnoses, train and evaluate medical interns, discuss with colleagues special clinical cases and participate in surgical procedures.

3) Medical interns. There are five rotating medical interns in the area who are responsible for the care of five or six patients. One of their main responsibilities is to create clinical histories whenever a new patient arrives in the hospital. They are also responsible for providing care and following-up on patients during their stay in the hospital. Other tasks for which medical interns are responsible have a more collaborative nature, such as participating in ward rounds with attending physicians and in meetings where clinical cases are discussed.

Scenario: A typical day of a medical intern

To illustrate the different activities, as well as, “rhythms” [23] experienced by hospital workers we present a scenario that describes a typical working day of one of the medical interns observed. Figure 2 depicts the changes between activities described in the scenario:

The medical interns meet at 7 am with the attending physician at the internal medicine office, where they briefly discuss the night’s events described by the intern who was working on the night shift. After the discussion, the interns gather the information related to the patients assigned to them and place it in each patient’s bedroom. They walk down to the laboratory to gather the laboratory results of the patients, and attach them to the medical record. Later, the medical interns meet at the internal medicine office and for one or two hours, they listen to a colleague’s assessment of a particular medical issue. After that, they go to the bed wards where along with the physician they conduct the ward round. They discuss each patient’s clinical case consulting the patient’s medical record and their studies. Finally, once the medical intern has finished the round, which occasionally lasts until 1-2 pm, the rest of the shift is spent mostly doing paperwork at the internal medicine office.

The total time of detailed observation was about 196 hours and 46 minutes, with an average time of observation per informant of 13 hours and 7 minutes. To enhance our understanding of their practices and to clarify issues, we conducted one hour interview with each informant after the period of observation.

To understand the medical behaviors experienced by those observed, we conducted a qualitative analysis of the data collected. The particular qualitative approach we followed was inspired by the techniques to derive grounded theory originally proposed by Strauss and Corbin, [25]. For our particular case, the qualitative technique of analysis involved continuous sense making of the information collected including interview transcripts, personal notes and documents. As a result of this analysis, we developed a coding scheme...
that describes the activities performed by hospital workers. This coding scheme was cross analyzed by the team of researchers and some hospital workers to validate and refine it. In the following lines we described some of the characteristics and properties of our coding scheme.

A. Hospital Workers’ Activities

From our cross comparative, basic fundamental activities emerged. These are the meaningful behaviors that could be extracted from the data collected through the qualitative analysis as understood by researchers and validated by hospital workers. To clarify each activity goal discussing the artifacts used, the people involved and its location, we described, in the following lines, each activity in more detail:

1) Clinical case assessment (CCA)

This activity refers to the actions performed by hospital workers to make a clinical decision to assess the evolution of a patient; by examining clinical evidence; by discussing a patient diagnoses with colleagues and by consulting reference material. This activity is generally performed in front of the patient where interns and physicians jointly make a decision; while nurses generally performed it alone.

2) Patient care (PC)

This activity involves the actions that hospital workers must perform to provide primary care for patients by examining the patient health, monitoring vital signs, administering medication and advising the patient. Also, primary care might require from medical workers to perform specialized procedures such as a catheter insertion. Thus, while performing this activity hospital workers are always interacting at least with the patient by jointly manage information artifacts (i.e. medical record or nurse sheet) and physical artifacts (i.e. thermometers or medicines).

3) Coordination (C)

This activity refers to the actions performed by hospital workers to manage personnel and to supervise the quality of care hospital staff provides to patients; by coordinating and notifying pending tasks.

4) Preparation of medicines and material (PM)

This activity refers to the actions performed by hospital workers to set up the environment in order to provide patient care. This includes the preparation of medicines or material. This activity is executed only by nurses who consult the nurse sheet (and sometimes the medical record) to gather the material and medicines required for each patient.

