Quantifying Human Indoor Activity Using a Software Radio-based Radar

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***Abstract*—Human activity quantification consists of computing a numerical or qualitative metric that indicates the amount of movement a person engaged in a given time interval. Such a metric has important applications in elderly care, wellness and healthcare given the strong empirical relation between a person's health and his or her activity level. This paper proposes and evaluates methods to quantify the level of human activity in an indoor environment using a continuous wave radar. An experimental evaluation is carried out using a flexible and low-cost software defined radar platform. Results showed a good correlation between the proposed metrics and the motion sequence performed by the subject suggesting that accurate activity quantification in indoor environments can be achieved using a few simple off-body sensors.**

***Index Terms*—Activity Monitoring, Radar, Software Radio, Remote Sensing.**

I. INTRODUCTION

Human activity characterization has important applications in elderly care, wellness and healthcare given the strong empirical relation between a person's health and his or her activity pattern. Such a characterization in home environment may involve quantifying the overall activity level, identifying human activity, or classification of the type of human activity. Human activity quantification consists of computing a numerical or qualitative metric that indicates the amount of movement a person engaged in a given time interval. This has inspired the design of activity monitoring systems that range from fitness training [1] to early discharge support of post-operative patients [2]. Seniors living independently by wish or circumstances may also benefit from having their activity level monitored as a means of assessing their health status or identifying accidents or unusual behavior [3]. This information can be fed to companies specialized in providing swift help in case of need [4], healthcare providers or concerned family members.

The monitoring of human subjects in health and wellness applications may span long periods of time. As a consequence, user compliance is very sensitive to burden level imposed by the underlying sensor technology. Radar is an attractive technology for long term monitoring of human movement because it does not need to be carried by the user, can be placed behind walls and is able to cover a large area depending on its operating parameters. Furthermore, the coarseness of the information provided by radars is less prone to raise privacy concerns when compared to cameras.

Deploying radars in health and wellness applications at the user's home will be facilitated if such systems are low cost, easy to deploy and safe. Low radiation emission ensures safety for the user while multiple room coverage per radar unit eases deployment at home. This paper describes a system designed for human activity quantification that addresses these important requirements. The following main contributions to the area of unobtrusive monitoring in health and wellness applications are presented:

- Two activity metrics derived from radar signals in indoor environments are proposed for activity quantification and evaluated through experiments. The first metric is derived from variations in the power of the received signal while the second metric relies on the phase differences between transmitted and received signals.
- An experimental radar platform based on low cost software-defined radio hardware and open source software is described and its use for indoor monitoring of human movement is validated. The platform offers the opportunity of realizing field experiments at an expedited pace and low budget.

The remainder of the paper is organized as follows: Section II reviews major previous works in human activity characterization. The methods used to compute the activity index and displacement are described in detail in Section III. Section IV describes the software defined radar platform (which consist of GNU Radio and universal software radio peripheral) and the experimental setup used in the validation experiments. The estimation results are presented and discussed in Section V. Finally, conclusions are drawn in Section VI based on the results obtained.

II. RELATED WORK

The data required for human movement analysis in indoor environments can be gathered through on-body or off-body sensors. In the former category, triaxial accelerometers have been widely investigated for quantifying and classifying human activities [5]. The main disadvantage of on-body sensors is that these must be carried by the monitored subject at all times, a true inconvenience when monitoring periods span weeks or months. In elderly care applications, where long monitoring periods are expected, subjects can also be forgetful or uncooperative thus hampering the data collection process.

Off-body sensing for movement analysis can be performed using technologies such as cameras [6], ultrasound [7] or PIR (pyroelectric infrared) sensors [3]. These approaches suffer however from limited range indoors, which is usually constrained to a single room. The range limitation of these technologies means that many sensors are required to cover a single building. Furthermore, these multiple sensing units must be networked for data collection thus increasing the deployment and maintenance complexity of the system. Radars on the other hand are able to monitor large areas. Depending on the transmission parameters, radars can also be used for through-the-wall sensing [8].

Human tracking using radars has been extensively researched for military surveillance and rescue scenarios [9][10][8][11]. In these contexts, the radar designer must ensure that the system is able to operate reliably under extremely unfavorable conditions. The total amount of radiation emitted in such applications is however not much of a concern. On the other hand, the system described in this paper is meant to be deployed in people's homes thus safety of the users must be ensured. Moreover, the system should be low cost, flexible and easy to deploy. It achieves these requirements by essentially employing the same off-the-shelf wireless technology that is already present in people's houses for accessing the Internet.

