# Above-knee Prosthesis Control Based on Posture Recognition by Support Vector Machine

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***Abstract*—In order for individuals suffering from trans-femoral amputation to walk in a variety of circumstances, the above-knee prosthesis based on posture recognition was presented. The body posture of lower limb was classified into four classes, "stair", "sitting", "standing", and "walking". For measure the amputee's movement intent, surface EMG signals which can reflect amputee's movement intent and can be measured without invasion were applied to identify postural adjustments by support vector machine. The result of this study indicates that this method can recognize every postural adjustment with a higher identification rate, and has a great potential in practical application of artificial lower limb.**

***Keywords*—above-knee prosthesis, surface electromyography signal, posture recognition, support vector machine**

## I. Introduction

Above-knee (A/K) prosthesis is an artificial device used to replace the missing limb of a trans-femoral amputee. Although the evolution of the above-knee limb prosthesis over the recent decades has progressed from purely mechanical systems to systems that include microprocessor control, most commercially available prostheses are passive [1]. Their mechanical properties, these remaining fixed, are not optimal during the whole gait cycle, for different walking speeds, terrains, especially the sudden posture irregularities.

The development of a powered prosthesis changes significantly the nature of the user-prosthesis interface and control problem. Unlike a passive device that can fundamentally only react to a user's input, a powered device can both act as well as react. In order for individuals suffering from trans-femoral amputation to walk in a variety of circumstances, the A/K prosthesis should be able to detect stairs, sitting down, and other non-standard gait behaviors and respond appropriately [2]. Therefore, posture recognition was applied to reflect the changing of posture.

Studies of the anticipatory postural adjustments suggest that there are three major components that influence anticipatory postural adjustments: motor action, perturbation, and postural task [3]. The electromyography (EMG) signals are the signal detecting the superposed motor unit action potentials. Especially the surface EMG, which is the approach used by actively powered myoelectric upper extremity prostheses, incorporates surface electrodes (often in the prosthesis socket) to extract command signals from the muscles in the residual limb [4] [5].

Human motion is actuated by the cooperative activities of several muscles with the EMG signals reflecting the activity of each muscle, and it can be applied to measure the amputee's movement intent [6]. After a limb is amputated, the brain continues to send signals to the remainder of the limb. Therefore the surface EMG signals were applied to identify the changing of posture.

By taking into account the similarity among profiles within functional groups, the number of basic functions was reduced. Through the analysis of the average EMG profile in every posture, five muscles were applied to classification. The body posture of lower limb was classified into four classes, "stair", "sitting", "standing", and "walking".

Therefore, this study will contribute in realizing the power knee which can detect non-standard gait behaviors and respond appropriately. Support vector machine (SVM) algorithm was applied to recognize different posture of lower limb by surface EMG signals.

## II. Our Apprpach

This study proposes an intelligent control framework for the control of the powered trans-femoral prosthesis as shown in Fig. 1. It is composed of pattern recognition, self-lock control, gait control, motor control, and physical feedback.

The EMG signals were translated into state signals and posture signals by pattern recognition, and these signals were

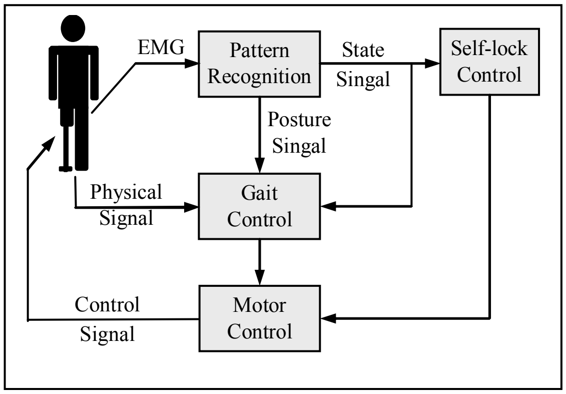


Figure 1. The above-knee prosthesis model

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applied to gait control on account of natural gait. In addition, the state signals were applied to self-lock control on account of safe requirement, and control the power knee through motor control. Otherwise, physical quantities sampled from prosthesis' knee joint such as moment and angle of knee joint construct a physical feedback. Those signals were combined organically with the input of control system.

