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Research Article

Yaşlılarda Düşme Riskini Değerlendirmek için İvmelenme Sinyalinin Frekans Domeni Özellikleri

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Öz

Her yıl dünya üzerinde 65 yaş ve üzerindeki insanların yaklaşık %28-35'i en az bir kere düşer ve bu sayı önümüzdeki yıllarda hızla aratacaktır. Düşme sonrası fiziki yaralanmanın dışında tedavi sonrasında bağımlılık, özerklik kaybı ve depresyon gibi düşme sonrası sendromlarda görülür. Düşmenin hem bireye hem de ekonomik olarak topluma olan etkisi göz ardı edilemeyecek seviyededir ve giderek artmaktadır. Ancak doğru yaklaşımlarla düşme önlenebilir. Düşmenin engellenebilmesi için yaşlıların sık sık denge değerlendirmesinin yapılması ve düşme riski olan yaşlılar için gerekli önlemlerin alınması gerekmektedir. Denge değerlendirmesi için basit anketlerden bilgisayarlı karmaşık testlere kadar geniş yelpazede araçlar bulunabilir. Ancak anketler sübjektiftir. Bilgisayarlı testlerin ise maliyet ve yer kaplamaları nedeniyle birinci basamak sağlık kuruluşlarında kullanılmaları uygun değildir. Bu yüzden birinci basamak sağlık kuruluşlarında kullanılabilecek basit bir yöntem geliştirmek oldukça önemlidir. İvmeölçerler hafif ucuz ve basit yapıları ile giyilebilir teknoloji alanında yerini almış ve denge değerlendirmesinde kullanılabilmektedir. Bu çalışmada PhysioNet veri tabanında yer alan 38'i kontrol 35'i düşme riski olan yaşlıdan kayıt edilen üç eksen ivmelenme sinyali kullanılarak yaşlılarda düşme riskini tanımlayıcı parametreler bulunmaya çalışılmıştır. Bunun için ivmelenme sinyalinden önce yerçekiminden kaynaklanan bileşen çıkarılmış, 0,5 Hz yüksek geçiren 25 Hz alçak geçiren filtre ile filtrelenmiş ve en büyük değere normalize edilmiştir. Daha sonra 25 model derecesinde özbağlanımlı model kullanılarak Burg yöntemi ile ivmelenme sinyallerinin güç spektrum yoğunlukları bulunmuştur. Güç spektrumunda oluşan birinci ve ikinci en büyük tepelere ait tanımlayıcı özellikler, güç spektrumunun statiksel özellikleri, güç spektrumunun enerjisi ile ilgili özellikleri olmak üzere 29 özellik her üç eksen için elde edilmiştir. Bu özellikler bağımsız-örneklem t-testi kullanılarak %99 güvenilirlik seviyesinde karşılaştırılmıştır. Sonuç olarak toplam da dört farklı özelliğin istatistiksel olarak iki grup arasında anlamlı fark gösterdiği görülmüştür. Bu özelliklerden güç spektrumunun kurtosisi ve ikinci en büyük tepenin genişliği özellikleri literatüre bu çalışma ile eklenmiştir.

Anahtar Kelimeler: İvmelenme sinyali, Zaman-domeni özellikler, Yaşlılarda düşme

Frequency Domain Features of Acceleration Signals to Evaluate Fall Risk of Elderly

Abstract

Every year, about 28-35% of people aged 65 and over in the world fall at least once, and this number will increase rapidly in the coming years. Apart from physical injury after fall, it is seen in post-fall syndromes such as addiction, loss of autonomy and depression after treatment. The impact of the fall on the individual and economically on the society is at a level that cannot be ignored and is gradually increasing. However, the fall can be prevented by correct approaches. In order to prevent fall in the elderly, balance assessment should be done frequently and precaution should be taken for individuals at risk of fall. A wide range of tools are available for balance assessment, from simple questionnaires to complex computerized tests. However, questionnaire are subjective. Computerized tests, on the other hand, are not suitable to be used in primary health care centers due to their cost and volume. Therefore, it is very important to develop a simple method that can be used in primary health care centers. Accelerometers have taken their place in wearable technology with their light, cheap and simple structures and can be used in balance assessment. In this study, it was tried to find parameters that define fall risk of the elderly by using the three axis acceleration signal recorded from the elderly with 38 non-faller 35 faller in PhysioNet database. For this, the component caused by gravity was first removed from the acceleration signal, filtered with 0.5 Hz high pass and 25 Hz low pass filter and normalized to maximum. Then, power spectrum density of acceleration signals were found using autoregressive model with 25 model order by Burg's algorithm. 29 features were obtained for