III. Activity index & Displacement Estimation

Human activity quantification requires a numerical or qualitative metric that indicates the amount of movement of a subject in a given time interval. In this Section two numerical metrics for human activity quantification are presented, both derived from the signal received back at the radar being reflected off a person. The first metric, activity index, relates the overall activity of a person to power fluctuation of the received signal; the second metric is an estimation of the total displacement of the person based on phase variation of the received signal.

A. Radar Signals

Assume a radar transmits an unmodulated continuous wave (CW) signal given by:

$$s(t) = ae^{j(\omega t+\phi_o)} \tag{1}$$

where a, ω and ϕ_o are the signal amplitude, frequency and initial phase respectively. A signal reflected from a moving human reaches the radar antenna with a time varying amplitude $a(t)$ and phase $\phi(t)$ and can be described by $a(t)e^{j(\omega t+\phi_o+\phi(t))}$. In baseband, the resulting waveform reduces to $a(t)e^{j\phi(t)}$. The actual signal received by the radar is in fact a summation of many reflections bouncing from the different parts of the human body and other objects in the indoor environment. The after-sampling baseband signal resulting from D reflected signals can thus be represented as:

$$y\left[n\right] = \sum_{d=1}^{D} a_d\left[n\right] e^{j\phi_d[n]} \tag{2}$$

where $y[n]$ is a sample at time instant $t_n = nT$ where T is the sampling time. The following Sections describe metrics based on the numerical manipulation of this signal.

B. Activity Index

A possible way to define a metric that quantifies human movement based on radar signals is to track the power fluctuation due to multipath fading. The movement of humans inside the monitored area changes paths and propagation parameters of the radar signal thus causing a fluctuation of the total received power. An activity index (AI) can therefore be defined as the standard deviation of the power of the signal in a given time interval. However, this computation makes the AI dependent on the distance between the radar and the human target. This dependency can be avoided by normalizing the standard deviation with the average power of the signal.

A time varying index is able to describe the variation of the activity level as a function of time. Therefore, the AI is best represented by the ratio of a moving standard deviation to a moving average of the power of the signal. Let $P\left[n\right] = \left|y\left[n\right]\right|^2$ be the power of the signal at time instant t_n. The normalized activity index at time $t_{n'}$ is defined as:

$$AI\left[n'\right] = \frac{\sqrt{\frac{1}{L}\sum_{n=n'}^{n'+L-1}(P[n])^2 - \left(\frac{1}{L}\sum_{n=n'}^{n'+L-1}P[n]\right)^2}}{\frac{1}{L}\sum_{n=n'}^{n'+L-1}P[n]} \tag{3}$$

where L is the number of signal samples taken in each consecutive computation. L is chosen considering the time interval at which AI needs to be updated; thus, n' is set to multiples of L.

The normalization factor ensures that the index is a real number in the interval $[0, 1]$ if the statistical dispersion of the signal power over time is smaller than the average signal power over the same period.

C. Displacement

A rather intuitive approach to quantify human movement is to estimate a person's torso displacement over time. The more displacement in a given interval, the more the person was engaged in movement.

Distance of a target is commonly estimated using pulse radars by measuring the time delay of the signal reflected back off the target. However, a wideband pulse radar is required to detect short-range targets [12]. On the other hand, it can be noticed that transmission of a pulse is not required to estimate displacement. Displacement of a target can be estimated using a simple unmodulated (narrowband) radar by computing the change in phase of the received signal as described next.

