Activity Monitoring Using Wearable Sensors in Manual Production Processes - An Application of CPS for Automated Ergonomic Assessments

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Abstract. The automated identification and analysis of human activities in a manufacturing context represent an interesting challenge to support the workers, providing novel solutions for managing and optimizing existing manufacturing processes. If on one hand real-time coupling of events and activities is a relatively easy task for activities which are executed by means of information systems, on the other hand, the coupling of events and human physical activities remains an unsolved problem. In this paper we present a novel paradigm based on the integration of a light-weight, low-cost body sensor network and a software solution based on machine learning for tracking working operations. This enables the fast identification of inconvenient ergonomic behaviors and process aspects, which are objective of workflow analysis, process improvement and optimization activities. To assess the usability and functionality of the system a study under real conditions was conducted in the logistic plant of a big automobile manufacturer.

Keywords: Activity Recognition, Process Identification, CPS, Wearable Sensors

1 Introduction

The paradigms of Industry 4.0 and Industrial Internet aim at enabling the automation of production processes by means of the development of smart factories using the Internet of Things [1]. Smart factories integrate information systems and physical entities to trace components during every production step and to receive information from the machines during their lifecycle. This enables to deduce the workflows of production and business processes for a better process management. Process discovery approaches, by means for instance of process mining techniques, enable to

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check the conformity of accomplished processes and process models, in order to identify anomalies and inconvenient situations during the process execution [2].

Manual activities still play an important role in the industry. Semi-automated and manual manufacturing systems are largely present in industrial contexts and the complete automation of several manufacturing sectors represents a utopian target [3]. Activities with high human involvement are often necessary and hardly replaceable by machines. Nowadays, even in very automated manufacturing contexts, certain types of assembly tasks, loading and unloading operations cannot be automated.

The goal of this paper is to provide an approach for IoT-based systems for monitoring and assessing work situations in manual work processes. We propose an automated system, which combines wearable technology and machine learning for detecting workflows and operations during logistic processes with high human involvement. We integrate activity recognition approaches with process identification techniques, in order to detect human activities for identifying information about executed processes and possible anomalies. By means of this information, the system is able to learn patterns for correlating inconvenient ergonomic behaviors and process steps, making possible to predict potentially dangerous working activities.

This paper aims at answering following research questions:

- How can we integrate body sensor networks and AI techniques based on machine learning for identifying and analyzing human activities in manufacturing?
- Is it possible to combine ergonomic and process information for predicting potentially inconvenient or dangerous process activities?

The result of our research is an infrastructure based on hardware components and a software framework, which makes possible the automated conformity check between process model and process execution, supporting the workers with relevant feedback.

1.1 Methodology and paper structure

According to Hevner's design science research approach [4], our research follows seven guidelines to be rigorous and relevant. Our newly implemented IT infrastructure for a low-cost body sensor network, presented in section 4 and developed according to the requirements described in section 3, represents the innovative and purposeful artifact (Guideline 1) The introduction section and the related work specify the relevance of the research the problem domain (Guideline 2). The aspects concerning the evaluation of the artifact (Guideline 3) are considered in section 5. A prototypical implementation has been developed to demonstrate our artifact and to show the feasibility of the system and its innovative strength (Guideline 4). The prototypical implementation presented in this paper represents our proof of concept. It enables the real-time recognition of human activities during logistic operations, which permits to deduce information about inconvenient ergonomic behaviors and their correlation with workflow and process steps. Section 1 shows the respect of a rigorous methodological research approach, which reflects the coherence and the consistency of the artifact (Guideline 5). Conceiving the design science as a search process (Guideline 6), in section 2 we show that the presented approach considers the relevance of previous related work. The purpose to permit the communication of the research (Guideline 7) is expressed publishing this paper.