5) Information management (IM)

This activity refers to the actions performed by hospital workers to formalize the notes taken on the move creating medical evidence in the form of medical notes or nurse sheets. This activity requires from hospital workers gathering the information required (such as medical records and nurse sheet) and monitoring the status and availability of information, such as laboratory tests by interacting with hospital workers. Although, this activity is mainly executed in base stations, nurses often do it in front of the patient. The place where the activity is executed defines how long the activity lasts and the artefacts used to formalize the information.

6) Tracking (T)

This activity plays a secondary role aimed at locating colleagues, medical equipment and documents to gather the information required by hospital workers to execute an activity with a primary role such as patient care. This activity has a very short period of duration and it’s constantly performed by navigating the hospital premises at different periods of time, as well as, asking hospital workers for people, equipment or documents.

7) Classes and certification (CC)

Refers to activities related to the training of hospital staff. These activities involve assisting to a class session where
The activities identified are patient-centered and have the common goal of providing clinical care; thus, hospital workers, independently of their role, to a higher or lesser degree execute these activities. As described in Table I, most of the time is spent in information management (20.17%), followed by clinical case assessment (19.26%) and coordination (16.21%). An important part of the work of those observed is focused on activities that have a secondary role of caring for patients such as information management, coordination, tracking, and, finally, preparing the patient census.

When analyzing the information per role, there are indeed differences regarding how much time each type of worker (nurses, physicians or interns) invests in performing these activities. We found that, the time nurses and medical interns spend performing administrative duties surpasses the time they invest providing clinical care. In contrast, physicians spend more time evaluating clinical cases and visiting patients. This happens because nurses and medical interns spend considerable time “setting up” the environment for physicians so they can focus on their main goal: providing clinical care. In addition, another significant difference is the nature of the activity being performed. For example, although, physicians, interns and nurses provide patient care, the actions executed by each role are quite different. Nurses are in charge of monitoring vital signs, administering medication and so on, while physicians and interns are in charge of providing specialized care such as catheter insertions.

Another characteristic, we observed is that some of the activities performed by hospital workers are fragmented due to the need of tracking people or documents necessaries to achieve each activity goal, taking care of emergencies or by interruptions. This fragmentation demands from hospital workers to continually switch between tasks regulating the time they last. As Fig. 2 shows, the most fragmented activities are coordination and tracking with 5 minutes of approximated duration; while, clinical case assessment, classes and certification and, preparation of medicines are conducted for longer periods of time (20-50 min. aprox.). Information management and patient care could be either fragmented or not, depending on the location of the artifacts needed to perform those tasks. For example, while nurses are taking a patient’s vital signs, they constantly need to move throughout the hospital premises looking for thermometers and other medical equipment. Thus, they interrupt the activity being performed to gather equipment or information. Another characteristic shared by the activities performed by hospital workers is the location where they take place. We observed that these activities could take place either at a “base location” (that is the main place where the subjects spend most of their time) or “on the move” (while outside of it). For nurses, the base locations were either the nurse pavilion or the nurse office. For medical interns and physicians it referred to a common office shared with other personnel of the department. Also, the artifacts used and the people engaged in the execution of the activity are relevant.

As we discussed, each activity performed by hospital workers is dependent on contextual variables such as the user’s location and identity, the time of the day, the people with whom they collaborate and the artifacts used during the execution of the activity, as well as, the activity duration. From this, we decided to design an approach to estimate the hospital worker’s activities based on such contextual information.

III. ESTIMATING USER ACTIVITIES WITH NEURAL NETWORKS

As mentioned before, activities are dependent on several contextual variables, which differ in the way that might be codified. For example, location could be codified by assigning to each place a number between 0 and 1. While, the artifacts used must be codified using a binary representation, one if it’s being used and zero in the other case. Thus inferring and managing these contextual variables is not trivial for a
computer. Back propagation neural networks (BP-NN) allow managing several contextual variables, codified in different ways, as inputs or outputs; allowing thus, dealing with this complexity. Hence, we decided to use them as the inferring engine to estimate the users’ activity, by mapping from these contextual variables to activities.