As indicated in (2), the signal received at the radar is a summation of many sinusoids. These can be grouped into two main components. The first component, represented as $a_1\left[n\right]$, consists of the summation of signals reflected solely by static objects; whereas, the second component, $a_2[n]$ is the signal reflected by the torso of a moving person. Note that during time interval $[t_{n-1}:t_n]$, component $a_1[n]$ does not change in magnitude or phase. Contrarily, component $a_2[n]$ experiences a change in phase $\Delta\phi_2[n]$ in each signal sample due to the person's movement. Thus, (2) can approximately be written as:

$$y[n] = a_1 e^{j\phi_1} + a_2[n]\, e^{j(\Delta\phi_2[n]+\phi_2[n-1])} \tag{4}$$

In narrowband signals, the change in phase can be directly related to the change in propagation delay and hence to the change in distance (displacement) of objects in the environment. The total radial displacement, $\Delta x[n]$ of a moving person with respect to the transmission direction in the time interval $[0, t_n]$ can be given in terms of the phase change $\Delta\phi_2$ as:

$$\Delta x[n] = \frac{\lambda}{4\pi}\left(\sum_{i=1}^{n} \Delta\phi_2[i]\right) \tag{5}$$

The change in phase in (4) can be estimated using the arctangent demodulation method [13], which is given by:

$$\begin{aligned}\Delta\phi_2[n] \;=\; & arctan\{(y[n] - a_1 e^{j\phi_1})\cdot \\ & (y[n-1] - a_1 e^{j\phi_1})^*\}\end{aligned} \tag{6}$$

where * represents a complex conjugation. The zero frequency component, $a_1 e^{j\phi_1}$ can be estimated by averaging the signal over the considered time interval. If only humans are moving in the indoor environment, the change in phase $\Delta\phi_2[n]$ is very small ($\Delta\phi_2[n] \ll 2\pi$) for sampling rates of a few hundred Hz and radar transmission frequencies less than 10 GHz. Consequently displacement ambiguity does not emerge from aliasing.

The signal reflected off a person's torso is expected to be the major phase varying component received back at the radar; however, other phase varying components may also be present that constitute the background signal. This background signal is the result of reflections from other moving objects in the environment, receiver noise and other noise sources in the indoor environment. The presence of the background noise implies that displacement detection ($\Delta\phi_2[i] \neq 0$) may occur even when the person remains in the same location. In order to avoid false displacement estimation, arctangent demodulation can be combined with dynamic background noise subtraction as described next.

1) Dynamic background noise subtraction: Background noise differs from the static component, $a_1 e^{j\phi_1}$ in (4) as it spreads over the frequency range containing Doppler components from which the person displacement is estimated. Dynamic background noise subtraction can be done in the frequency domain based on the assumption that the expected value of its magnitude at each frequency remains the same during intervals in which the person's torso moves and intervals in which the torso is motionless.

Let $Y[k,n']$ represent the short time Fourier transform (STFT) applied to the received radar signal:

$$Y[k,n'] = \sum_{n=n'}^{n'+L} y[n]\, e^{-j2\pi nk/N} \tag{7}$$

where n', which is set to multiples of L, represents the start of the moving window transform, k represents the k^{th} frequency component of the signal, and N is the size of the FFT. The magnitude of the background signal spectrum at each frequency, $Y_{back}[k]$ is estimated by averaging over windows when the person is static (there is no motion), *i.e.*, $\hat{Y}_{back}[k] = E\{|Y_{back}[k,n']|\} \approx \frac{1}{N}\sum_{n'=1}^{N} |Y_{back}[k,n']|$. These static moments can be detected based on a signal strength threshold detector over the frequency of interest. The estimated background noise spectrum is then subtracted from the spectrum of the signal. This approach is analogous to speech background noise subtraction methods that rely on non-speech intervals [14][15]. Thus, a general expression is defined using a flexible constant γ to get a subtracted spectrum, $\widetilde{Y}_m[k,n'] = \left|\widetilde{Y}_m[k,n']\right| .e^{j(\angle Y[k,n'])}$, where:

$$\left|\widetilde{Y}_m[k,n']\right| = \begin{cases} |Y[k,n']| - \gamma\hat{Y}_{back}[k] & \text{, if } |Y[k,n']| > \gamma\hat{Y}_{back}[k] \\ Y_{SF} & \text{, otherwise} \end{cases} \tag{8}$$

Y_{SF} is the magnitude of the spectral floor. A short time IFFT is then applied to $\widetilde{Y}_m[k,n']$ in order to get the time domain signal.

The spectrum of the resulting signal is made flat (white) when there is no torso motion; thus, the expected change in phase from sample to sample is zero as the phase change is the sum of vectors of equal amplitude and random phase distributed in $[0, 2\pi]$. Therefore, when the radial displacement estimate in (5) is applied over multiple samples, the estimation error will be minimal.

