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Recognizing People based on their Footsteps using a Wearable Accelerometer

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***Abstract*— Collaboration of mobile robots and people generate the need for methods allowing the robot to reliable identify a person. The robust identification of the user is especially important in the context of people tracking when there are frequent occlusions. In this paper we present a novel approach for recognizing the user of a mobile robot. Our approach assumes that the user wears a mobile footstep sensor whose data are fused with footstep data extracted from leg movements of people. It relies on a recursive Bayesian estimation scheme to calculate a posterior about the potential associations between the different footstep perceptions. Our approach has been implemented and tested on real data. In simulated experiments, in which we use ground truth leg movement data recorded with a motion capture suite, and with a real robot we demonstrate the robustness of our method even when multiple people are present.**

I. INTRODUCTION

People detection and tracking is an important ability for mobile robots in populated environments. Besides safe navigation it is fundamental for most kinds of collaboration between robots and humans. For user-centered tasks, such as guiding or following, person detection is insufficient. Rather, the robot must be able to recognize its user especially when he or she enters the field of view or re-appears after an occlusion. In practice, it is furthermore useful if the robot can robustly identify a previously unknown person. A typical example are robots that have to guide people through exhibitions or markets where the robot should be able to reliably keep track of the person it is providing service to. In such applications, the robust identification is further complicated by the fact that typically multiple people are in the vicinity of the robot which makes it hard for the robot to identify its user. Straightforward approaches would be to define a simple criterion for the identification like the closest person around the robot or to include prior knowledge in form of a limited database of possible users. More sophisticated approaches as proposed by Fritsch *et al.* [1] use speaker localization. However, it remains unclear how such an approach can be applied in noisy situations and when multiple people are around. For a realistic collaboration scenario the robot must be able to reliably detect its user and the recognition itself should work despite varying environmental conditions. Furthermore, it should work independently of the appearances of people and should not require any prior such as a database of possible users. We believe that an approach that offers these features will tremendously extend the range of possible applications for a mobile robot collaborating with humans in crowded environments.

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Fig. 1. The mobile footstep sensor carried by the user. Dimensions are 8.5 x 5 x 2 cm (width x height x depth).

This paper presents a novel approach to identify the user for a mobile robot and to reliably keep track of it. Our approach requires that the user wears a small mobile footstep sensor depicted in Figure 1 and carries it as long as he or she needs support of the robot. This device includes an accelerometer and a wireless communication interface comparable to most modern cell phones. The accelerometer is used to detect the footsteps of the user. First, a people tracking module was simulated by data of a motion capture suite. To work on data comparable to that of a people tracker based on laser range finders, the fully recorded body posture was reduced to leg positions on a fixed height. Second, we made experiments with a real robot. The individual footsteps extracted from the recorded leg movements of the people tracker were compared to the footsteps measured by the mobile footstep sensor. We formulate the problem as a Bayesian estimation problem and present an appropriate sensor model to calculate a posterior over the potential assignments of the leg movements to the footstep sensor data.

II. RELATED WORK

In the area of robotics, there has been extensive research on person recognition and tracking. Popular approaches use laser range finders as primary sensor for this task as this sensor typically is also used for obstacle avoidance and mapping tasks. People tracking approaches as proposed by Arras *et al.* [2] are able to track multiple people even in the context of short-term occlusions. Lee and Stone [3] propose a more complex person model which explicitly models the movements of the individual legs. Additionally, several authors have demonstrated that the use of multiple

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range scanners reduce the number track losses, especially when occlusions occur [4], [5]. Person tracking approaches as proposed by Kobayashi *et al.* [6] that do not detect legs are not suited for the problem discussed here because they offer no means to detect footsteps. This also applies to group tracking approaches as proposed by Lau *et al.* [7].

Several approaches combine computer vision and laser range finders to detect people more reliably. Schulz [8] tracks the contour of a person in images and with the aid of laser range data. Zivkovic and Kröse [9] apply an omnidirectional camera to detect body parts. They fuse the visual information with leg positions detected with a laser range finder to improve people detection. A combination of face recognition and clothing colors has been presented by Bellotto and Hu [10]. Purely computer-vision-based methods are not mentioned in detail here, because it is unclear how these methods could detect footsteps of a person. An overview and comparison of computer vision approaches and combinations with laser range finders has been presented by Schiele *et al.* [11].

