Considering the privacy-protected detecting algorithm for periodic motions with visual IoT

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Abstract

In the fields of nursing and caregiving, there is an increasing demand to monitor the condition and movements of patients due to chronic manpower shortages and the anticipated decrease in the future workforce. ICT technologies are expected to address this need. In this study, we considered a detection algorithm for various periodic motions through video analysis. We calculate the magnitude of movement by comparing video frames at different intervals. The detection results include only the magnitude and period of movements, reducing the risk of invading the subject’s privacy compared to capturing full video data. By using video as a motion sensor, the system can monitor while protecting the subject’s privacy.

Keywords: IoT, Video analysis, Privacy protection

1. Introduction

Currently, many countries are grappling with the challenges posed by an aging population. Japan, in particular, is facing an unprecedented level of population aging, having entered a super-aged society in 2007, with over 21% of the population being 65 years or older[4, 6]. As society continues to age, the shortage of caregivers and the increasing burden placed on them have become significant social issues. However, with the rapid advancement and widespread adoption of the Internet of Things (IoT) in recent years, its application has extended beyond industrial sectors to encompass caregiving, childcare, and healthcare fields. By harnessing the power of IoT, a vast amount of data can be collected from various sensors and cameras, connected through networks, making it an invaluable approach for “monitoring” purposes. For example, there is a high demand in nursing and caregiving for detecting excretory behavior in persons who require nursing care, particularly at night when caregivers need to assist with excretion, handle bed-changing, and perform cleaning tasks due to incontinence or unclean acts, which impose a significant burden on them. However, the use of camera data often raises concerns due to its highly sensitive and personal nature, leading to instances where camera recording is declined.

We have developed a monitoring system for elderly individuals using small sensors to monitor indoor environmental factors such as temperature, light, noise, and more[2, 5, 8, 9]. This system enables remote estimation of residents' activities and monitors their daily lives by issuing alerts when unusual situations are detected. It has been used as a non-invasive monitoring system in various settings, including homes with families dealing with dementia, homes of elderly individuals living alone, and nursing homes. However, to achieve more accurate activity estimation and detect subtle behaviors, video monitoring is highly advantageous.

We are currently in the process of designing a new monitoring system that safeguards individuals' privacy by storing monitoring data without identification. In this system, we will employ preprocessing techniques to exclude raw video data. In this study, we present preliminary results on a privacy-protected detection algorithm aimed at identifying the periodic movements associated with various actions performed by the subjects.

2. Methodology

Recent studies in computer vision enable the easy detection of humans, moving objects, and characteristic motions[1, 3, 7, 11]. In this study, we employed a simple motion detection method, as depicted in Figure 1, to detect motion in the video. The input consists of a 30-second video of a metronome set at a tempo of 120 beats per minute (bpm), recorded in Full HD with a resolution of 1920×1080 pixels and a frame rate of 30 frames per second (FPS).

The process is as follows: (1) the original frames are read as grayscale images; (2) frame-difference images are generated by skipping a predetermined number of frames (ΔF); (3) the resulting frame-difference images are combined using a logical AND operation to identify the moving objects in the video. We consider the resulting image as representing the moving objects at the exact moment of the second frame in the