Using EMG information, they can provide for a more natural gait by discriminating different posture changes. It can be programmed to detect the posture changes and other pathological behaviors and react appropriately.

### A. Stair Recognition

The ability to successfully negotiate stairs and steps is an important factor for functional independence [7]. But passive A/K prosthesis can't produce power to make the person walk, and can't climb stairs on the amputee's own initiative. It drives the keen joint by body, and makes the amputee be tired with a long-playing dressing. The power knee should provide the user with an external source of energy for lifting the body when climbing the stairs [8] [9]. So it is necessary for the knee joint to recognize the stair movement.

### B. Walking Recognition

The conventional above-knee prosthesis walks with a fixed speed, and it is easy to make the disabled people tired. Subjects naturally selected a walking velocity associated with a minimum of muscular activity. Hence it is required that the speed will be changed within one stride and that the knee will react immediately as the change in speed occurs.

The surface EMG profiles strongly depend on walking speed, and the general trend is that increase of EMG amplitude increase also walking speed [10] [11]. So it can be applied to recognize the walking speed, such as slow, normal, and fast.

### C. Standing Recognition

Standing also a common functional activity of daily living, and a principal and importance requirement for the A/K prosthesis is avoiding collapsing during stance (giving way), namely the knee moment must be generated to guarantee stability all along the stance phase, and the knee was flexed in the swing phase. Otherwise people should stand before and after walking when he change his posture between walking and sitting. So it is necessary for the knee joint to recognize standing.

### D. Sitting Recognition

Rising from a chair and sitting down are common functional activities of daily living. In the past two decades, researchers have studied the biomechanics of sit-to-stand and, to a lesser extent, stand-to-sit activities [12]. The EMG parameters of muscles indicated a significant difference in the course of sit-to-stand and stand-to-sit [13]. So the surface EMG signals can be applied to identify the convert of sit to stand. But the peak EMG activities of rectus femoris and tibialis anterior increased with decreasing chair height, and they were affected by the foot position. So it is necessary to eliminate these disturbances.

## III. Algorithm Description

Support Vector Machine represents a new approach for pattern classification that has attracted a great deal of interest in machine learning. It succeeded in solving many pattern recognition problems and performed better than non-linear classifiers [14].

### A. Support Vector Machine

The object of the SVMs is finding the optimal hyperplane to separate clusters in the nonlinearly separable context. Unlike neural networks, SVMs training always finds global minimum of the risk function and small size problems. It uses SRM principle to construct hyperplane, which makes the class interval among every class of data be maximum [15].

Given a training set of instance-label pair $(x_i, y_i)$, $(i = 1, \ldots, l)$ where $x_i \in R^n$ and $y \in \{1, -1\}^l$. The decision function:

$$D(x) = \mathbf{w}^T \mathbf{x} + b . \tag{1}$$

where is an $m$-dimensional vector, $b$ is a scalar, and

$$y_i D(x_i) \geq 1 - \xi_i \qquad i = 1, \ldots, m . \tag{2}$$

Here $\xi_i$ are nonnegative slack variables.

The distance between $D(x) = 1$ and $-1$ is

$$2 / \|w\| = 2 / \sqrt{w^T w} . \tag{3}$$

The problem of constructing optimal separating hyperplane can translate into constrained minimization problem:

$$\min_{w,b,\xi} \; \left(\frac{1}{2}\|w\|^2 + C \sum_{i=1}^{m} \xi_i\right) . \tag{4}$$

subject to the constraints:

$$\begin{aligned} & y_i((w^T x_i) + b) \geq 1 - \xi_i \quad (i = 1, \ldots, m) \\ & \xi_i \geq 0 \end{aligned} . \tag{5}$$

where $C$ is the parameter that determines the tradeoff between the maximization of the margin and minimization of the classification error.

This problem can convert into the dual problem. So support vector machines require the solution of the following optimization problem:

$$\begin{aligned} & \max \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \phi(x_i)^T \phi(x_j) \\ & 0 \leq \alpha_i \leq C \quad \sum_i \alpha_i y_i = 0 \end{aligned} . \tag{6}$$

Here training vectors $x_i$ are mapped into a higher dimensional space by the function $\phi$. The SVMs finds a linear hyperplane with the maximal margin in this higher dimensional space. C >0 is the penalty parameter of the error term.