Besides person tracking, a user-centered task needs to distinguish between a user and others. Most of the approaches mentioned above can cope with short or partial occlusions. If continuous tracking cannot be guaranteed, additional effort must be taken to recognize a reappearing user as such. For systems purely based on laser range data there, to the best of our knowledge, exists no approach to distinguish between a reappearing and an unknown person. Computer vision can in principle solve this problem, for example by face recognition as shown by Lee and Stone [12] or by color histogram matching like by Zajdel *et al.* [13]. Face recognition can even allow for the identification but comes with additional requirements such that a reappearing user must face the camera. For approaches using color histogram it is unclear if they are sufficiently robust for real-world applications with potentially changing lighting conditions and only slight differences in cloths.

There also has been work on person tracking using devices attached to the user. Devices as proposed by Nagumo and Ohya [14] or Gigliotta *et al.* [15] can be tracked directly. Besides a fixed position where the device is attached, they require a direct line of sight, something that cannot be guaranteed in general and especially not in crowded environments. Using radio frequency as done by Arora and Ferworn [16] allows free orientation but increases the technical complexity for receivers.

The approach in this paper has several features which make it suitable for a wide range of scenarios in which possible users are either unknown, change often or their appearances are too uniform to distinguish between them. Compared to computer-vision-based methods we make no assumptions about the environment or the appearance of the user. This makes our approach feasible for environments where people all look the same because of working cloths. Combined with user identification methods as proposed by Gafurov and Snekkenes [17] the additional benefit of identification that face recognition approaches offer are outweighed.

Fig. 2. A person wearing the motion capture suite which provided ground truth data to analyze the mobile footstep sensor. We also used this suite to record the leg movements of people used in the experiments.

Compared to approaches relying on carried devices that can be located no line of sight is needed. Furthermore the footstep sensor has no fixed position. Rather it can even be carried in a pocket. The footstep sensor works user independently and does not require any adaption for a specific person. Therefore our approach can be used to track an arbitrary person carrying the sensor. Our method allows to identify the correct user at the beginning of a task and to robustly recognize when the user reappears after an occlusion. Furthermore, our method has very little computational requirements as only sparse data need to be processed.

III. FOOTSTEP SENSOR

Throughout this work, we used a developmental prototype of a footstep sensor (see Figure 1). It has a 3-axis accelerometer, Bluetooth interface, and a micro-processor. In principle, one could also use modern cell phones that include accelerometers and Bluetooth or WLAN. The footstep sensor samples the accelerometer at 100 Hz. The footstep detection algorithm averages over 5 samples subsampling the signal to 20 Hz. Then it computes the absolute acceleration value and detects trend changes of this value. A trend change from negative to positive is accepted as footstep if it has a preceding trend change of similar type with gap of less than 1 second. The footstep sensor sends each footstep represented by its timestamp over the Bluetooth interface via a pre-defined protocol to a connected PC. To develop a sensor model for this mobile sensor we carefully analyzed the footstep detection procedure.

We recorded sequences of data in which the person wearing the footstep sensor was walking and also standing still. Thereby we varied the speed. To obtain ground truth, we simultaneously recorded data with a motion capture suite shown in Figure 2. The footstep sensor detects footsteps

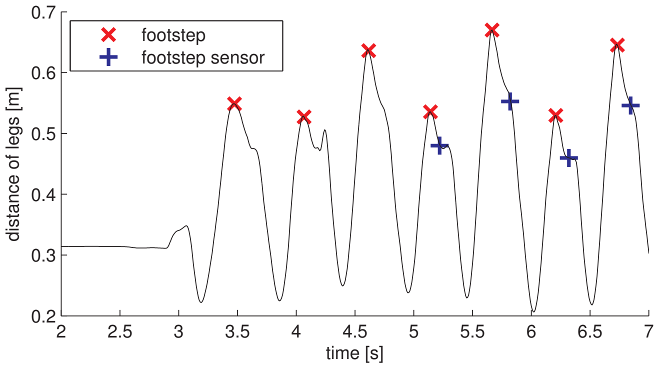

Fig. 3. Distances of legs extracted from body postures of a person starting to walk recorded with the motion capture suite. Whenever we observe a maximum above half the stride length succeeding a minimum below the half stride length we assume that a footstep has been carried out (red crosses). The footsteps detected by the worn footstep sensor are marked with blue plus-symbols.

when the heel strikes the ground. We found this to be equivalent to the maximal distance between the feet as observed in the motion capture suite data. To detect the footsteps in the motion capture data, we used a heuristic approach and assumed that the user has performed a footstep whenever a local minimum of the distances of the two feet was followed by a local maximum. A simple false positive rejection was applied which only accepted footsteps if the minimum was less and the maximum above half of the maximal stride length d_{max}. This heuristic did not detect steps with a small stride length which was negligible as the step sensors did not detect these steps either. Figure 3 displays an excerpt of a data set. Whereas the motion capture suite provides data at 100 Hz, the footstep sensor has a temporal resolution of 0.05 seconds.