2 Related Work

2.1 Activity Recognition for Process Identification of Manual Operations

The issue of process identification and analysis of manual working activities represents an interesting workbench for testing cutting-edge technologies and redesigning traditional paradigms for manual manufacturing. Tracking working activities enables to gain important information to better control and manage business processes, in different areas of application [5,6]. For instance, process reengineering takes advantage of process identification to shape ideal target processes [7]. In production scheduling and planning, process identification and analysis techniques are employed to model dynamic process planning system [8]. To be able to identify specific processes, it is, of course, necessary to detect activities and relevant process steps during their execution. Different methods and technologies are used for process identification tasks. According to the classification of human motion of Aggarwal and Cai 1999 [9], human motion analysis can be distinguished into body structure analysis and tracking of human motion. From a technical point of view, analysis and tracking of human activities can be done by means of optical tracking or integrating sensor-based cyber-physical systems. Marker-based optical systems can be employed to recognize steps of a process and specific objects, which are useful to infer information about workflows and processes. Systems based on optical tracking with markerless technology can provide classifications of work tasks in industrial environments [10]. Similar approaches have been used in manufacturing to extract the temporal structure of workflows [11, 12]. Sensor-based cyber-physical systems can be wearable or non-wearable. Wearable computers are one approach to track physical activities of humans with a focus on tracking of assembly steps in car manufacturing [13, 14]. Lee and Mase 2002 [15] developed one of the first systems of body sensors to detect activities and location of the user. Kitagawa and Windsor 2008 [16] compare different motion capture approaches from industry. Even if they are very common, traditional systems for activity recognition based on motion capture and optical technology present big limitations: the very large computational power and storage needed, the limitation of the workers' movements to the field of view of the cameras and the reduction of the workers' privacy, which limit the acceptance of the system.

2.2 Real-Time Ergonomic Analysis

Within manufacturing and logistic processes, musculoskeletal disorders caused by manual tasks represent one of the main factors of all work-related disorders [17]. Ergonomic analyses are usually done by methods of observation, which evaluate the ergonomic situation after that the exposure to critical postures, or positions, has taken place [18]. Different tools are used to evaluate the ergonomic working conditions. Examples are the "Ovako Working posture Analysis System" (OWAS) [19], the

“Rapid Upper Limb Assessment” (RULA) [20] and the Ergonomic Assessment Worksheet (EAWS) [21]. All ergonomic evaluation methods by observation have own advantages and focus. Since 2009 EAWS is the standard in the automobile industry [22]. These methods of observation serve primarily the structural prevention (external factors for a better working environment; i.e. redesigning the workplace or reducing physical demands within the working conditions). The other part is the behavioral prevention, which focuses on the individual behavior of the worker and tries to improve the working condition through training and education [23]. There are only a few existing systems for providing real-time ergonomic feedback. The RULA score can be used to assess the criticality of the posture, or position, and the modalities for feedback are acoustic and haptic [24]. Battini et al. 2014 combine a set of ergonomic methods (RULA, OWAS etc.) which can be chosen appropriately for the working condition. However, EAWS is not part of it. For the feedback, the system uses the visual modality [25]. Last two cited systems are based on motion capture technology, which, as we already analyzed, presents several limitations.

3 Requirements of the System

3.1 Requirements for Human Activity Identification in Manufacturing

Based on our concept idea and on the shortcomings of the state of the art analysis, we derived specific requirements for our artifact.

Requirement 1. ***The framework must be able to implement the corpus of sensor data.*** In order to automatically recognize patterns to be associated with related human operations, the framework must recognize and implement the available sensor data. Since the framework is based on machine learning techniques, several in-lab tests of the system must be accomplished before the framework reaches a sufficient training set of data, which is necessary for the good operation of the system. Moreover, preparatory tagging operations for the machine learning process of the system must be done before the start of the study under real conditions in the manufacturing plant.

Requirement 2. ***The feedback mechanism does not have to interfere with the working activities of the user.*** Since the manufacturing contexts are often very loud because of the presence of working machine, the use of acoustic feedback will not be considered. Haptic and visual feedback will be used to interface with the user, by means of a mobile device which is attached to the forearm of the user. This enables to perceive haptic feedback and to check the monitor of the device, in case the manual activity which the user is performing allows it in safety. The use of Head Mounted Displays (such as Google Glasses) as a feedback source for the user has been considered and the developed framework can integrate this typology of devices.

Requirement 3. ***The framework must be able to integrate data from different sources.*** In case of ambiguous or unclear identification of a working operation, further external sensor sources must be able to be integrated into the framework for solving ambiguities of interpretation. Data concerning ambiguous or unclear working activities are combined with external data (i.e. position data coming from the Wi-Fi net) and with available process information which has been already detected.