all three axes, namely the descriptive features of the first and second dominant peaks in the power spectrum, the statistical features of the power spectrum, and the features related to the energy of the power spectrum. These features were compared using the independent-sample t-test at 99% confidence level. As a result, it was observed that a total of four different features showed statistically significant difference between the two groups. Among these features, the kurtosis of the power spectrum and the width of the second largest hill are added to the literature with this study.
Keywords: Acceleration signal, Time-domain features, Fall in the elderly.

1. Introduction

Falls and related injuries are major public health problems that often require medical attention. More than 50% of falls at the age of 65 and over require hospital care. If a hip fracture occurred as a result of fall in the elderly, 20% of these cases will result in death. In addition, falls can result in some post-fall syndromes that include addiction, loss of autonomy, immobilization, and depression, which will lead to further restrictions in daily activities. Due to the increase in life expectancy, fall cases in the elderly will increase. If preventive precautions are not taken in the near future, the number of injuries from falls will be 100% higher by 2030. Apart from physical injuries, with the fall fear of the elderly, there are worrying psychological consequences such as social isolation, decreased quality of life and decreased movements. In addition, there is a great economic impact of fall from reasons such as the treatment of post-fall injuries and the loss of workforce in the care of the patient at home. The effects of the fall on health services and economic costs increase significantly all over the world (WHO 2007).

As a result, prevention of fall in elderly, which has serious physical, psychological and economic effects, is very important for both the society and the individual. An effective prevention program first begins with the identification of the elderly at risk of fall and continues with appropriate prevention precaution (Castellini, Gianola et al. 2019, Wu, Lee et al. 2019). For this, it is recommended to make a balance assessment in the annual checks when yes is given to any of the questions such as whether they have fallen in the previous year, how many times they have fallen, if there is an injury (Moncada and Mire 2017). Even if there is no problem related to balance, it is thought that the risk of fall and loss of balance in elderly can be detected early, and this will allow rehabilitation practices to start on time and prevent fall by evaluating individuals over 65 in terms of balance and walking in their routine controls, not annual (Koyuncu, Tuna et al. 2017). It is clear that evaluating the elderly in primary healthcare center in terms of balance and fall in their routine controls will provide an effective fall control.

Balance is examined in two sub-sections, static and dynamic balance. The common disadvantage of all tests used in static balance assessment is their inability to evaluate adaptive postural responses used in most daily life activities (Balaban, Nacır et al. 2009). Therefore, dynamic balance must be measured in order to evaluate an accurate fall risk. Evaluation of the dynamic balance can be done in different ways, from surveys and simple tests to advanced measurements with computer-controlled complex devices (Balaban, Nacır et al. 2009, Koyuncu, Tuna et al. 2017). The questionnaire and simple physiological tests used for fall risk assessment are not an exact objective method, but subjective and qualitative (Najafi, Aminian et al. 2002, Howcroft, Kofman et al. 2013, Sun and Huang 2019). It is impossible to use advanced computer controlled devices in primary healthcare center due to their disadvantages such as space, expert requirement, test time and cost (Balaban, Nacır et al. 2009, Yang and Hsu 2010, Howcroft, Kofman et al. 2013). For these reasons, it is understood that an inexpensive, easy-to-use, objective and quantitative method is required to early detect and prevent the fall in the elderly.

Accelerometers have been accepted as useful and practical sensors for wearable health devices in measuring and evaluating physical activity (Mathie, Coster et al. 2004). In the literature, accelerometers are used in physical activity monitoring and evaluation studies such as posture and motion classification, energy expenditure estimation, sudden fall detection and balance control (Yang and Hsu 2010). In recent years, it has been used in the early detection of fall in the elderly. In the studies carried out for this purpose, time, frequency and time-frequency dependent features were extracted from the acceleration signals recorded from accelerometers, especially during walking. The obtained features were either evaluated statistically and it was examined whether there was a difference between the groups or classified by creating a classification model (Howcroft, Kofman et al. 2013).