If both data sets detected a footstep, we labeled it as a true positive. Footsteps only detected by the footstep sensor or the motion capture suite were labeled as false positive respectively false negative. To get a comparable rate for a standing person we divided the overall time a person was standing by the mean duration of a footstep d_t. We computed d_t over pairs of succeding true positive labled footsteps. The resulting confusion matrix for the used footstep detection is shown in table I.

When examining the footstep detection as depicted in Figure 3 more closely one can realize a start-up phase. Looking at the first 6 footsteps in detail reveals that the footstep sensor misses the first 3 footsteps more often than later. The true positive rate for the first 3 footsteps is below 0.1. This is due to the used footstep detection algorithm which partly relies on periodic gait characteristics. Secondly, the footstep sensor reported footsteps with an offset in time. The offset is due to missing time synchronization between the footstep sensor and the connected PC. The footstep sensor only provided the length of intervals between consecutive footsteps. The absolute timestamp needed for comparison is created at the PC-side adding the time needed for transmitting the data. This offset turned out to be a Gaussian distribution with a mean μ_{off} and varianz σ^2_{off}.

TABLE I

CONFUSION MATRIX THE FOOTSTEP SENSOR

	person walks	person stands
footstep detected	1145 (80,98%)	13 (4,18%)
no footstep detected	269 (19,02%)	298 (95,82%)
total	1414	311

IV. USER RECOGNITION

The user recognition works on footstep sequences represented by timestamps. Spatial information about people is not used. The footstep sensor carried by the user provides sequences of footsteps which serve as reference signal. Comparing this reference to footsteps of tracked people in the vicinity allows us to maintain a posterior representing the probability of a person to be the robot's associated user. Figure 4 displays the information flow.

Our approach relies on a representation of tracked people which allows to calculate the timestamp of a person's footstep. Most laser-based people tracker track the position of the legs of a person. In such timeseries we can find the timestamp of footstep by look for maximal distances of the legs. Other people tracking approaches could replace a laser-based tracker as long as they offer means to calculate the timestamp of a footstep.

A. Matching footstep sequences

A straightforward approach using only the most recent footstep of a person proved to be insufficient. Due to the above-mentioned start-up phase the first footsteps would be misclassified and thus decrease the probability associated to the corresponding person. However, for the targeted application the first few footsteps are crucial. If it takes too long to recognize a user, he might have walked away before the robot will detect him.

The first step of our approach is to match the reference footsteps coming from the footstep sensor to footsteps of a tracked person. We use a nearest neighbor filter to match these series of footsteps. Two footsteps are matched if the

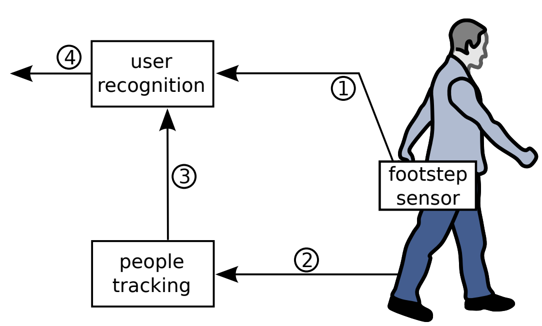

Fig. 4. Information flow between the components: (1) The footstep sensor provides timestamps of each detected footstep as reference signal. (2) A people tracking module detects all surrounding people. This module was simulated by the motion capture suite for the experiments in this paper. (3) The states of all tracked person are sent to the user recognition module which calculates timestamps of footsteps for each person based on their leg distances. (4) If a person is selected as user, the user recognition provides the position of the user to the overall system.

difference in time falls in the 99% confidence interval for corresponding steps. This interval is defined by μ_{off} and σ_{off} which we calculated for corresponding footsteps in the previous section. The result of the matching forms sequences of events: matched footstep (MA), missed footstep (MF), and missed reference (MR).

In case of standing people and a standing user no matching is possible as no footsteps are detected. However a standing user holds information as valuable as a walking person. We explicitly model the absende of footsteps to get a representation for a standing person comparable to that of a walking. We achieve this by introducing a virtual event "no-step" (NS) for periods in which a person stands and no reference signal is present. These events recur in intervals of length d_t as long as no other data is present.