3.2 Requirements for Ergonomics and Feedback Interaction

To prevent critical ergonomic situations the analysis and feedback of postures must follow a designated and reproducible set of feedback criteria, as shown in the introduction and related work section.

Requirement 4. *The framework must use a standardized procedure for the assessment of physical stress.* For our system, the Ergonomic Assessment Worksheet (EAWS) [21] has been chosen as a guideline for feedback and input, for the workflow management system (and therefore to fulfill interlinking between structural and behavioral prevention). EAWS differentiates between standing, walking, sitting, and kneeling or squatting. These postures concern the upper body. Our system must enable feedback after exceeding the following EAWS positions: “Diffraction” ~60°; “Rotation” ~30°; “Tilt” ~30° and “Hands over the head”.

Requirement 5. *The framework must provide real-time ergonomic feedback about critical ergonomic postures.* For the score of the ergonomic assessment through EAWS, points are accumulated over two factors: intensity and duration of the inconvenient posture [26]. For providing feedback about the criticality of the ergonomic posture in real-time, these measures must be combined and adjusted, according to a normalization process. For this reason, our system accumulates points when reaching a specific threshold within the values of the pressure and strain sensors (see EAWS positions above). After exceeding the threshold values over a timespan of two seconds, an alarm is triggered. The purpose of this design is that postures which are ergonomically critical can be avoided in advance. In the EAWS method, points are calculated only when a timespan of four seconds is exceeded. With our system, the user can avoid postures, which would result in a worse EAWS score, because of the possibility to leave the critical ergonomic posture within the two seconds of difference, which is calculated between our feedback system and the point where the EAWS method would calculate points for its score.

4 System Design and Development

4.1 Hardware Architecture

The hardware components are based on a flexible textile shirt with strain sensors, hydrostatic pressure units and an electrical part for analog/digital conversion with serial-send-unit. Sending process will be done with a 5 GHz Wi-Fi connection to a router. The mobile device feedback is also connected to this access point. For the experiment, the shirt was equipped with a high stretchable textile material to fit a variety of different human body families. Furthermore, these sensors have the capability to be physically calibrated in the same kind of variety. With the help of the strain sensors, the system is able to measure the demanded EAWS positions, diffraction, rotation and tilt of the upper body. In this way, the sensors are situated in the middle of the back to the waistband, symmetrically on both sides from the shoulder diagonally to the complementary side at the waistband and at last on each body side left and right. For the investigation of the position of hands in reference to the head, pressure elements attached to the top of the shoulder are used. The electronic components, which are fixed on the user's back, measure the singular values, convert them and send them in a specific order via a serial output to the host.

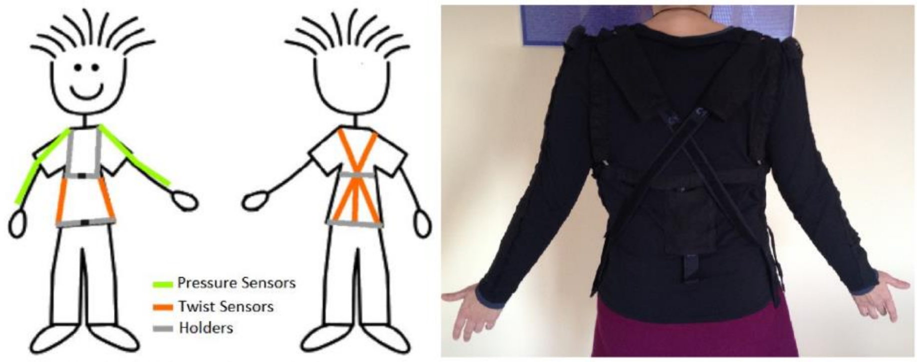

Figure 1. Representation and photo of the body sensor network which we used.