In this study, a fall assessment method that can be used in primary health care center has been studied. It has been decided that the accelerometers commonly used in wearable technologies and its acceleration signals recorded during walking are suitable for this purpose. Power spectra of acceleration signals obtained from Physionet database were calculated and some features that define the walking of the person were extracted and these features were evaluated statistically. As a result, it was found that the second dominant peak of power spectra and Kurtosis of power spectra which were not mentioned in the literature show a statistically significant difference between faller and non-faller.

2. Material and Method

2.1. Subjects

Long Term Movement Monitoring Database contains 3-day and 1 minutes 3D accelerometer recordings of 71 elder community residents, used to study gait, stability, and fall risk. (Goldberger, Amaral et al. 2000). The mean age of the participants is 78.36 ± 4.71 years and range is 65-87 years. Participants walked for 1 minute at a comfortable, self-selected speed while wearing a gait belt in laboratory. The 3-day recording was taken at home by self-use of participants. Subjects were classified as fallers and non-fallers based on their self-report of previous falls. If subjects had at least 2 falls in the past year, they were considered as fallers; otherwise they were considered non-fallers (Weiss, Brozgol et al. 2013). In this study, our aim is to predict fall risk of participants using simple methods to use primary health center. So using one minute records as a short and clean data are more convenient for our aim.

2.2. Signal Preprocessing

The raw signals acquired were three acceleration axes, vertical acceleration (V), mediolateral acceleration (ML) and anterior posterior acceleration (AP). The first process on these signals is filtered with a median filter (n = 3) to eliminate unwanted noise spikes. The recorded signals has two components resulting from body and gravitational accelerations. In order to distinguish these two components, the raw accelerometer signal is first passed through a 0.3 Hz low-pass filter to find the component resulting from gravity acceleration. Then, gravity acceleration component was removed from raw acceleration signals to find body acceleration resulting from gait (Karantonis, Narayanan et al. 2006). Obtained body acceleration signals are then passed through a 0.5Hz-25Hz bandpass filter and are normalized to maximum. These operations were applied to the signals recorded from three acceleration axes.

2.3. Frequency Based Acceleration Features

In gait analysis, frequency-based features are widely used. In addition to the commonly used frequency domain features, features like quality factor of dominant peaks area under the PSD of acceleration signal, area under the (PSD) of some band and it's ratio, mean and first half mean and second half mean of PSD, median of PSD and some of another statistical measure like skewness and kurtosis of PSD were added to this study. In order to extract these features, first power spectral density (PSD) of acceleration signal was found using autoregressive (AR) model using Burg method with a model order of 25. Then measure explained below was computed for three acceleration axis Abbreviations and brief explanation of these measure given below. All the features were repeated for all three accelerometer signals. Sample of a PSD acceleration signal and some of features are seen in Figure 1. The number of features obtained for each acceleration axis is 29 and total number of features is 87. The axis that the measure belongs to is shown by the suffix added to the measure names when results are given.

1. Dominant Frequency (F1): Frequency of at which the PSD of the acceleration signal is maximum.

2. Second Dominant Frequency (F2): Frequency of at which the PSD of the acceleration signal is second maximum.

3. Magnitude of Dominant Frequency (MagF1): Magnitude of F1

4. Magnitude of Second Dominant Frequency (MagF2): Magnitude of F2

5. Width of Dominant Frequency (wF1): It is a measure of the steepness of the F1 peak. It is frequency difference between points on both sides of F1 peak where amplitude decreases to half of AmpF1 (Weiss, Sharifi et al. 2011).

6. Width of Second Dominant Frequency (wF2): It is a measure of the steepness of the F2 peak. It is frequency difference between points on both sides of F2 peak where amplitude decreases to half of AmpF2 (Weiss, Sharifi et al. 2011).