B. Recursive Bayesian estimation

To estimate the posterior distribution over all people we formulate the task of user recognition as a recursive Bayesian estimation problem. We calculate the likelihood of event sequence to represent the user of the robot. The basis of our filter scheme is

$$p(P_i \mid E_{i,t}) = \eta \cdot p(E_{i,t} \mid P_i) \cdot p(P_i), \tag{1}$$

where P_i stands for person i, $E_{i,t}$ is the event t of person i, and η is a normalizer. We do not use a complex person model. Rather, people are represented by their footsteps respectively a sequence of events. Incorporating this person model in Equation (1) results in

$$p(P_i \mid E_{i,t}) = \eta \cdot p(E_{i,t} \mid E_{i,t-1}, \ldots, E_{i,0}) \cdot p(P_i). \tag{2}$$

Besides the most recent footsteps, we consider the dependencies between footsteps insignificant when they are by 2 or more footsteps apart. The found warm-up phase of the footstep sensor is the main reason for this remaining dependency. This assumption allows us to restate Equation (2) as follows.

$$p(P_i \mid E_{i,t}) = \eta \cdot p(E_{i,t} \mid E_{i,t-1}, E_{i,t-2}) \cdot p(P_i) \tag{3}$$

Taking the dependency of footsteps into account allows to better classify some sequences. For example the sequence NS-NS-MA is actually less likely to appear than the confusion matrix from table I would suggest. The opposite is true for the MF-MF-MA sequence. Because the first footsteps of a person are very unlikely detected this sequence is very likely the user starting to walk.

We implement the likelihood $p(E_{i,t} \mid E_{i,t-1}, E_{i,t-2})$ in Equation (3) by a look-up table because it only consists of discrete events. Having triplets with four values for each element, creates a total of 64 entries. We model these entries on basis of the confusion matrix and the characteristics of the footstep sensor. Sequences like MA-MF-MA (a single missed footstep) or MA-NS-NS (a stoping person) have a high likelihood. Sequence most likely coming from a random person (e.g. MA-MR-MR or MF-MR-MR) have a low likelihood. Some sequences as NS-NS-MF or NS-MS-MS could originate from a starting person as well as from a random person. To reflect this ambiguity these sequences have a moderate likelihood.

Starting with a uniform distribution as prior, we accept a person as the user if the assigned probability exceeds a given threshold τ.

V. EXPERIMENTS

The experiments represent two different scenarios. In the first one, the user takes the footstep sensor and activates the robot. When the robot is activated, it starts to detect the people in its vicinity and seeks to identify the person which wears the footstep sensor. In the second scenario, the robot looses track of its user while moving along a corridor because the user disappears behind a corner. As soon as the robot has turned around this corner it is confronted with a group of people from which it has to recognize its user to correctly resume to its task. In both cases no prior knowledge can be used to select the user.

A. Simulated experiments

For the experiments we recorded data with the motion capture suite (see Figure 2). The motion capture suite provided much richer information as a people tracking module could. We reduced the complete posture of a person to the positions of legs at height of 0.25 m above ground. This produced a data representation comparable to a laser-based people tracker on a mobile robot. To obtain larger variations, we split the recorded data whenever a person stood for some time. To recombine these sequences we normalized the data relative to time. We furthermore combined different sequences to simulate a greater variability, which could easily be achieved because our approach only works with the timestamps of footsteps. Besides the distance of legs we used no spatial information.

The only assumption throughout our experiments was that the robot's user was present and carried the footstep sensor. We performed experiments with different group sizes of 2, 3, and 5 people. All people stood and started walking simultaneously. The synchronous start formed an even harder task. If people start walking one at a time the estimation problem can easily be solved since one only has to decide which persons starts walking almost simultanously to the footstep sensor reporting steps.