2) Accuracy of the displacement estimator: The accuracy of a radar displacement estimator depends on a number of factors. First and foremost, only radial displacement with respect to the radar transmission direction can be estimated. This limitation can be overcome by using two radars positioned at an angle so that movements in orthogonal axes can be detected. A second determining factor for the estimation accuracy is the relative strength of the signal directly reflected from the person's torso compared to other signal components. According to the arctangent demodulation method, the phase change of the torso component is estimated from the phase change of the aggregate signal received at the radar. The stronger the torso component is, the more the estimation will reflect the factual torso displacement of the person. This concept is illustrated in Figure 1 for a few multipath components. The direct path torso component, whose phase change α needs to be estimated is shown in dark lines. Applying the arctangent demodulation provides an estimation of angle β, which is the phase difference between the sum of all signal components.

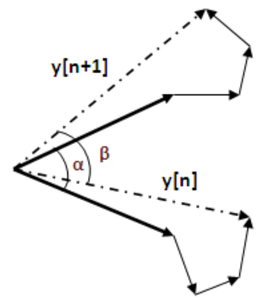

Figure 1. Arctangent demodulation accuracy

The phase estimation error $|\beta - \alpha|$ is thus dependent on the ratio of the magnitude of the torso component with respect to the magnitudes of the other time varying components.

Lastly, the accuracy of the displacement estimation depends on the assumption that the expected value of the background signal spectrum remains the same during intervals in which the person's torso moves and intervals in which the torso is motionless. As this assumption may not always hold, the background spectrum estimation should be updated whenever small intervals of torso motionlessness are detected. The rate at which the background spectrum computation is updated yields a trade-off between complexity and accuracy.

IV. GNU Radio-based radar

The metrics to quantify human movement presented in Section III were evaluated using a GNU Radio-based radar. GNU Radio is an open source and free programming toolkit for realizing software defined radios [16]. The toolkit consists of a set of signal processing blocks that can be configured to work with different hardware components. The Universal Software Radio Peripheral (USRP) is a general purpose programmable hardware that is designed to be used as a frontend for GNU Radio [17].

GNU Radio and USRP have been widely used for prototyping in communication systems research [18]. Their adoption in a wide range of applications is motivated by the low cost and relative ease to use. However, the use of USRP as a platform for building active radar is limited due to its low power and limited bandwidth. A possible design of USRP based long-range pulse radar is discussed in [19]. To the best of our knowledge, our work is the first using USRP and GNU Radio as a short-range (indoor) active radar.

In our experiments, a USRP is used in conjunction with GNU Radio to implement an unmodulated continuous wave radar. The USRP was equipped with a XCVR2450 daughterboard, which works as the radar RF frontend operating in the $2.4 - 2.5$ and $4.9 - 5.9$ GHz bands. Figure 2 shows the schematics of our radar. The setup uses two separate USRPs, one for transmission and the other dedicated for reception. A cable between the boards ensures that the two boards are synchronized to a common clock.

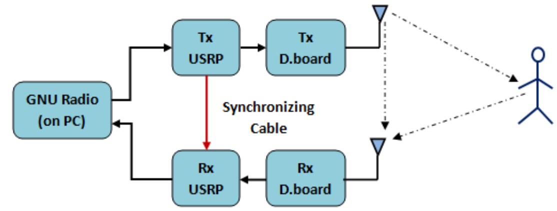

Figure 2. Experimental Setup

Clock synchronization between transmitter and receiver is not required if the radar is only computing the activity index based on the power variation of the signal. In this case the synchronization cable can be removed and the radar can be easily arranged in a bi-static configuration in which transmitter and receiver are placed in different locations. A bi-static configuration is more sensitive to movements in the area surrounding the imaginary line containing transmitter and receiver modules.

This radar platform is both low-cost and very flexible. The carrier frequency, transmit power, receiver gain, and other parameters are easily configurable in software.

Since, excessive radiation can cause health hazards [20], the maximum transmit power of a radar should comply with the regulations of human exposure to radio frequency. The FCC has set the maximum safety limit of power density beyond which human beings should not be exposed in uncontrolled (home) and controlled (laboratory) environment. The maximum power density allowed in a living room environment is $1mW/cm^2$ [20]. The radiated power in our experiments is set below 30 dBm considering this safety limit.