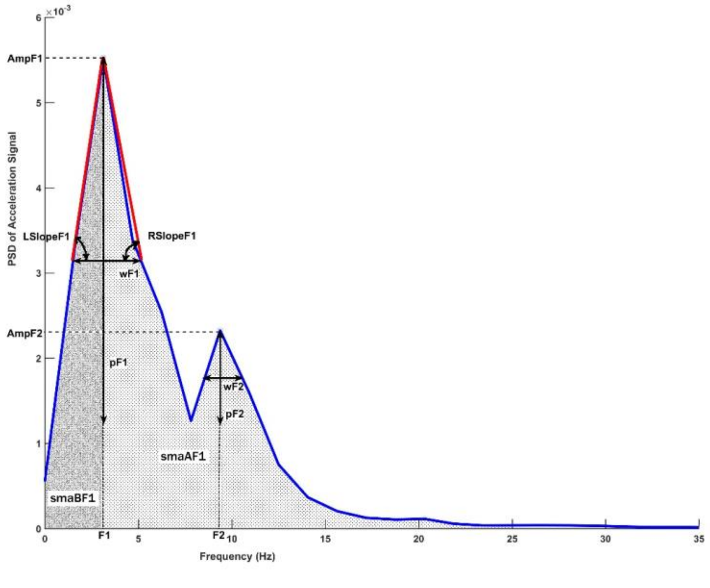

Figure 1. Features of PSD of the acceleration signal.

7. Prominences of Dominant Peak (pF1): It shows relative height of first dominant peak

8. Prominences of Second Dominant Peak(pF2): It shows relative height of second dominant peak

9. Mean of Peaks (pksMean): Mean of all peak values of PSD.

10. Distance between F1 and F2 (bwF1F2): Absolute differences of F1 and F2.

11. Quality Factor1 (QF1): Quality factor of F1 (QF=F1/wF2)

12. Quality Factor2 (QF2): Quality factor of F2 (QF=F2/wF2)(Altunkaya, Kara et al. 2013).

13. Left Slope of Dominant Frequency (LSlopeF1): The slope of a line passing through from points where amplitude decreases to half the amplitude of AmpF1 on the left side of the F1 peak (Weiss, Sharifi et al. 2011).

14. Right Slope of Dominant Frequency (RSlopeF1): The slope of a line passing through from points where amplitude decreases to half the amplitude of AmpF1 on the right side of the F1 (Weiss, Sharifi et al. 2011).

15. Signal Amplitude Area (sma): Area under the all PSD.

16. Signal Amplitude Area of before Peak (smaBF1): Area under zero to F1 band of the PSD.

17. Signal Amplitude Area of after Peak (smaAF1): Area under F1 to infinity band of the PSD.

18. Ratio of smaBF1 to smaAF1 (smaR): Ratio of smaBf1 to smaAF1

19. Mean of the PSD (meanPSD): mean of PSD.

20. Mean of the First Half of PSD first half (mean1PSD): mean of PSD from 0 Hz to Fs/4 band

21. Mean of the Second Half of PSD (mean2PSD): mean of PSD from Fs/4 Hz to Fs/2 band

22. Median of PSD (medPSD): median of PSD of acceleration signal.

23. Variance of PSD (varPSD): Variance of PSD of acceleration signal.

24. Skewness of PSD (SkewPSD): It characterizes the degree of asymmetry of the distribution around the mean. It is calculated as follows where X is PSD, μ is mean of PSD, σ is standard deviation of PSD and the E is expected value

$$\text{SkewPSD} = \frac{E(\mathrm{X}-\mu)^3}{\sigma^3}$$

25. Kurtosis of PSD (KurtPSD): It characterizes the degree of steepness and flatness of the distribution around the mean.

$$\text{KurtPSD} = \frac{E(\mathrm{X}-\mu)^4}{\sigma^4}$$

26. Interquartile range of PSD (iqr): It is the difference between the third quartile and the first quartile range of PSD of acceleration signal.

27. Square Root Mean (rms): It is the effective value of PSD of acceleration signal.

28. Shannon Entropy (ShanEntPSD): Shannon entropy is a measure of the uncertainty of a random process (Diego Galar 2017). It is calculated as follows where X is PSD, i is time index:

$$ShanEnp(x) = -\sum_i {x_i}^2 \log({x_i}^2)$$

29. Mean Absolute Deviation (mad): It is the average of the differences between each value of the acceleration signal and the arithmetic mean.