The parameters used for the matching of the footstep sequences were obtained from the data recorded to analyze the footstep sensor in section III and are shown in table II

We regard an experiment as correct, if the right person was selected and remained selected until the end of the sequence. The remaining cases were divided into three categories:

TABLE II

PARAMETER USED FOR THE EXPERIMENTS

d_{max}	d_t	μ_{off}	σ_{off}	sequence likelihoods			τ
				low	medium	high	
0.7 m	0.6 s	0.05 s	0.06 s	0.3	0.5	0.7	0.7

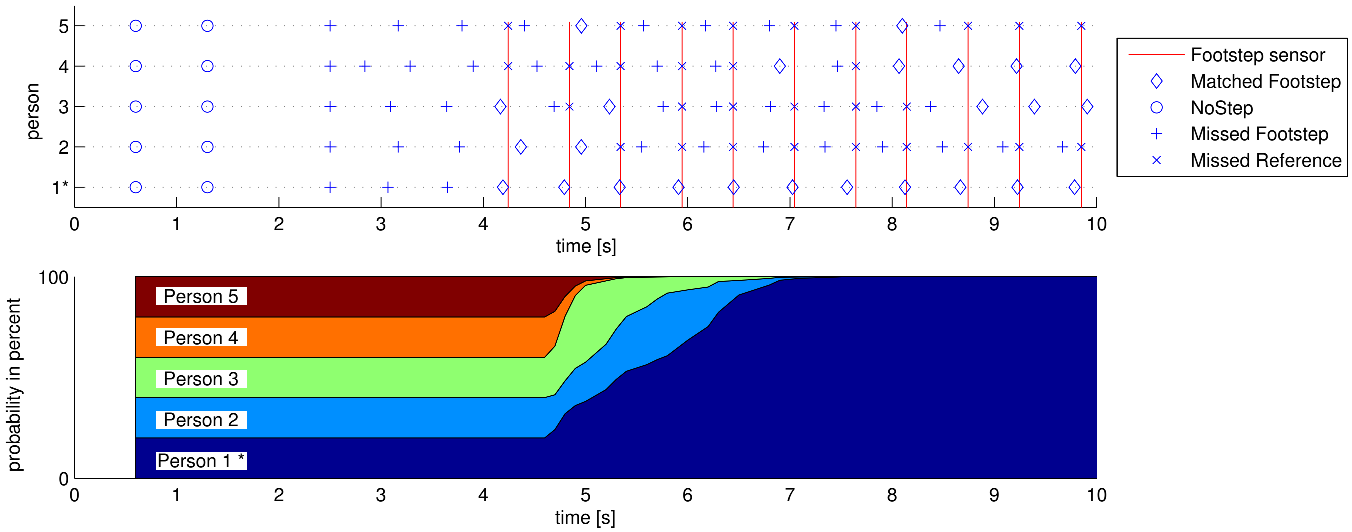

Fig. 5. Example run with 5 people. The actual user is marked with a star. (top) Footsteps of tracked people (diamonds and bars) extracted from leg distances and reference footsteps (vertical red lines) from the footstep sensor represented by event sequences resulting from nearest neighbor matching. (bottom) Posterior distribution $p(P_i \mid E_{i,t})$ as calculated by the Bayesian filter.

- wrong person, when the system selects the wrong person as its user,
- unable to make a decision, when the probability was equally spread over 2 or more persons, and
- the selected person changed during the run, when the system selected a person but canceled its first decision during the run in favor of a different person.

Whereas we had 1,190 simulated runs for two people, the number of data sets with three and five people was 1,225 each. For simulated runs with three or five people we randomly combined recorded walking sequences thereby making sure of only unique combinations. Since we did only use abstract data and no spatial information we could simply merge these tracks. Only for a single track the recorded data of the footstep sensor was included as reference signal. This track represented the user. The knowledge of the user was used for evaluation purposes only. An exemplary run with 5 people is shown in Figure 5.

The results for all experiments are summarized in Figure 6. As can be seen, our system was able to correctly recognize the user in 80% of all cases. Additionally a wrong decision was only made in less than 3% of all runs. The fourth case in which the system changes its decision could be spread among the first two. If a person is selected in the first place, the robot would start following and shift its sensor focus to this person. This could result in tracking losses of the other person. Therefore, if the first decision was correct, the second wrong decision would not have occurred. This is true for the inverse case as well. For these experiments all the "decision changes" cases were counted as negative. When applied in a system with a possibility to give feedback to the user, a feedback of the robot could solve the third case "no decision" by informing the user that he is about to be lost. This corresponds approximately to the fourth case "decision changes" as well. For this paper both cases were counted as negative.