4.2 Software Architecture

Based on the requirements analysis, the software architecture covers the sensor processing, the process monitoring, discovery and analysis, as well as notification mechanisms for the user. The main component of the framework is the Process Engine. Its function is to analyze and process sensor data detected by the sensors and it has direct interface with every software component. Sensor data collected by the Sensor Body Network are sent and received via Wi-Fi and analyzed. The Process Engine deals with the ambiguity of activity recognition by means of applying context knowledge, according to the specificity of every process instance and considering the specificity of the knowledge domain where it operates. Its use of operative BPM tools enables the reasoning over existing model artifacts. Modeling notation techniques (such as eEPC and BPMN) are used from the Process Engine for enabling process type recognition and monitoring the course of detected processes. This connection with operative BPM systems makes possible the evaluation of the process history and the comparison between the planned model of the process and real process. For analyzing and processing complex events, it is necessary to consider the specifically involved entities. Therefore, the Process Engine is able to recognize the different process instances and to infer probabilistic considerations about the involved users. If for instance the system recognized that a specific user is performing an activity, but it is not able to distinguish between two very similar activities, the framework merges together different kinds of data (such as location data or older process instances of the user) to provide an accurate survey of the performed process instances.

A large amount of data from multiple sources is combined to infer specific process patterns and to solve potential equivocal behaviors, these are represented in Fig.2 as "External Sensors". After a process of filtering, normalization, aggregation and segmentation of the received information, the Process Engine initiates the storage of the event data on the Data Layer. The Process Engine is able to correlate newly received data with process histories and models, according to the specificity of every process instance. The system learns from received sensor data, enhancing the knowledge of the system about specific actions. This enables the possibility to provide related feedback to the user. By means of a Mobile Device attached to the forearm of the user, the Process Engine provides haptic and visual feedback about inconvenient or dangerous working operations. This feedback information is not only related to inconvenient ergonomic behaviours, but it is also about probabilistic considerations concerning sensor-based process activity predictions. A further possibility for receiving feedback is represented by the use of Head Mounted Displays, which have been considered for being integrated into the system.

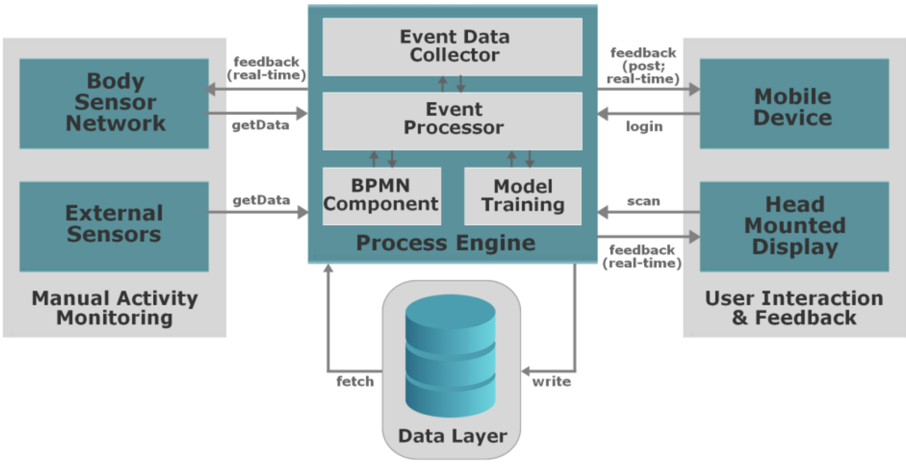

Figure 2. Architecture of the system

4.3 Sensor-Based Process Activity Prediction

The sensors as indicated in Figure 1 can be utilized to monitor the body posture and hence the load for certain body regions over time. As the actual load largely correlates with the task at hand, i.e. the action that the user performs, proactive support to prevent ergonomically bad situations by predicting the next actions, i.e. the next process activities based on the sensor data. In our model, we hence formulate the value ranges of the different sensors with t for the various twist sensors and p for the pressure sensors. We use this sensor data as the input vector to learn situations as a binary or multi-class-classification problem. We either learn, if an alarm occurred as a binary classification problem and the process activity a as a multi-class classification from the set of process activity types A. Due to the high intra-individual differences in the actual sensor values we translated the actual sensor values to an 80-item score scale that interpolates the score according to threshold values determined in an individual calibration being performed with every participant. This causes all t and p values being transformed to t' and p' respectively. Hence, the alarm prediction using binary classification can be formulated as follows:

$$\langle t'_1, \dots, t'_5, p'_1, p'_2 \rangle \rightarrow \begin{cases} 1, if\ alarm \\ 0, else \end{cases} \quad (1)$$

In a similar way, a simple multi-class classification that performs the process activity prediction can be formulated as follows:

$$\langle t'_1, \dots, t'_5, p'_1, p'_2 \rangle \rightarrow a \in A \quad (2)$$

As the sensors capture mainly upper extremity movements, this approach is not entirely appropriate to distinguish under extremity movements. Hence, we also filter the results from (2) with all permitted activity types from the process model.