V. Evaluation Of Metrics

The accuracy of the activity quantification methods described in Section III is evaluated in a set of experiments using the GNU Radio-based radar setup described in Section IV. A person's movement in a confined area was measured using a radar transmission frequency of 5 GHz and transmission power of 30 dBm (including antenna gains). The received signal is recorded in a data file and processed offline using MATLAB. A sampling rate of 500 S/s, a window size of 100 samples $(0.2$ $s)$ and FFT size (N) of 500 are used for the computation of the quantification metrics. The accuracy of a metric was defined by comparing its value with the actual motion performed by the subject.

A. Activity Index

Experiment-1: During this experiment, the transmitter and receiver are placed at opposite corners of a room (~90 m^2) in a bi-static radar configuration. Transmitter and receiver were equipped with a 3 dBi antenna. A person moves freely in the environment for approximately 40 s and has its movement logged by a 3-axial accelerometer attached to the torso (EQ-01 Equivital [21]). An activity index was computed for both the radar and accelerometer signals as shown in Figure 3. The

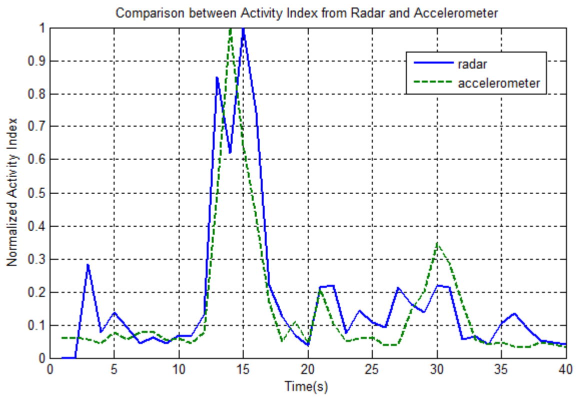

Figure 3. Activity Index of Accelerometer and Radar

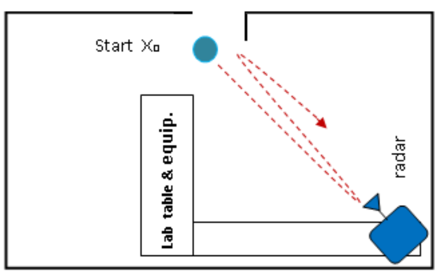

Figure 4. Experiment-2

activity index for the accelerometer data was defined as the square root of the sum of the signal variances over the 3 axes. Both indices were normalized to represent maximum activity in the time interval as 1.

Figure 3 shows that there is a good correlation between the activity index computed and the movement sequence performed in the experiment.

B. Displacement

The following experiments were performed to assess the accuracy of the displacement estimations using the pseudo-monostatic configuration depicted in Figure 2. Transmitter and receiver were equipped with a 20 dBi micropatch antenna.

Experiment-2: A person remains motionless for 10 s and then moves back and forth towards the radar as depicted in Figure 4. The person follows the motion sequence for a total time duration of 10 s before returning to the inactive state for another 10 s. The distance between the motion starting point and the radar was 2.5 m when measured manually.

The displacement estimated using the arctangent demodulation method without background subtraction is shown in Figure 5. Note that the displacement estimation closely follows the motion sequence indicated by the dotted lines in Figure 4. Moreover, the estimated displacement is quite close to the actual value of 2.5 m. The estimation error due to background noise is not significant in the first 10 s whereas it becomes significant after 20 s. It is thus clear that background noise subtraction is required for a better displacement estimation.