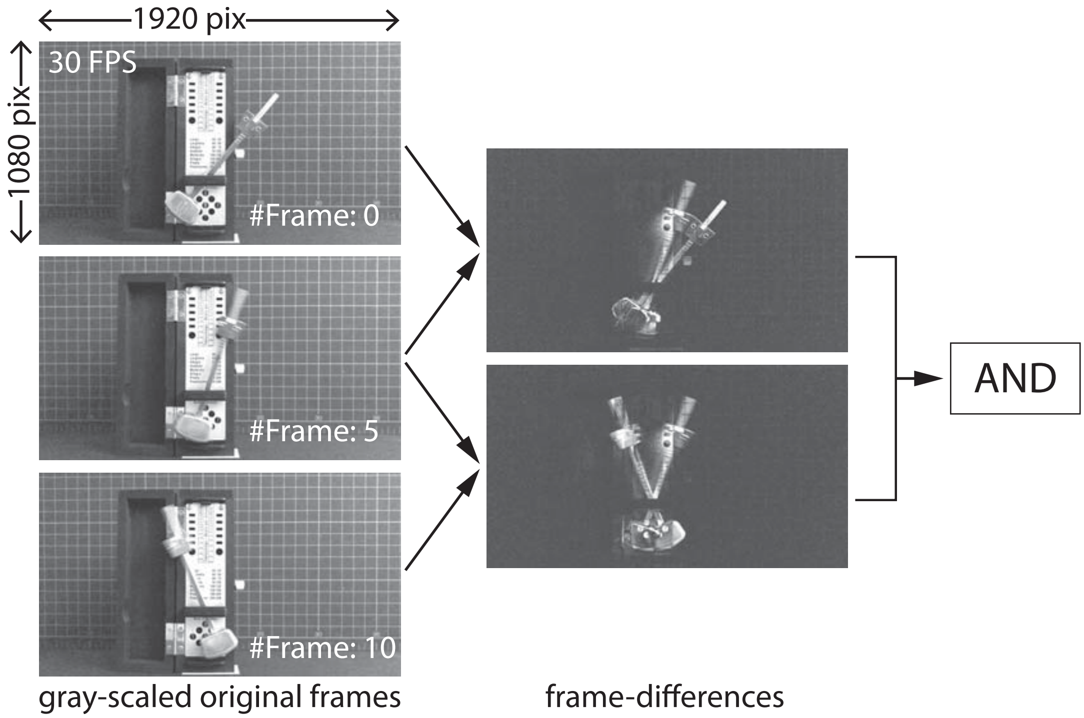

Fig 1: Diagram of the method overview in this study. The left three panels show the grayscale frames of the original input video with skipping predetermined frames. The right two panels show the frame-differences.

original video. In this study, we obtained processed images at a time resolution of 10 frames, resulting in the total number of frames being one-tenth of the original video.

Figure 1 illustrates an example of the process with ΔF set to 5 frames. Note that a metronome set at a tempo of 120 bpm produces metallic sounds at both ends twice per second. This means that the metronome's pendulum completes one round trip at the ends t times within t seconds, and it passes through the same spot $2t$ times in other locations. Consequently, the cumulative intensity of the frame-difference image theoretically becomes zero with a ΔF of 30 frames (1 second).

3. Results and discussion

Figure 2 shows the the total intensity of the processed image captured with different ΔF values: (a) 20, (b) 25, (c) 30, and (d) 35 frames. The total intensity was determined by summing the pixel intensities within each processed image. The intensity when ΔF was set to 30

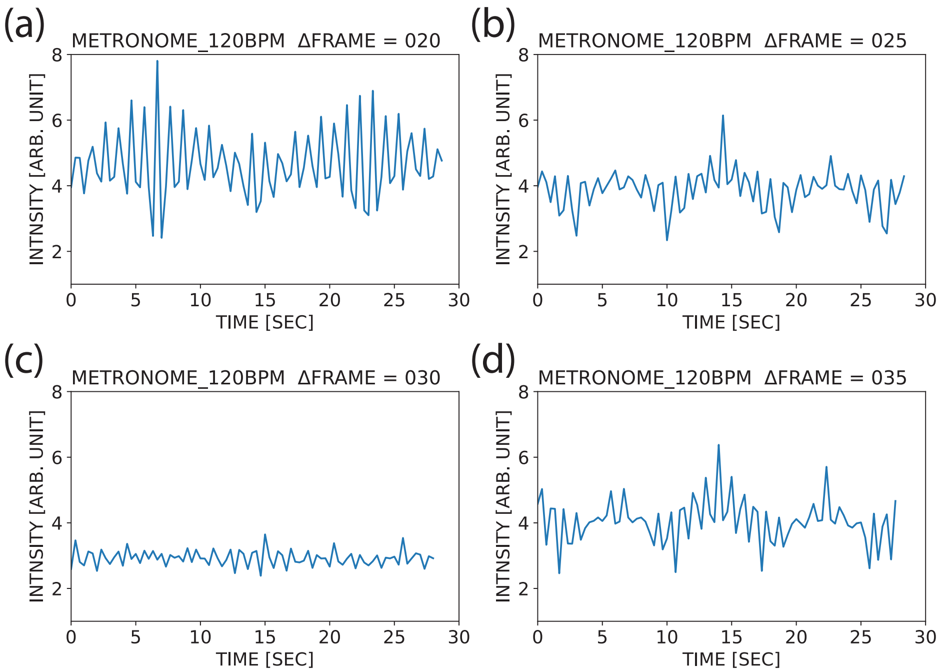

Fig 2: Time series of the total intensity in the processed video image of the metronome set to a tempo of 120 bpm with varying (a) ΔF=20, (b) ΔF=25, (c) ΔF=30, and (d) ΔF=35.

frames (Figure 2c) reveals a distinct decrease in intensity compared to the other.