A. Use of a supervised pattern recognition algorithm

Neural networks are models that have a significant performance on the recognition of complex patterns. A neural network is, more specifically, a supervised non-parametric model that learns from training examples, they can learn to map input sequences (artifacts being used, time, collaborators and location) to output sequences (activities). Once trained, the neural network can be used to classify incoming patterns into labeled classes [8].

The learning method we used was backpropagation, which has several variants from which we utilized the Bayesian Regularization algorithm as it provided the best results [9]. We used the Matlab Neural Network Toolbox and, finally, as activation function we used the sigmoid function on the hidden layers and identity function on the output layer.

B. Architecture of the neural networks

Three neural networks were trained to estimate the activities, one for each role (physicians, medical interns and nurses). This is due to the fact that every role uses different artifacts and perhaps visits different places at specific times during their shifts. Although, they all perform activities such as taking care of the patient, they generally perform different medical procedures and use different artifacts.

![Fig. 3 A simplified network to estimate work activities.](image)

As figure 3 shows we used five contextual variables to train the network. Four of them, location, artifacts, role and time, were used as inputs, while the other one, activity, was used as output. The code for each contextual variable was taken from our qualitative analysis. As Figure 4c illustrates, this information was reported in an observation format, in which, based on the qualitative information recorded (referred in the format as “what they were doing”) each contextual variable was codified following our coding scheme. For example, location was coded based on the operation centers identified. We called operation centers to the physical places where hospital workers conducted their work, places such as laboratories, hospital departments, nurse’s areas, trauma areas, etc. [18] We classified them in 8 operation centers which correspond to the bed wards, the hallway, personal areas, offices and so on. Thus, in Figure 4c the location column presents the operation centers where hospital workers’ perform different activities.

Next, the information coded in the observation format is thus transformed into inputs and outputs to the corresponding neurons, as Figure 4b illustrates. The network uses, as inputs, 1 neuron for time of the day, 1 neuron for user location, 1 neuron for every significant artifact the role might use and, 1 neuron for each role with whom they might collaborate; and, for outputs, 1 neuron for every possible activity performed by the role.

Whenever an artifact or collaborator is involved in certain activity the corresponding input neuron receives a value of 1 (one), otherwise, the input value is 0 (zero). The number of neurons used for artifacts and people varies depending on the role. For example, to predict if a physician is formalizing notes, a relevant artifact is a computer or a typewriter. Nurses do not have access to such artifacts, thus there is no need to include a computer as a relevant artifact to train the nurse’s network. Thus, the architectures used to train the networks are role dependant. For all three roles we used a single hidden layer with 16 neurons. Hence, the resulting networks are composed of three layers, with the following number of neurons: 22-16-7 for nurses, 27-16-6 for medical interns and, finally, 25-16-5 for attending physicians.

![Fig. 4 (a) Sampling example from a physician for clinical case assessment. (b) Sample from the training set (c) Coded fragment of the observation report](image)

C. Codification and pre-processing of the data sets

As we discussed, the amount of time hospital workers spend in each activity is role dependant. Thus, for particular roles we could not gather enough samples to train the network. For example, for the activity of preparation we gathered 41 samples for interns and 36 for physicians, while for nurses there were 663 samples. Since this activity in nature is similar with others such as patient care, having this small number of
samples to train and test the network, generated confusion. Hence, we decided to eliminate from our experiments these activities. For all three roles the activity of tracking was eliminated. For the medical interns we also eliminated preparation, and for physicians we eliminated preparation and classes and certification. Table II shows the total samples obtained from the qualitative analysis (discussed on section II) and the samples used to train and test the network.