To avoid computing the transformation $\phi(x)$ explicitly, the scalar product is replaced with $K(x_i, x_j)$ instead.

$$K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j) . \tag{7}$$

Solving (4) gives a decision function of the form

$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{m} \alpha_i y_i \, \mathrm{K}(x_i, x_j) + b\right). \tag{8}$$

The degrees of freedom of the SVMs model are decided by the choice of kernel, the parameters of the kernel and the choice of the regularization parameter as shown in Table I [16].

## B. Application of SVM to Posture Recognition

On account of SVM was originally designed for two-class problems, the body posture of lower limb was classified into four classes, “stair” (up stair and down stair), “sitting” (sit-to-stand and stand-to-sit), “standing”, “walking” (different speed: slow, normal and fast) as shown in Fig. 2.

# IV. Evaluation And Experimental Results

The surface EMG signals were recorded to recognize state pattern by the hybrid NN-GA algorithm. By taking into account the similarity among profiles within functional groups, the number of basic functions could be reduced. Through the analysis of the average EMG profile among the 14 leg muscles, five muscles were applied to classification.

TABLE I. Walking Experiment Parameters

| **Kernel’s types** | $K(x_i, x_j)$ |
|---|---|
| Linear kernel | $K(x_i, x_j) = x_i^T x_j$ |
| Polynomial kernel | $K(x_i x_j) = (\gamma x_i^T x_j + r)^d$ |
| Gaussian radial basis function kernel | $K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2)$ |
| Sigmoid kernel | $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$ |

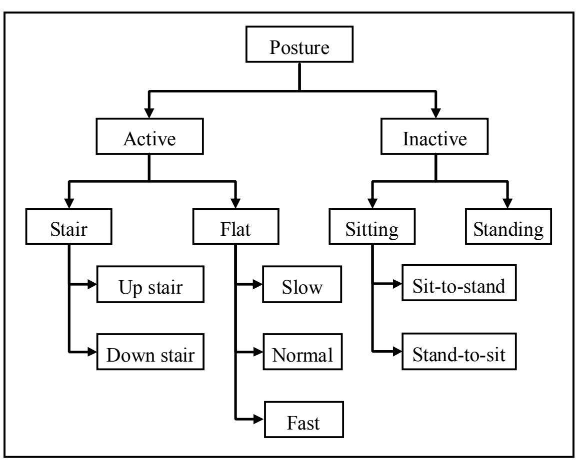


Figure 2. Flow-chart of posture recognition.

## A. Signal Recording

The surface EMG signals of five muscles (EMG1: rectus femoris, EMG2: biceps femoris, EMG3: semitendinosus, EMG4: gastrocnemius medialis, EMG5: soleus muscle) were recorded by means of surface electrodes over the skin of the leg simultaneously on the right side of the right side of the body in each of 5 normal subjects (4 male and 1 female), and 2 disable subjects. Otherwise, two sensors were put under the heel and toe inside the shoe to provide the synchronization signal for the heel strike (when the foot first hits the ground) and toe-off (when the foot leaves the ground for swing), and a angle sensor was applied to record the synchronization angle of knee joint.

The surface EMG sensor automatically converts this signal to a root mean square (RMS) signal (an analog rectification is done inside the circuitry), and the active range is from 20 to 500 Hz. After preprocessing and feature extraction of EMG signals, SVM algorithm which was based on the theoretical learning theory and can be used for pattern classification or regression, was applied to recognize the posture of lower limb. Otherwise, cross validation is used to select the kernel function and parameters.

## B. Standing Recognition

In the trial scenario, the standing experimental subject started with a transition from standing to walking. After four strides of walking, a transition from walking to standing was performed. For these transition, the subject was asked to walk at a self-selected pace. Fig. 3 shows a set of surface EMG signal from a subject.