5 Use Cases

5.1 Execution of the Experiment

We conducted a study under real conditions in the plant of the Volkswagen Konzern After Sales, in Kassel (Germany) and we identified three different processes with high involvement of human operations, which constitute our three use cases. These are represented by three process models which differ for sequence and types of working operations. All use cases present analogous process activities, which represent the pool of detectable manual activities. In the first use case, the worker should move small but heavy car components to collocate them in appropriate places. For doing this, the worker has to load the components on a forklift, drive it to the right place and manually unload the components. In the second use case, the worker must interact with a semi-automated warehouse system, by means of a computer. After receiving requests on the monitor of the computer, the worker should manually load and unload car components from a goods lift to a different goods lift. The components are light and they have small dimensions. In the third use case, the worker should place several large and bulky car components inside of a container and then drive the forklift to bring the container to the warehouse. In every use case, the worker must place a printed barcode on the component before moving it to the appropriate place. In some case, if required, the worker must scan the barcode using a manual barcode-scanner. The experiment has been conducted in a real manufacturing plant by real workers as test persons. The study took place during six different days and every use case has been tested during two different days with 15 users. A total of 30 instances (10 per every use case) have been tested. Every instance lasts about 30 minutes and has been performed by one single user. During the same instance, the user performed the same working activities two times. During the first iteration, in case of inconvenient ergonomic position, the user did not receive any feedback, whereas during the second iteration the user did. Every user wore the described sensor body network and had a mobile device tied to the left forearm for receiving eventual feedback.

5.2 Evaluation

The design of the experiment has an A/B testing scenario. Before starting the experiment, every user rated the workload through a standardized questionnaire based on the NASA Task Load Index (NASA-TLX) [27]. This enables to examine the characteristics of subjective workload within following dimensions: mental, physical and temporal demand, performance, effort and frustration. By means of the questionnaire, loads on the users and design attributes of the system have been rated. During the experiment, all users have been monitored by an eye tracking device, in order to properly evaluate the system [28]. Eye tracking technology makes possible to determine and quantify the usability of the system since the reactions of the users could be recorded and associated with specific process activities. As an indicator of attention, the following parameters from the eye tracking device were analyzed: “Overall fixations”, “Overall gaze duration of the fixations”, “Look path, “Fixations on the display” and “Gaze duration of the fixations on the display”. All parameters were standardized (1/s) to allow comparability over all conditions. At the end of the experiment, all users filled out the NASA-TLX questionnaire again and rated the system with a second questionnaire according to ISO 9241-110 [29]. The second questionnaire enables to examine usability characteristics within following features: suitability for the task, suitability for individualization, conformity with user expectations, self-descriptiveness, controllability and error tolerance. Accuracy, relevance and utility of feedback provided to the users have been evaluated. Sensor data for every instance have been compared to determine the influence of feedback for avoiding inconvenient working operations. The precision of the prediction of process activities in relation to the available sensor data has been also evaluated.

5.3 Results

The items of the ISO 9241-110 have an average score of M=4.97 with an SD=0.49, which represent good results. However, the average score has still potential to be improved. The results show no significant increase in subjective workload in the NASA-TLX. The average values of the items changed from M=9.8 with an SD=3.2 without feedback to M=10.0 with an SD=3.5 at the condition with active feedback from the system to the user. The eye tracking parameters show the same results of questionnaires. No significant changes happen within the two conditions and this probably confirms that the choice of the questionnaires is appropriate and all available results are coherent. The change of the eye tracking parameters is shown in Table 1. This is an indicator that no serious additional demand was needed or generated by our system. The fixation on the display with an average frequency of M=0.63 per minute and an SD=0.37 in combination with the gaze duration of the fixations on the display (on average M=0.96s per fixation and an SD=0.67s) suppose that not much attention had to be drawn away from the manual activity to execute the feedback.

Table 1. Results of eye tracking.