<table>
<thead>
<tr>
<th>A-ID</th>
<th>Nurses</th>
<th>Medical interns</th>
<th>Physicians</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total sample</td>
<td>Train/ Test</td>
<td>Total sample</td>
</tr>
<tr>
<td>CCA</td>
<td>608</td>
<td>150/80</td>
<td>479</td>
</tr>
<tr>
<td>PC</td>
<td>899</td>
<td>150/80</td>
<td>156</td>
</tr>
<tr>
<td>C</td>
<td>347</td>
<td>150/80</td>
<td>513</td>
</tr>
<tr>
<td>PM</td>
<td>663</td>
<td>150/80</td>
<td>-</td>
</tr>
<tr>
<td>IM</td>
<td>121</td>
<td>72/40</td>
<td>667</td>
</tr>
<tr>
<td>T</td>
<td>69</td>
<td>-</td>
<td>176</td>
</tr>
<tr>
<td>CC</td>
<td>28</td>
<td>15/10</td>
<td>36</td>
</tr>
</tbody>
</table>

All these samples were grouped by activities which were divided into two data sets: one for training and another for testing the network. To avoid a bias due to a larger amount of training data available for some of the more common activities such as patient care (PC), we decided to balance the training and testing sets. For instance, figure 4a shows the way the total samples (1258) were reduced to 230 samples for a physician performing clinical case assessment (CCA). Once the data sets were reduced we used 65% (150 samples) of the data for training and 35% (80 samples) for testing.

By choosing this size we intended to approach the way in which the network will work in the real setting. For example, during a complete working shift, hospital workers will probably assess a clinical case at most 60 times (on average).

We conducted several experiments using different configurations of the network as well as different size of the training set, however due to lack of space we present only some of them. In the following section we discuss our results.

IV. RESULTS AND DISCUSSION

This section presents the results of our approach showing a confusion matrix per role, discussing the strategies to increase accuracy and the limitations of our approach.

A. Confusion matrices by role

We present our results in the form of confusion matrices. The rows in this matrix correspond to the values of the real activity performed (the activity codified in our observation format), and the columns correspond to the values estimated by the pattern recognition algorithm. The values in bold in the diagonal represent instances when the neural network correctly estimated the activity. While the other values divided between the total samples used to test the network represent the percent average error.

Table III indicates the confusion matrix of the nurses’ activities with a percent average error of 27.49%. The activity corresponding to classes and certification is the most accurate activity estimated with 100% of accuracy, followed by preparation with 75% and patient care with 77.50%.

<table>
<thead>
<tr>
<th>A-ID</th>
<th>CCA</th>
<th>PC</th>
<th>C</th>
<th>PM</th>
<th>IM</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCA</td>
<td>10.00</td>
<td>13.75</td>
<td>3.75</td>
<td>6.25</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>PC</td>
<td>1.25</td>
<td>77.50</td>
<td>5.00</td>
<td>16.25</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>C</td>
<td>7.50</td>
<td>13.75</td>
<td>73.75</td>
<td>5.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>PM</td>
<td>7.50</td>
<td>2.50</td>
<td>13.75</td>
<td>75.00</td>
<td>1.25</td>
<td>0.00</td>
</tr>
<tr>
<td>IM</td>
<td>16.67</td>
<td>2.38</td>
<td>0.00</td>
<td>19.05</td>
<td>61.90</td>
<td>0.00</td>
</tr>
<tr>
<td>CC</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>100</td>
</tr>
</tbody>
</table>

Train 150, test 80, pct. Error. 27.49%

Table IV presents the confusion matrix of the medical interns’ activities with a percent average error of 33%. As it shows, information management is the most accurate activity estimated with 73.75% of accuracy, followed by classes and certification with 72.73% and coordination with 67.50% of accuracy. Upfront, it is clear that the estimation accuracy for the medical interns is lower that obtained for the nurses.

<table>
<thead>
<tr>
<th>A-ID</th>
<th>CCA</th>
<th>PC</th>
<th>C</th>
<th>IM</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCA</td>
<td>66.25</td>
<td>10.00</td>
<td>13.75</td>
<td>3.75</td>
<td>6.25</td>
</tr>
<tr>
<td>PC</td>
<td>1.25</td>
<td>77.50</td>
<td>5.00</td>
<td>16.25</td>
<td>0.00</td>
</tr>
<tr>
<td>C</td>
<td>7.50</td>
<td>13.75</td>
<td>73.75</td>
<td>5.00</td>
<td>0.00</td>
</tr>
<tr>
<td>IM</td>
<td>7.50</td>
<td>2.50</td>
<td>13.75</td>
<td>75.00</td>
<td>1.25</td>
</tr>
<tr>
<td>CC</td>
<td>16.67</td>
<td>2.38</td>
<td>0.00</td>
<td>19.05</td>
<td>61.90</td>
</tr>
</tbody>
</table>

Train 150, test 80, pct. Error. 33%

Table V shows the confusion matrix of the physicians’ activities with a percent average error of 28.75%. As it shows, patient care is the most accurate activity estimated with 78.75%, followed by coordination with 72.50% and information management with 70%.