Figure 3a displays the variation of mean intensity, obtained by averaging the total intensity of the processed images throughout the entire 30-s video duration. This clearly shows a decrease in intensity around $\Delta F = 30$. To be more precise, the minimum intensity occurred at $\Delta F = 29$. This slight shift in ΔF at the point of minimum intensity can be attributed to the precision limitations of the analog metronome used in this study, which lacks the necessary accuracy to distinguish intervals of 1 frame (1/30 s). It is worth noting that the intensity reaches its minimum even at $\Delta F = 59$, approximately to twice the period, and at $\Delta F = 1$, where the motion of the pendulum is extremely small, resulting in negligible frame difference intensity.

Figure 3b illustrates the areas where motion was detected in the input video's field of view. The contour colors indicate the corresponding value of ΔF when the mean intensity reaches its minimum. The region of the metronome's pendulum motion in the images of input video closely corresponded to the region with $\Delta F \simeq 30$.

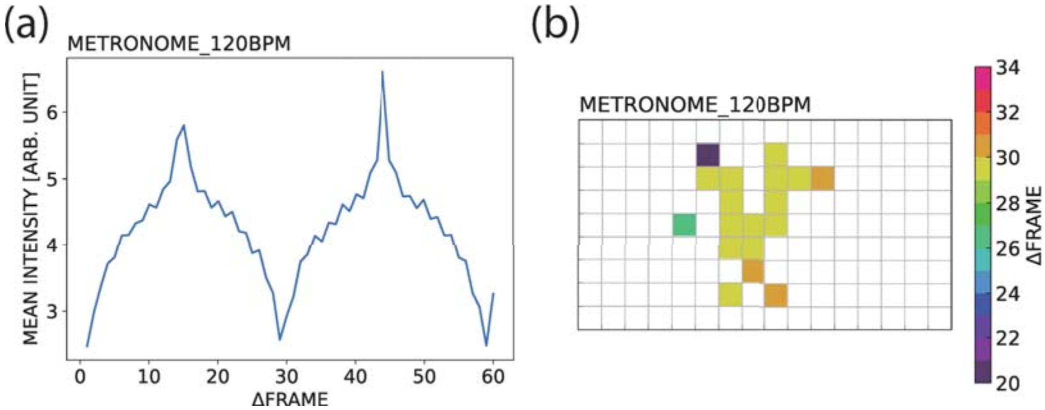

Fig 3: (a) Mean intensity variations with different frame gaps. (b) Contour plots illustrating the detected areas of periodic motion in the 9×16 resolution images with a 120×120 binning of the original FHD image.

These results suggest that the characteristics of periodic motion in a video can be recognized by calculating the frame difference while exploring a range of ΔF values that encompass the target period of the motion. This recognition method is significantly faster than performing frequency analysis using the Fast Fourier Transform (FFT) technique on all frames of the video. Additionally, it can be executed on edge devices as it does not heavily rely on machine power. By storing only the images shown in Figure 3, it is possible to monitor specific movements without collecting any personally identifiable information, such as facial data.

4. Conclusions

We reported a procedure for extracting periodic motion from the test input video (1920×1080 pixels, 30 FPS). The motion and its corresponding areas in the images can be recognized by comparing the intensities of frame differences with varying frame intervals.

This method will be adopted for the new monitoring system, where the input video will undergo a conversion process to generate privacy-protected frames, as illustrated in Figure 3b, before being stored. The system is designed to function as a personalized monitoring system capable of detecting specific motions that we aim to identify, such as fidgety movements associated with excretion or scratching caused by atopic dermatitis, by defining their respective periods in advance. Consequently, it has the potential to substantially alleviate the physical and psychological burdens experienced by caregivers.

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