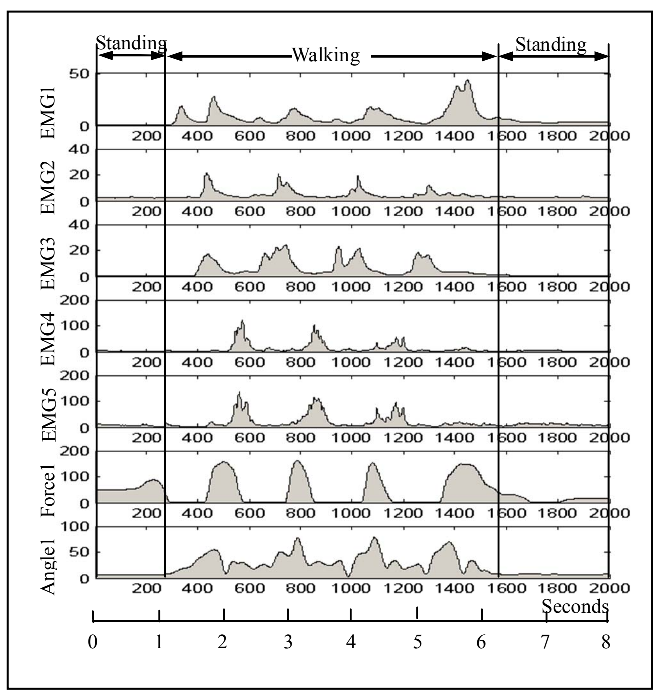


Figure 3. The EMG signal from standing to walking, and then to standing.

As can be seen, the transition from standing to walking and walking to standing can be identified easy by the changes of EMG signals.

### C. Terrains Status

*1) Stair Recognition:* In the trial scenario, the standing experimental subject started with a transition from flat to up-stair walking. After 10 stairsteps of walking, a transition from up-stair to flat walking was performed, and then the person went down stairs. At the end of this trial, a transition from down-stair to flat walking was performed.

Fig. 4 shows a set of surface EMG signals from a subject. Fig. 4 (A) reflected the transition from flat to up-stair walking, and then to flat walking, and Fig. 4 (B) reflected the transition from flat to down-stair walking and then to flat walking. As can be seen, each muscles reflected different characteristic between the transition from flat walking to up-stair walking and transition from flat walking to down-stair walking, and it can be applied to identify the changes of EMG signals.

*2) Flat Recognition:* Subjects walked on a motor driven treadmill (2.0*0.7m) at the selected walking speeds. The standing experimental subject started with a slow walking, and then accelerated to normal and subsequently to fast walking. After two strides of fast walking, the person decelerated to normal and then slow walking. Fig. 5 shows a set of surface EMG signals from a subject. The minimum, maximum and average speeds for each class of walking speeds are shown in Table II.

As can be seen, the surface EMG profiles increased as the increase of walking speed. So it can be applied to recognize the change of walking speed by the changes of EMG signals.

### D. Sitting Recognition

In the trial scenario, the standing experimental subject started with a transition from standing to sitting. After several seconds resting, a transition from sitting to standing was performed. Fig. 6 shows a set of surface EMG signals from a subject.

As can be seen, the transition from standing to sitting and sitting to standing can be identified easy by the changes of EMG signals. Although the surface EMG signals were influenced by the ratio of chair height to the leg's length, and they were affected by the foot position, the trend was same and it can be applied to identify the change of sitting and standing.

### E. All Posture Recognition by SVM

For prove the feasibility of this algorithm, a test sequences was preformed by the data collection consisted of sitting to

TABLE II. WALKING EXPERIMENT PARAMETERS

| Walking Mode | Speed (m/s) | | |
|---|---|---|---|
| | *Minimum* | *Average* | *Maximum* |
| Slow | 0.58 | 0.62 | 0.66 |
| Normal | 0.95 | 0.97 | 1.02 |
| Fast | 1.38 | 1.41 | 1.43 |