<table>
<thead>
<tr>
<th>A-ID</th>
<th>CCA</th>
<th>PC</th>
<th>C</th>
<th>IM</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCA</td>
<td>63.75</td>
<td>10.00</td>
<td>12.50</td>
<td>13.75</td>
</tr>
<tr>
<td>PC</td>
<td>2.50</td>
<td>78.75</td>
<td>13.75</td>
<td>5.00</td>
</tr>
<tr>
<td>C</td>
<td>11.25</td>
<td>5.00</td>
<td>72.50</td>
<td>11.25</td>
</tr>
<tr>
<td>IM</td>
<td>11.25</td>
<td>7.25</td>
<td>12.50</td>
<td>70.00</td>
</tr>
</tbody>
</table>

Train 150, test 80, pct. Error. 28.75

Some activities, such as information management, are estimated with less accuracy. This is due to the fact that some activities share several characteristics such as the place, time of day, people with whom they are conducted, and the artifacts that are used. For example, as illustrated in Table III, our approach incorrectly estimated the activity of information management by confusing it, 16.67% of the time, with that of
clinical case assessment.

In addition, by analyzing the information per role, we can see differences in the level of accuracy with which some activities are estimated. For example, for nurses the activity of patient care was estimated correctly 77.50% of the time, for interns 67.27% and for physicians 78.75%. In this case, we observed that the task switching experienced by each role affects the way in which this activity is estimated. For example, as Table III shows, the activity of patient care is confused with coordination. We observed that, in a short period of time, medical interns and physicians constantly switch between these activities. In this case, the network doesn’t have enough evidence to differentiate among them, since the contextual information (of the user and the environment) does not change during such period.

However, by identifying particular attributes of each activity (such as its duration), we might be able to differentiate among these activities.

### B. Strategies used to increase accuracy

We applied different strategies to increase the estimated accuracy. We observed that some of the estimated activities were selected with some degree of uncertainty. By comparing those Uncertain Estimated Activities (UEA) with the real activities executed, we found out that some of such activities are performed by extended periods of time presenting a recurrence phenomenon, which means, that the probability of remaining executing an activity is higher than changing to execute another one. For example, a physician assesses a clinical case for an approximate duration of 15 to 20 min. Hence there is a good probability that a physician performing this task will to continue with it rather than switching to information management. Thus, if the neural network provides an uncertain estimation that after a clinical case assessment the physician changes of activity to do information management, this estimation might be inaccurate. This could be detected by comparing the estimations for both activities. If the one corresponding to information management has a higher value but still close to clinical case assessment, it might be safer to assume that the activity has not changed. By taking advantage of the UEA duration, we have a greater probability that the hospital workers will keep performing those UEA rather than changing activity, we call this the recurrence principle. To cope with this, we first identified those UEA and then, by taking into account the UEA duration we applied our recurrence principle.

The approach we used to identify the activity estimated is to select the output unit of highest value. Despite this, sometimes selecting the highest value does not provide enough evidence to assure that the selected activity is the real one, resulting thus, in a UEA. To identify the UEA two strategies were used. The first strategy involves the identification of those activities corresponding to neurons with activation values of less than 0.55. In this case, there is no strong evidence supporting one activity. In the same way, there is confusion when two neurons have similar activation values that are close to 1. For example, one activity with a value of 0.70 and a second one with 0.67. In this case, we calculate the difference between the values of the activity chosen and the ones rejected. If such difference is less that 0.12 we consider this activity estimated as an UEA.