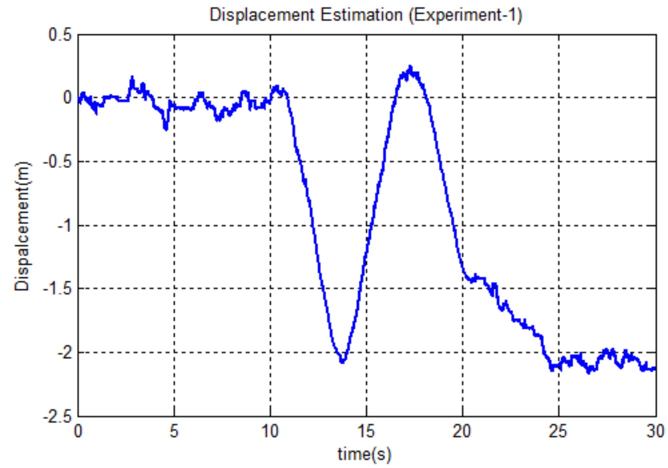

Figure 5. Displacement versus time from experiment-2

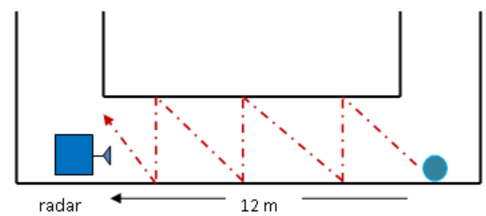

Figure 6. Experiment-3

Experiment-3: In this experiment, a person performs a sawtooth motion in a 2 m wide, 12 m long corridor as shown in Figure 6. Initially the person remains motionless for 5 s and then moves towards the radar in the aforementioned movement pattern. The person reaches the radar at 22 s.

The displacement estimated from this experiment is depicted in Figure 7. Note that the total estimated displacement with background noise subtraction is about 12.4 m, which differs only 3.33% from the actual distance of 12 m. The displacement remains almost constant during the tangential motions; this shows that the displacement estimator is performing well, as the radar measures the radial component of the actual displacement. If background noise is not eliminated, the person displacement is overestimated when he or she is not moving. This effect is the result of colored noise (clutter).

VI. Conclusion

Human activity quantification consists of computing a numerical or qualitative metric that indicates the amount of movement a person engaged in a given time interval. In this paper two activity metrics derived from radar signals are proposed for indoor environments and evaluated through experiments using a GNU Radio-based radar platform. The first metric, referred to as activity index, quantifies human movement by tracking the power fluctuation of radar signals due to multipath fading in the environment. The activity index is computed as the ratio of the standard deviation of the received signal energy in a given time interval and the total

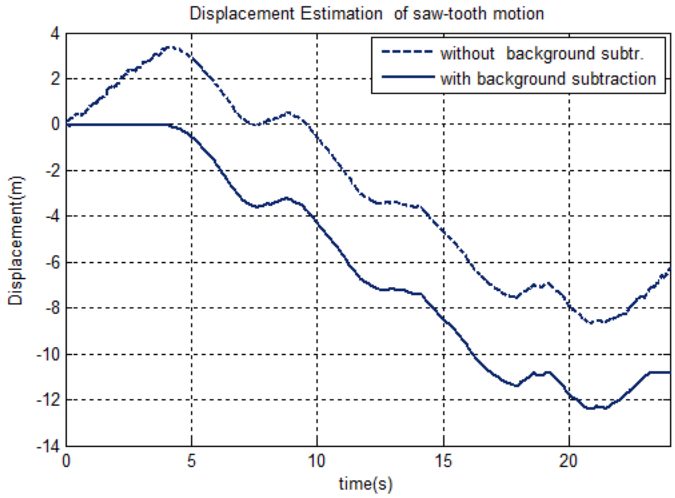

Figure 7. Displacement from sawtooth motion

energy of the signal in this same interval. The experiment described in Section V indicates that a good correlation exists between the activity index obtained and the movement sequence performed by a person in an indoor environment. A second metric presented for the quantification of human activity is physical displacement. The estimation of a person's displacement in an indoor environment is based on a two-signal component model and arctangent demodulation method. The main components are comprised by signals reflected from the person's torso and signals reflected from static objects. According to the experiments conducted, this simple model seems accurate enough to estimate displacement of a moving person, but incurs in significant errors if the person's torso is not moving. When the torso is quasi-static, background noise originated from other objects in the environment is significant and may not constitute uncorrelated random process. This problem can be addressed by subtracting background noise from the received signal as suggested in Section III-C1. A limitation of displacement estimation using radars is that only the radial component of the displacement is perceived by the radar. A better estimation of the movement can thus be achieved by combining information from two or more radars adjusted to monitor distinct directions.

A main limitation of the present study is that it addresses monitoring of the movement of a single person in the indoor environment. Single person monitoring may be useful in real scenarios, *e.g.*, in senior residences, but such scenarios are considered exceptional. Thus, expanding this work to multi-mover scenario is essential. In future work, strategies to discriminate the activity of multi-movers in a given environment will be considered.

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