3. Results and Discussion

The mean and standard deviation of 87 features obtained from vertical, mediolateral and anterior-posterior axis are given in Table 1. The columns are divided into three for three axes and each axis is divided to two for non-faller and faller. In order to understand whether a measure will be used to separate the non-faller and the fall group, using the independent-sample t-test, whether there is a significant difference between the means of the features is compared at the 99% confidence interval. As a result of comparison, it is seen that Dominant Frequency (F1-AP), Width of Dominant Frequency (wF1-AP), Kurtosis of PSD (KurtPSD-AP) recorded from the anterior-posterior axis and Width of Second Dominant Frequency (wF2-ML) recorded from the mediolateral axis show statistically significant differences. In Table 1, these features are written in bold. Figure 1 shows the column graphs of these features. In the graph, the first column shows the average and standard error values of the non-faller group and the second column faller group.

It is seen that there are 23 features obtained from the frequency domain that show statistically significant difference (Howcroft, Kofman et al. 2013). Similar to the literature, the dominant frequency and related features (F1_AP and wF1_AP) showed a statistically significant difference in our study too. In addition, features like quartile frequency, entropy and magnitude area which are found to be significantly different in the literature, do not show any significant difference in our study. Quartile frequency features in (Cho and Kamen 1998) was obtained standing on the floor. Entropy of power spectrum in (Kojima, Obuchi et al. 2008) was obtained with maximum walking speed. Also magnitude area measurement was taken during alternate step test (Liu, Redmond et al. 2011). But we were taken all of measurement during walking with comfortable speed in our study. Differences can be explained between our study and literature due to the measure taken by different activity or different walking speed. Another difference is frequency band of analyzed signal. All of study used different frequency band of acceleration signal. In our study we chosen 0.5 to 25 Hz frequency band which was relatively high and so descriptive features were obtained from the second dominant peak. Also, statistical features of PSD like central moments, skewness and kurtosis that we don't see in the research about fall risk assestment of elderly were calculated. As a result, unlike the literature the width of the second dominant peak (wF2_AP) and the kurtosis of the PSD (Kurtosis of PSD) obtained from anterior-posterior axis showed significant difference between the two groups in our study.

Table 1. Average and standard deviation values of all features

Axis	Vertical Acceleration		Mediolateral Acceleration		Ant-Post Acceleration	
Groups / Features	**Non-Faller** mean±sd	**Faller** mean±sd	**Non-Faller** mean±sd	**Faller** mean±sd	**Non-Faller** mean±sd	**Faller** mean±sd
F1	2,1±1,59	2,14±1,42	4,81±2,04	4,69±1,86	**2,26±1,24**	**1,61±0,26**
F2	7,28±3,98	8,04±4,45	9,83±7,38	11,21±7,32	7,94±3,69	7,59±2,6
AmpF1x10^3	9,59±6,21	9,24±5,82	7,4±6,42	4,9±4,76	16,22±13,85	21,76±16,15
AmpF2x10^3	2,97±1,88	2,56±2,17	2,11±2,51	1,2±1,48	3,76±2,65	3,5±2,47
wF1	1,46±1,07	1,5±0,78	1,42±0,6	1,67±0,82	**1,67±0,78**	**1,23±0,45**
wF2	**1,25±0,71**	**1,03±0,42**	0,98±0,43	0,75±0,18	1±0,5	1,06±0,46
pF1x10^3	9,04±6,08	8,54±5,54	5,95±6,14	3,59±4,43	15,32±13,73	20,31±15,58
pF2x10^3	1,31±1,33	1,31±1,55	0,77±1,45	0,28±0,43	1,03±0,97	1,58±1,57
pksMean x10^3	2,07±0,95	1,93±1,13	1,56±1,24	1,06±0,95	2,97±2,03	3,55±2,07
bwF1F2	6±3,71	6,7±3,89	7,57±5,32	8,3±5,48	5,84±3,22	5,98±2,53
QF1	1,48±0,61	1,47±0,71	3,6±1,52	3,18±1,38	1,49±0,83	1,38±0,26
QF2	7,63±7,24	9,05±6,5	11,7±9,5	15,92±11,22	8,75±4,21	8,09±3,66
LSlopeF1x10^3	5,49±3,96	5,19±3,7	3,4±3,59	1,82±2,7	8,81±8,42	13,09±9,93
RSlopeF1x10^3	4,69±4	4,04±3,31	3,06±3,29	1,81±2,64	7,76±9,01	11,48±10,21
sma x10^3	22,33±9,03	22,03±11,89	20,76±13,6	15,38±10,23	35,55±15,57	38,33±17,75
smaBF1x10^3	6,32±4,54	6,45±5,08	9,91±8,02	7,54±5,09	11,53±9,91	11,78±8,3
smaAF1x10^3	16,01±6,5	15,58±8,88	10,86±8,02	7,84±5,99	24,02±8,47	26,55±10,83
smaR	0,43±0,34	0,51±0,53	1,14±0,77	1,45±1,21	0,51±0,43	0,43±0,2
meanPSDx10^3	6,85±2,76	6,78±3,65	6,57±4,2	4,93±3,16	10,91±4,74	11,84±5,46
mean1PSDx10^3	13,29±5,36	13,16±7,08	12,75±8,14	9,57±6,14	21,16±9,2	22,96±10,61
mean2PSDx10^5	2,54±2,22	1,89±1,72	2,25±1,83	1,38±1,29	6,69±4,44	6,31±4,55
medPSDx10^5	17,01±14	13,4±13,89	15,57±12,65	9,62±8,62	41,61±23,43	38,85±26,22
varPSDx10^5	4,43±5,74	4,39±4,73	3,98±6,37	1,97±3,8	14,61±31,24	22,34±30,03
SkewPSD	3,71±1,07	3,63±0,97	2,88±0,97	2,83±0,79	3,62±1,03	4,26±1,04
KurtPSD	17,73±7,79	16,73±7,44	11,66±6,79	11±5,46	**16,83±7,7**	**21,72±7,93**
iqr x10^3	0,4±0,23	0,35±0,25	0,39±0,33	0,3±0,29	0,6±0,24	0,55±0,28
rms x10^3	1,97±1,06	1,95±1,1	1,72±1,29	1,24±0,9	3,29±2,31	4,1±2,72
ShanEntPSDx10^3	1,46±1,44	1,49±1,35	1,36±1,81	0,75±1,1	3,8±5,58	5,4±5,97
mad x10^3	0,99±0,43	0,99±0,54	0,96±0,63	0,72±0,47	1,58±0,79	1,76±0,95