Once the UEAs are identified, we selected those activities which present the recurrence phenomena by calculating each activity average time of duration. Although, clinical case assessment, as well as, classes and coordination presents this recurrence because of their nature, each activity level of recurrence depends on the role of the user who executes it. For example, although information management, for interns and physicians, is performed for longer periods of time, nurses generally switch between patient care and this task, fragmenting its duration. For instance, while a nurse is taking the vital signs of a patient, she reports in the nurse sheet his temperature, pressure and heart rate. Thus, the nurse conducts both activities by frequently switching between them. The activities which present the recurrence phenomena, in addition of clinical case assessment and classes and certification, for nurses are coordination and preparation of medicines and material and; information management in the case of medical interns. Once the UEAs were identified and the recurrence principle was enforced we reduced the estimation error by approximately 5%.

### C. Limitations of the approach

The results obtained are constrained by the data used to train the neural network. Although, the data is exhaustive, it was collected in the internal medicine area of a mid-size hospital. Hence, it is not possible to derive findings that can be directly extended to other hospitals. However, the activities performed by hospital staff are in general the same in other hospitals in Mexico and other countries as reported in [2, 23], thus we believe that the general findings that we obtained are not restricted to this hospital in particular. However, we want to clarify that our efforts centered on acquiring a vast and detailed understanding of the practices of a few individuals across a varied set of circumstances. Therefore, the significance of our results lies in the qualitative nature of the inquiry and the analysis process that we conducted. The technique used to gather the data requires extensive field work. This is a disadvantage of the approach. However, a smaller field study could be made to tune the classifier to a new setting.

Additionally, implementing our solution would require the deployment of technology within the hospital to infer the location of people and the artefacts being used to estimate the activity of users. However, some of these technologies are gradually being introduced in hospital environments.

Finally, we estimate the activity by taking into account contextual information, such as location and artefacts being used, which would be estimated through other methods. These methods are also prone to errors which would affect the accuracy of the estimation.

### V. Activity-aware applications

Although, several efforts have been conducted to estimate activities with a low level of abstraction such as if a user is walking, sitting [16] or chewing [3]; this information is not
enough to inform a context-aware application how to adapt its behavior in support of the complex work performed in hospitals. Thus, we need to estimate activities with a higher level of abstraction such as, if a physician is evaluating a clinical case or providing clinical care. By knowing these activities we can discover the contextual information relevant to the task at a hand or infer secondary context such as user availability.

In this section we discuss how the results obtained with the activity estimation method proposed can be applied in activity-aware applications. In particular, we discuss how our results could be applied to enhance the interface of a voice-based hospital communication system and providing quicker access to relevant hospital information.

A. Activity-aware collaboration

The need for mobility and collaboration generates a need to contact colleagues within the hospital, either to discuss a case with a specialist or request help to transfer a patient. Several mechanisms are used for these purposes and technology has been developed to assist in this task; such as the Vocera communication system which enables users to contact a fellow hospital worker either by name, role or location using a hands-free voice communication system. The problem is that these systems are largely unaware of the social situations surrounding their usage and the impact that their actions have on these situations. If the system could be aware of the user’s availability, they could use this information to negotiate interruptions at appropriate times, improving thus, human computer interaction [10]. Availability is information that can be derived from knowing the activity being performed by a person. For example, when hospital workers’ are involved in clinical case assessment, patient care, classes and certification and even, preparation they, in general, don’t want to be interrupted. We recurrently observed that medical workers, especially interns, wait until the discussion finishes in order to approach a physician. In contrast, when they are engaged in other activities, such as information management or coordination, the level of their interruptibility is higher.