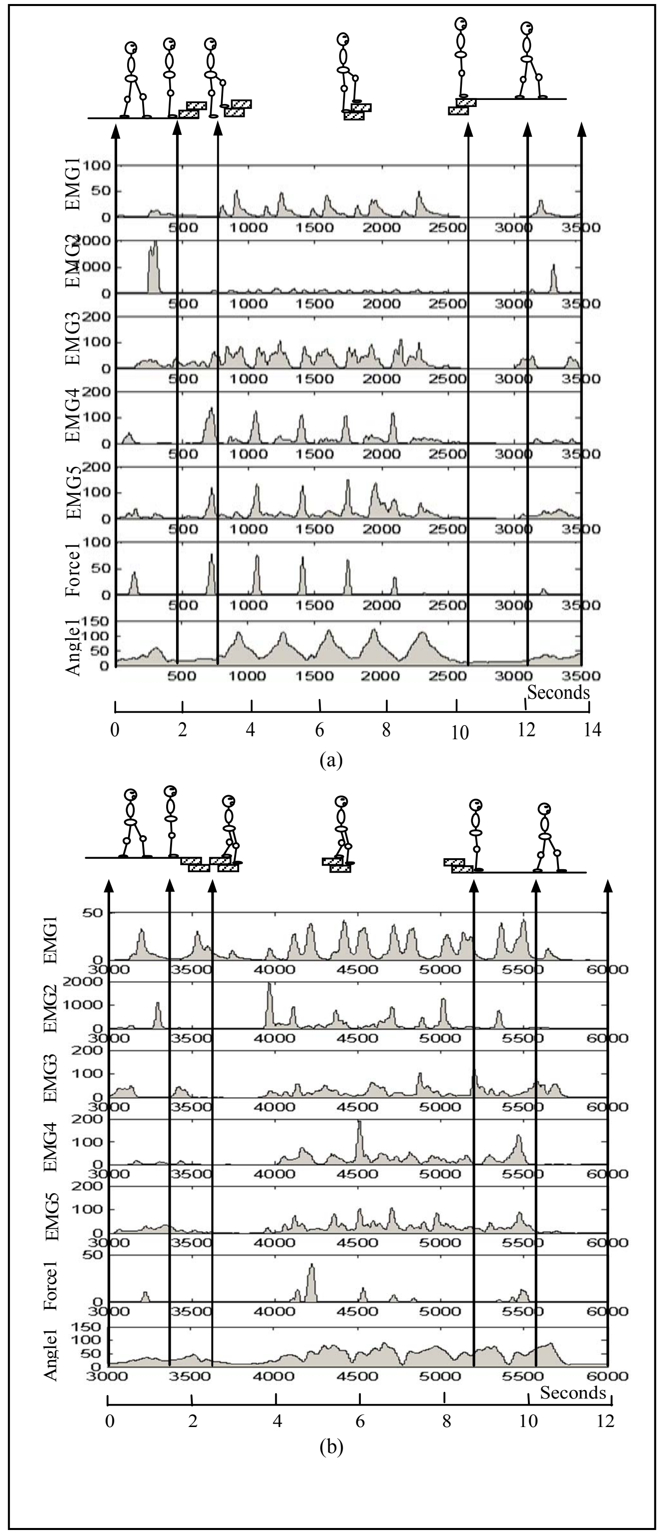


Figure 4. The EMG signal in the stair experiment: (A)from flat to up-stair walking, and then to flat walking, (B) from flat to down-stair walking and then to flat walking.

standing, standing to walking, walking (slow walking, normal walking and fast walking), up stair walking, down stair walking, walking to standing, and standing to sitting.

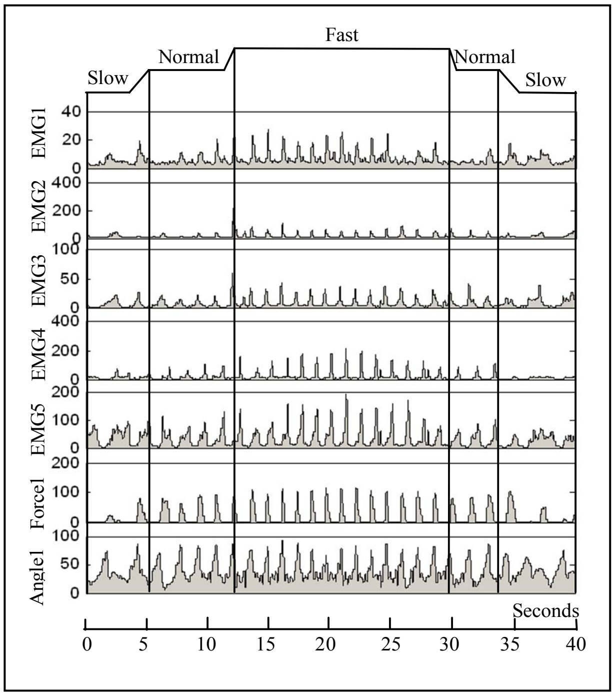


Figure 5. The EMG signal with slow, normal and fast walking.