Note that the threshold τ for accepting a person as a user was carefully chosen to obtain the best trade-off between correct estimates and the mean time needed to make a decision. Large values decrease the number of false positives but at the same time increases the mean time required until a decision can be made. With the used threshold, the average time needed until the user was selected was 5.5 seconds or 9 footsteps with a standard deviation of 3.7 seconds respectively 6 footsteps. This is due to two factors. First, a newly reported footstep provides only sparse data. This is intensified as footsteps occur roughly every 0.6 seconds providing only few updates by the footstep sensor compared to update rates of other commonly used sensors. Second, the above-mentioned start-up phase of the footstep sensor which introduces a certain delay. Switching to a different footstep detection algorithm that detects footsteps beginning with the first one would decrease the needed number of observed footsteps by 3 respectively and thus lead to a mean time by about 3 seconds.

B. Experiments with a real robot

We carried out first experiments using a Pioneer P3-DX robot equipped with a Sick laser range finder installed 35 cm

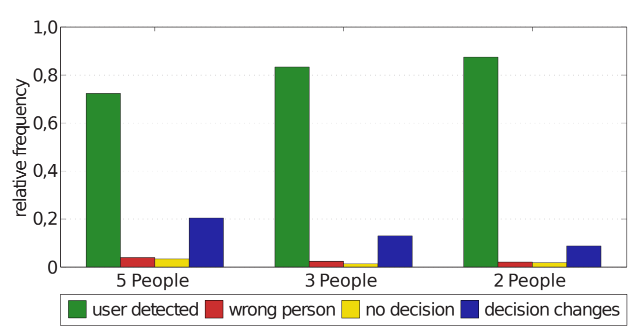

Fig. 6. Results of the experiments for each scenario. Total number of experiments were 1,225 for 3 and 5 people each and 1,190 for 2 person scenarios.

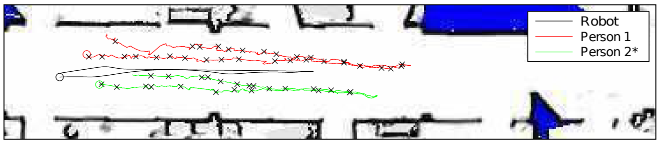

Fig. 7. Paths of the robot and 2 people walking in a corridor. Footsteps obtained from leg distances are marked with black crosses. In this example person 2 carried the footstep sensor.

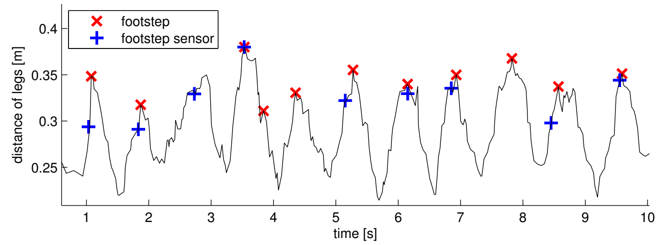

Fig. 8. Excerpt of leg distances for person 2 of figure 7. Although the footstep detection for leg distances had misclassifications our approach corretly recognized the person.

above ground. As people tracker we used the approach proposed by Arras *et al.* [2]. The system was running at 30 Hz. Due to the higher scanner plane compared to simulated experiments we set d_{max} to 0.4 as legs are less apart at this height. People were reliably tracked up to a distance of 6 m.

Figure 7 shows a typical example. Two people walked along the corridor followed by the robot. Although the calculated leg distances from tracked leg positions contained more noise, the adjustement of d_{max} was enough to reliably detect footsteps. Figure 8 shows an excerpt of the leg distances of person 2 of that example. Out approach corretly selects person 2 after 6 footsteps.

To summarize, the simulation experiments demonstrate that our approach is able to recognize people by their footsteps. The footstep sensor turned out to work reliably and seems not to be affected by the way people wear it. In the experiments, people used different ways of wearing it, for example at the belt or in the pocket. Experiments using a real robot showed that our approach can cope with noisy data. The computational demands of our approach are low due to the use of sparse data, the efficient matching approach, and the effective estimation of the posterior.

VI. CONCLUSION

This paper presented a novel approach to recognize the user of a robot among a group of people. Our approach assumes that the user carries a mobile footstep sensor and it calculates a posterior for all people in the vicinity of a robot that they are the user of a robot. We proposed a sensor model that we apply in a recursive Bayesian update scheme to calculate this posterior. We implemented and evaluated our approach using data recorded with a motion capture suit. The experiments demonstrate that our approach can robustly recognize the user of a robot. Compared to other methods for user recognition, our approach has the advantage that it is unaffected by environmental factors or user appearance. Future work will focus on reducing the time needed to recognize the user. This will be achieved by improving the sensor model, potentially with regression methods, and by reducing the startup-time of the footstep sensor through an improved footstep detection algorithm.

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