<table>
<thead>
<tr>
<th>Nurses</th>
<th>Interns</th>
<th>Physicians</th>
</tr>
</thead>
<tbody>
<tr>
<td>NA</td>
<td>89.58</td>
<td>10.41</td>
</tr>
<tr>
<td>A</td>
<td>20.61</td>
<td>79.38</td>
</tr>
</tbody>
</table>

**TABLE VI HOSPITAL WORKERS’ AVAILABILITY**

Error: nurses 14.01%, interns 18.33%, physicians 14.73%

In Table VI we present the activity estimation results obtained with our approach, but grouped by those activities that can be associated with the user’s availability. The table shows that the estimation accuracy ranges from 70 to 90%.

A system such as Vocera could use these results to decide whom to interrupt and when. For instance, if a physician needs the help of a nearby nurse, he can make this request and the system will decide, based on the availability estimation, which nurse to call at that particular moment.

B. Activity-aware information retrieval

Hospital Information Systems manage large amounts of information, both clinical and administrative. This includes patient records with laboratory results and medical images; medical guidelines and procedures; staff assignments; reference material, etc. Navigating through this information can be time consuming when the users want to consult a single piece of data. It has been suggested that a context-aware application could display the medical record when a physician is in front of a patient’s bed [19]. However, the physician could be there preparing medical equipment to perform a catheter insertion or prescribing medicine. In this case, he might want to consult medical guides or pharmacological databases instead of the patient’s health record. Thus, location information might not be enough to decide which information to present to the user or make more available. It is hard to stipulate what contextual information is relevant and how to adapt context-aware applications to present services and information that are suitable to the users’ current activity [12].

The users’ activity can be used to identify the information relevant to the action at hand and differentiate between useful and unwanted data (with many degrees in between) and use this differentiation to meet goals, such as timely care delivery. Therefore, to identify when, depending on the activity being performed, is more relevant to consult medical information (such as medical record and laboratory results) than other information (such as the location of colleagues or journal articles), we classified the activities for which medical information is needed. For example, when hospital workers’ are assessing a clinical case, caring for a patient or managing information they often consult that patient’s medical record in order to accomplish the goal of each action. However, when they are coordinating, tracking or in classes they don’t use such information.

Table VII shows the estimation of the need to consult patient medical information based on the hospital worker’s activity. As in the case of hospital worker’s availability the estimation accuracy increases when the activities are grouped according to this parameter.

<table>
<thead>
<tr>
<th>Nurses</th>
<th>Interns</th>
<th>Physicians</th>
</tr>
</thead>
<tbody>
<tr>
<td>NR</td>
<td>90.78</td>
<td>9.21</td>
</tr>
<tr>
<td>R</td>
<td>23.59</td>
<td>76.40</td>
</tr>
</tbody>
</table>

**TABLE VII HOSPITAL WORKERS’ NEED FOR PATIENT MEDICAL INFORMATION**

Error: nurses 12.66%, interns 20.33%, physicians 16.61%

Figure 5 shows the interface of a Hospital Information System. The upper frame shows the application with which the user interacts. Below the application displays 3 thumbnails of screens suggested to the user based on his current activity. If the user selects one of the thumbnails, the corresponding application will appear in the main screen.
C. Activity-aware task switching

The mobileSJ system was implemented to assist mobile users in the management of their multiple activities and collaborations [5]. This application implements the concept of a working sphere [11] in its computational representation: an e-sphere. A working sphere is a concept introduced to conceive the way in which people organize and execute their work activities. mobileSJ allows the user to manage their multiple activities and their information and contextual resources while away from the desktop, since it runs on a PDAs or SmartPhone. The user can define e-spheres for each of his activities and associate to them, information resources, contacts relevant to the activity, emails related to the activity and pending issues (Figure 6). When a user switches between e-spheres, each e-sphere is enabled to quickly gather and retrieve its own workspace state (windows positions, status and overlay order) and context information like opened documents, idle time, etc. in a silent manner. In addition, the mobileSJ allow sharing activities and resources, as well as, communicating with colleagues through either SMS messages or phone calls.