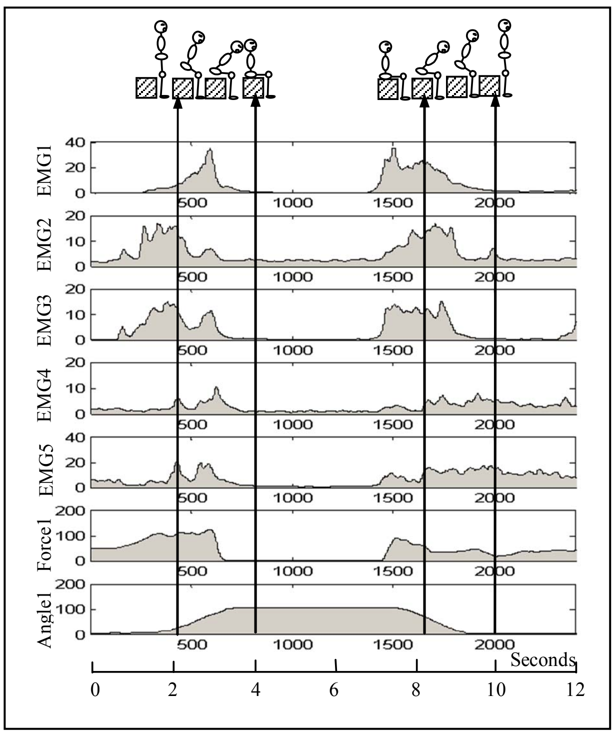


Figure 6. The EMG signal in the sitting experiment: starting with a transition from standing to sitting, and performing a transition from sitting to standing after several seconds resting.

Simulation result shows that surface EMG signal with adequate information to identify the changing of posture, such as sitting, standing, fast walking and so on as shown in Table III. And the SVM algorithm can be applied to posture recognition with a higher identification rate, and the root mean square error and maximum error are less than the other methods obviously. It can also effectively be used in other aspect of prosthesis recognition.

There are a great many of factors influence the classification effect. Cross validation is used to select the kernel function and parameters. Firstly, the training data are separated to several folds. Sequentially a fold is considered as the validation set and the rest are for training. The average of accuracy on predicting the validation sets is the cross validation accuracy.

## V. Conclusion and Future Work

This prosthesis with EMG signals control can both provide partial restoration of "normal" function and improve the performance, comfort, and energy consumption of a trans-femoral amputee through predicting the amputee's movement intent. It can satisfy the optional control and safety need by physiological method, and adapt to the external status, the location of prosthesis, the shift of body, and so on. It represents a more natural and efficient means of electromyography control than one based on discrete, transient bursts of activity, promising to reduce the mental burden of a user, and the dexterity of control.

From results of computer simulation, it is shown that this approach can predict the highly nonlinear relation between different posture of lower limb and EMG signals effectively. SVM are able generalize this relations, and it is a useful tool for identify body posture based on surface EMG signals with high accuracy and speed. By finishing the experiment, it is found that the selection of the model selection of SVM is key problem. Through more suitable model selection, it will reach a better classification result after training.

Otherwise, the postural adjustments discussed in this study were only a part of postural adjustments in the daily life. Other posture changing should be discussed in the further research, such as stumbling, slipping, and so on. And the surface EMG signals were generated by normal subjects rather than from the amputee, more surface EMG signals extracted from disable people will be analyzed further, and which muscles were sampled according to the condition of every amputee should be discussed carefully.

TABLE III. Identification Result

| **Posture** | **Change** | **Indentification Result (%)** |
|---|---|---|
| Standing | Standing to walk | 93.5 |
| | Walking to Standing | 92.1 |
| Sitting | Sit-to-stand | 94.1 |
| | Stand-to-sit | 93.4 |
| Stair | Up stair | 89.4 |
| | Down Stair | 90.1 |
| Flat Walking | Slow | 87.3 |
| | Normal | 89.2 |
| | Fast | 88.1 |

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