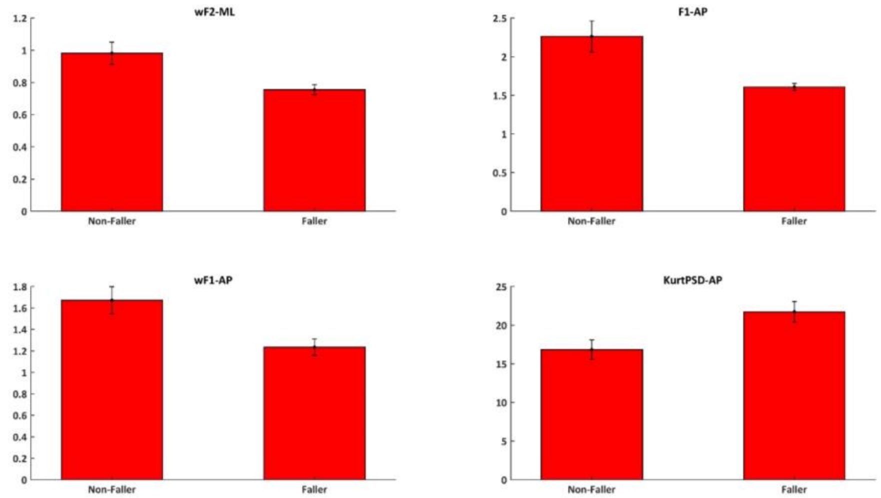

Figure 2. Column graph of features that show significant differences

4. Conclusion

In order to prevent fall in the elderly, the balance of the elderly should be checked frequently. In this cycle, the most suitable environment for balance control is the primary health care centers. Primary health care centers are not suitable for carrying out detailed tests in terms of both time and place. Therefore, using a simple, inexpensive method is very important. Therefore, the development of a simple, inexpensive method is very important. However, there is no definite method in the literature yet. In this study, the frequency domain features of acceleration signals obtained from accelerometers during walking, which are most suitable for use in the primary health care centers, and which are widely used in the field of portable technology, were investigated. As a consequence, it was found that the two new features showed a statistically difference between the faller and non-faller groups.

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