Condition	Overall fixations per second	Overall gaze duration per fixation	Look path per second
Without feedback	*M=0.82 SD=0.28*	*M=1.37s SD=0.46s*	*M=1.21cm D=0.57cm*
With feedback	*M=0.83 SD=0.27*	*M=1.33s SD=0.44s*	*M=1.21cm SD=0.54cm*

Every instance has been analyzed and in particular the quantity of inconvenient manual operations detected by the system by means of sensor data has been considered and analyzed. These values constitute a specific pattern in the sensor data and according to this pattern, feedback for the user are generated by the system. Comparing the iteration without feedback and the iteration with feedback for the user related to the same instance, we observe a reduction of 54% of the quantity of feedback. This would mean that if the users receive feedback from our system, the users will probably decrease by about 54% the quantity of inconvenient behaviors. By means of the evaluation of the artifact, we identified during which process activity more feedback for inconvenient behaviors is sent to the users. We identified 21 typologies of process activities, which are common for all three use cases and then we analyzed the quantity of feedback per every process activity (Fig.3). We can observe that the process activities with the highest rate of feedback for inconvenient behaviors are following: “2-hands lifting” (28,5%), “2-hands arrange” (28,3%) and “2-hands dropping” (18,2%). These results are coherent, if we consider that the highest quantity of inconvenient or dangerous behaviors has been identified during three process activities in which the main task implied the loading of heavy components.

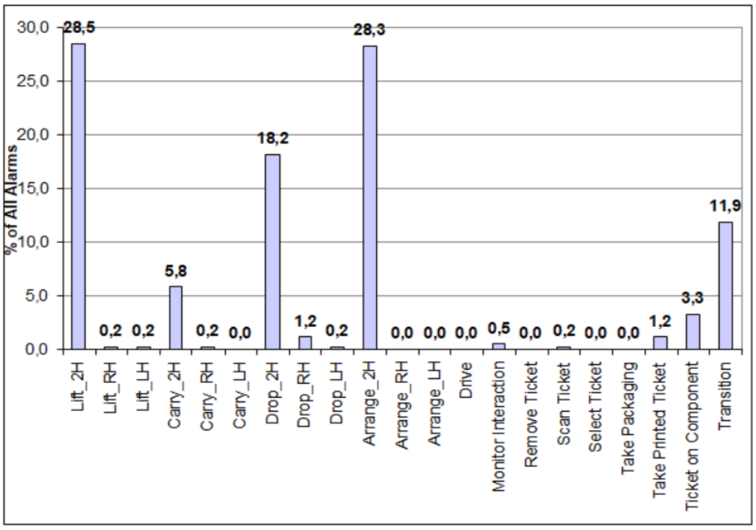

Figure 3. Percentage of alarm feedback per process activity.

In the practical evaluation, the system has been prepared and calibrated for every single user to cater to the individual physical characteristics (e.g. body height and shape) of each participant. The scoring system, as introduced in section 4.3, partially solves the problem of interpolating these values, however, it makes it somewhat more difficult to express the absolute values. For future serial production, the use of confection sizes could help this situation. The customer should be able to wear the shirt simply and comfortable - without doing a complex calibration. As the data showed, the prediction of process activities was limited by the sensor selection in the given suit. While this is appropriate for assessing the ergonomic situation of a person, it is not entirely possible to monitor all potential human activities of an actor in a business process. However, the results indicate, that the process discovery mechanism itself works. The limitation lies in the selection of sensors, which could be extended in future work. Another interesting effect was, that for the second use case, where the process was being followed in a more structured way by the employees, also the discovery accuracy was considerably higher.

6 Conclusion & Outlook

The approach presented in this paper introduced a new approach for discovering business processes from physical human activities captured by sensor data. The sensor data are being analyzed with a focus on ergonomic risks in the work process and associated with the given activities in a work process in order to determine organizational weak spots in the process or workplace design. The approach seems viable and useful from an end user’s perspective as well as for a general approach for process discovery based on sensor data. While the low-cost sensor setup ensures a high applicability of the approach in industrial practice, it limits the ability to discover arbitrary kinds of business processes. Hence, for discovery accuracy, future work has to incorporate more exhaustive sensor setups, while for industrial setups cost-benefit analysis has to be performed in order to define a sufficient yet minimal sensor setup for a given set of workplaces.

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