Given that hospital workers need to cope with multiple activities, which are often fragmented by interruptions, and which require them to gather and consult a variety of information resources, mobileSJ can provide users with mechanisms to easily manage their activities and their associated resources helping to achieve the necessary context when switching between activities. However, users must identify their working spheres and explicitly specify the resources (i.e. contacts) associated to that sphere, in order to obtain the benefits provided by mobileSJ. Also, a user must explicitly select the active sphere relevant to the task at a hand. By knowing the user’s current activity mobileSJ can proactively identify the relevant sphere, at a given moment. Thus, by taking into account the information of the activity being performed by hospital workers, mobileSJ could retrieve the e-sphere relevant to the task at hand. For example, a physician might encounter a colleague in the hallway, where they decide to discuss the clinical case of a patient both have in common. In this case, neither the hour of the day nor the hospital workers’ contextual information (such as identity or location) could inform, which sphere must be retrieved or which information associated to such sphere is relevant.

However, by knowing that both hospital workers are discussing a clinical case we can infer that they must want to share the patient’s laboratory results to enrich the discussion. In this case, mobileSJ will retrieve the relevant e-sphere and put the associated resources within easy reach of the users. Similarly, the application could suggest the users to append newly created resources to the corresponding e-sphere.

VI. RELATED WORK

Previous efforts have been made to infer the activities of people using different techniques. For instance, [17] reports a dead-reckoning method to recognize and classify user’s sitting, standing and walking behaviors by obtaining the acceleration and angular velocity of wearable sensors being bear by users. Activities have also been inferred by detecting the interaction of users with particular objects [22]. This is done by tagging every item of interest using RFID tags and reading them through a RFID-detecting glove. Similarly, as part of the MIT project house n [14], the deployment of MITes (MIT Environmental Sensors) is used to monitor people’s interaction with objects in the environment. All of these projects have a similar goal: the use of technology to support the Activities of Daily Living (ADL) and Instrumental ADL (IADL) of elders. In contrast, our work focuses on supporting the daily-life work activities of hospital staff which usually involve other sort of contextual variables completely different from those coming from the home setting.

As part of Georgia Tech AwareHome project, sound recordings were used to monitor and infer activities in the home environment [3]. Arrays of microphones were placed to infer activities such as meal preparation. Although sound could be used to detect the presence of a colleague, or the use of a particular artifact in a hospital, it will be difficult to directly infer activity from such information, given the complexity of he activities involved and the difficulty of controlling noise in such environment. In contrast with the very specific activities detected by this work (i.e. chewing), our aim is to estimate work activities at a higher level of abstraction.

The use of production rules has also been proposed to identify the activities performed by hospital workers [7]. The presence of artifacts and people with RFID tags attached to them are used to trigger the inference rules coded by a
knowledge engineer. However, the creation of these rules is a time consuming task that requires considerable expertise and knowledge of the setting. Furthermore, consistency among these rules is not easily achieved. No results are reported on the accuracy of this method.

As mentioned in section V, from the activity being performed by a person one can infer its availability. With the use of sensors and considerations of social behavior the availability of an individual in an office environment as been estimated with an 80% accuracy [10]. The results are similar to the ones we obtained for a hospital. However, rather than inferring availability directly, we first determine the activity being performed, information that could also be used by an activity-aware application.

VII. CONCLUSIONS

Estimating user’s activity, as we discussed, is not an easy task and, despite that the importance of knowing the user’s activity has been highlighted in ubicomp, few attempts have been conducted in addressing this problem. In this paper, we present an approach based in the use of neuronal networks to estimate hospital worker’s activity. To train the network, we used the information recorded from a case study conducted in a hospital. By following this approach we could correctly estimate hospital workers’ activities 75% of the time (on average). In addition, we discuss how once an application has strong evidence of the users’ activity, it could adapt itself by displaying information relevant to the task at hand, and infer secondary context, such as availability. To illustrate this, we discuss how these results can be used in the design of two activity-aware applications.

We plan to explore other estimation techniques such as the Hidden Markov Models to improve our results. Our hypothesis here is that by taking into account information of the past, we can determine the probability of switching from one state (the activity executed) to another (the activity to be estimated). In addition, we want to use our results in the implementation of an activity-aware hospital application and evaluate its practical implications.

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